Open-market Energy Procurement Strategies to Integrate Wind Energy

Genaro Longoria Martínez, MSc.

School of Science and Computing

Waterford Institute of Technology

This dissertation is submitted for the degree of

Doctor of Philosophy

Supervisors: Dr. Alan Davy and Dr. Lei Shi

Submitted to Waterford Institute of Technology, August 2020

These are the last words written in the thesis. And I did so because I knew it was going to be the preamble to my catharsis. It surprises me how much I have learned along this path. I am curious and I have learned to be inquisitive. I am independent and I have learned to be self sufficient. I am stubborn and I have learned to be humble. Throughout my life, through harsh and tempestuous times this learning has had a unique steadfast foundation. It has provided the encouragement to contribute and move forward. This work is to thank Elena Martínez Lozano and José Genaro Longoria Sánchez, my parents.

Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy, is entirely my own work and has not been taken from the work of others save to the extent that such work has been cited and acknowledged within the text of my work.

Genaro Longoria Martínez, MSc.

Submitted to Waterford Institute of Technology, August 2020

Acknowledgements

I am deeply grateful to Dr. Alan Davy and Dr. Lei Shi for their innovative support and push to go beyond limits. It was not an easy task. I would also like to express my gratitude to Dr. Pádraig Kirwan for the challenging opportunities he gave me. They made me develop skills and improve both professionally and personally. I would like to thank Ms. Paula Brazil, Ms. Sinéad Day, Ms. Sharon O'Connell for their valuable support all along these years. Furthermore I am thankful to Waterford Institute of Technology for believing in me and its commitment to Research and Education. I would like to say thanks to my friends. I have lifelong memories to cherish: from modeling to algorithm debugging to trip planners to hospital drivers and the infinitely many stories in between. Kriti Bhargava, Kanika Sharma, Sidhant Hasija, Mohit Taneja, Radhika Loomba, Mandy Lalrindiki. Lastly I am immensely grateful to the many people all over the world who have inadvertently helped me to accomplish this work. I am referring to the people and institutions that have taken time to write or record a full course, programming library, tutorial or a short answer to a question and made it publicly available: MIT OpenCourseWare, UC Berkeley, Stack Overflow, Matt Jackson (Stanford University), Kevin Leyton-Brown (University of British Columbia) and Yoav Shoham (Stanford University), Xugang Ye (Dropbox), Cameron Davidson-Pilon, the science bloggers and vloggers, . . .

Abstract

Technological breakthroughs in recent years have no precedent. From the hard to the fog, basically all infrastructures have been influenced or have had an impact from the strepitous progress. To make this possible at the core lies a key factor: Energy. Blessed by the geographic location, Ireland has one of the best wind resources in the world. Wind farms incur in nearly zero marginal costs. Reduce dependence on imported fossil fuels. Also, can be deployed at different scales with ease. Also decentralizes power generation and helps alleviate distribution congestion. The hard infrastructure (e.g. blade and nacelle) has reached a mature state which is reflected in the falling LCOE. Nevertheless, generating electricity from wind power is still dependent on support schemes. Incorporating wind energy into portfolios represents a significant challenge for Load Serving Entities. Therefore the sought after characteristics of wind energy hinder hefty balancing costs percolating to the end-customer, and thus meager or negative profit. Governments around the globe have incentivized renewable generation with tax-based safety nets to provide significant risk mitigation, foster investment and low-cost finance. This work focuses on reducing the need of exogenous support to integrate wind energy. Firstly, the research identifies the operational context of a typical price-taker wind power producer (WPP) and the gaps in the research literature. This gives place to a splitting of the portfolio concocting in two strategical horizons. Following, the research applies non-cooperative behavioral techniques and evolutionary programming to determine long-term bilateral contracts among power wholesalers and electricity retailers. The next step addresses the short term interaction among the WPP and the market. This work also sets the challenges of a micro grid peer-to-peer energy trading setting. Finally an analytics driven trading scheme is developed whereby the exposure to the more volatile balancing markets and penalty fees is automated and optimized.

.

Contents

List of Figures

List of Tables

List of Algorithms

List of Abbreviations

AI . . . . Artificial Intelligence
ANN . . . . artificial Neural Network
API . . . . Application Programming Interface
BM . . . . Balancing Markets
CG . . . . Conventional Generation
CM . . . . Capacity Market
CVaR . . . . Conditional Value-at-Risk
DA . . . . Data Analytics
DAM . . . . Day-Ahead
DDDQN . . . . Dueling Double Network for Deep Q Learning
DemCo . . . . Demand Company
DRP . . . . Demand Response Program
DS2S . . . . Recurrent Deep Sequence-to-Sequence Neural Network
EMCAS . . . . Electricity Markets Complex Adaptive Systems
ERCOT . . . . Electric Reliability Council of Texas
EU . . . . European Union
EV . . . . Electric Vehicles
FLH . . . . Full Load Hours
GA . . . . Genetic Algorithm
GenCo . . . . Generating Company
GT . . . . Game Theory
GW . . . . Gigawatts
HH . . . . High-high
HI . . . . High
HPP . . . . Hybrid Power Plant
HWPP . . . . Hybrid Wind Power Plant
ICT . . . . Information and Communications Technology
ID . . . . Intra-Day
i.i.d . . . . Independent and Identically Distributed
IoT . . . . Internet of Things
IPP . . . . Interval-Parameter Programming
I-SEM . . . . Integrated Single Electricity Market
ISO . . . . Independent System Operator
ISRM . . . . Interval-Stochastic Risk Management
kW . . . . Kilowatts

kWh	kilowatt-hour
LACE	Levelized Avoided Cost of Electricity
LCOE	Levelized Cost of Electricity
LEC	Large Energy Consumer
LL	Low-low
LMP	Locational Marginal Price
LO	Low
LSE	Load Serving Entity
LSTM	Long Short-Term Memory
LT	Long-Term
MAL	Meta Agent Learner
MDP	Markov Decision Process
MEQ	Market Equilibrium Model
MI	Mid
MK	Markovian trader
MRE	Modified Roth-Erev Reinforcement Learning Algorithm
MW	Megawatts
NI	Northern Ireland
O.F.	Objective Function
pdf	Probability Distribution Function
PI	Perfect Information trader
PPA	Power Purchase Agreements
PPAD	Polynomial Parity Arguments on Directed graphs
PSO	(levy) Public Service Obligation
PSO	(algorithm) Particle Swarm Optimization
QL	Q-learning
REFIT	Renewable Energy Feed-in Tariff
RESE	Renewable Energy Sourced Electricity
RGAn	Recursive Genetic Annealing
RL	Reinforcement Learning
ROI	Republic of Ireland
RQ	Research Question
SARSA	State-Action-Reward-State-Action
SDE	Stochastic Differential Equation
SEAI	Sustainable Energy Authority of Ireland
SEM	Single Electricity Market
SEMO	Single Electricity Market Operator
SGA	Standard Genetic Algorithm
SM	Spot Market
SONI	System Operator Northern Ireland
SPM	Stochastic Procurement Model
TET	Total Energy Trading cost
TOU	Time-of Use
TSO	Transmission System Operator
UC	Utility Company
UK	United Kingdom
US NEMS	United States National Energy Modeling System
VNN	Vanilla Feed-Forward Neural Network
wIsHood	Wireless Smart Neighborhood
WPP	Wind Power Producer

List of Symbols

LR	Low risk strategy.
HR	High risk strategy.
$\mathcal{G}$	Game in normal from representation.
$\mathcal{N}$	Set of players in $\mathcal{G}$.
$\mathcal{S}$	Set of pure strategies in $\mathcal{G}$.
D_i	Electricity demand of player i.
P_{CG}	Cost of conventional generation in LT contract.
w_i	Wind power procured by player i.
P_w	Cost of wind generation in LT contract.
p^t	Wholesale market clearing price of energy.
s_i	Strategy of player i.
$\mathbf{s_{-i}}$	Strategies of all players but i.
u_i	Utility of player i.
m^i_{jk}	Payoff matrix element.
U_i	Utility company i.
$\mathbb{E}[P_{\text{SM}}]$	Expected wholesale energy price.
n	Cardinality of $\mathcal{N}$.
$\mathbf{p_i^*}$	Nash equilibrium probability distribution over $\mathcal{S}$.
σ_i^{HR}	Portfolio share of the high risk power source.
σ_i^{LR}	Portfolio share of the low risk power source.
P^+_{CG}	Cost of conventional generation with elastic supply.
P^+_w	Cost of wind generation with elastic supply.
Δ	Difference of objective function and the worst in the pool.
T	Temperature parameter in the RGAn.
μ_{sm}	Long-range mean.
γ	Rate towards the long-range mean.
σ_{sm}	Diffusion term of the SM SDE.
μ_w	Drift term of the wind SDE.
σ_w	Diffusion term of the wind SDE.
Y_j	Magnitude of price jump (i.i.d random variable).
$N(t)$	Poisson counting measure.
$B(t)$	Brownian motion.
$\Phi(t)$	Solution to the wholesale price SDE.
$v(t)$	Wind speed.
$f(v)$	Rayleigh distribution.

α	Autocorrelation decay rate.
erfc	Complementary error function.
CEP	Cost of electricity procurement.
d_w	Share of wind electricity contracted.
$w(v)$	Wind power available.
g	Execution cost in an Options contract.
s	Reservation cost in an Options contract.
ζ	Comparison between wind power generation and
	procurement in the SPM.
x	Energy bought from the spot market.
d_c	Share of electricity allocated to a CG.
p_{sm}	Spot market price.
$\mathcal{P}$	Penalty for under fulfillment of committed demand
D.	
β	Confidence level for CVaR.
$\mathcal{R}_t(s,a)$	Reward function for state s and action a.
p^t_{ur}	Balancing price for up regulation.
p^t_{dr}	Balancing price for down regulation.
S_t	Power supply.
$\mathcal{D}_t$	Power Demand.
ϱ	Price prediction of the DS2S.
Δ^t_F	Difference between Δ_E and $\jmath^t_{st}$ plus $\jmath^t_{hm}$.
r_{up}	Upper reservoir level.
r^{max}	Maximum reservoir capacity.
κ	Share to procure from wholesale market.
$\varkappa$	Binary variable for procuring from the wholesale
market.	
$\mathbb{1}$	Indicator function.
$\jmath^t_{st}$	Stored power from the wind farm.
$\jmath^t_{hm}$	Power consumed from the pumped storage.
Δ_E	Forecast energy.
ξ	Domain of indicator function. Compares ϱ against
the	
	average of the market and Δ_E.
χ	Domain of indicator function in $\mathcal{R}_t(s,a)$.
θ	Boolean sign prediction of the difference between the
	next p_{sm} and the previous.
$\overline{\Delta}_E$	Average energy mismatch.
$\jmath^{\mathfrak{s},t}_{wf}$	Wind power forecast.
$\mathcal{D}^{\mathfrak{s}}_t$	Demand forecast.
$\overline{p}_{sm}(0:t-1)$	Average wholesale price.
r^{th}_{up}	Threshold level of upper reservoir.
$r(t)$	State of the pumped storage.
t	Trading time.
w_i	Positive constants.
λ, ζ, υ	Different time periods with a power outage.

Chapter 1

Introduction

1.1 Background and Motivation

This section provides brief historical context, background and motivation for the research field presented in this thesis.

The last decade of the 20th Century marked all areas of society. Important changes to electricity trading were initiated. It has been argued about the true motivations behind opening the energy sector to private investment but although the early winners of the privatization were mostly the industrial consumers the benefits later percolated to the small consumers [29]. Experience has proven necessary to closely and strictly regulate the industry [29, 71, 99]. Failing to do so can lead to undesirable outcomes such as the 2000 California Crisis [12]. Nearly three decades have passed since the liberalization trend of the electricity industry began in the UK [74]. Pioneering societies that endeavored in the journey today realize that it was a wise initiative but not an easy one [72, 89].

To catch up with progress regulation of the energy sector is constantly reviewed and updated. The strong linkage with the rest of the economy and the never ending pursuit of improving life quality have had a significant influence upon energy industry and its legislation. This is portrayed in the challenging targets set for greener and better electricity generation on the vast majority of the developed and developing countries. Which, at the same time, have required regulatory amendments to facilitate the integration of the newer renewable technologies. To kick start renewable projects, like many other capital intensive new technologies in the past, state support has been necessary [47]. Presently, countries like the Republic of Ireland (ROI), whose renewable electricity generation and energy market are steadfastly established, are firmly and steadily maneuvering to lessen the burden upon tax payers by halting renewable support schemes. Modification to critical infrastructure such as energy, requires careful scrutiny from all stakeholders. A paramount priority is to guarantee accessibility and affordability across the population without jeopardizing reliability of energy supply. This research aims to further pave the way for a support free renewable energy industry.

The rest of this section presents a concise introduction to energy markets, renewable electricity, in particularly wind energy, and the most recent figures with special attention on the Republic of Ireland.

1.1.1 Open Energy Markets

In developed and increasingly in developing countries, the energy supply industry has been radically struck forward from the old monopolistic vertically integrated utilities. The United States have experimented with different approaches to deregulation. Their history is a peculiar case since there has never been a single state-owned utility. However in the mid-1990's a degree of deregulation started [11]. On the other hand, the seminal case of the UK has taught other countries many lessons [48]. The state nationalized the electricity sector in 1948. In 1982 the government hinted its intentions of opening it back to private enterprises. It was not until 1988 that the government published a white paper with plans for liberalization. Finally, in 1990 the privatization commenced. Academics and researches agree that the openness has: 1. Optimized resource utilization and minimized overcapacity; 2. Improved efficiency and productivity; 3. Incentivized innovation and economic growth; and 4. Enhanced welfare.

The process of divesting utilities to introduce competition involves three key elements comprising multiple stakeholders. The first is the ownership change from public to private. The second is the reshaping of a new industrial corporate. Lastly, the legislation designing whereby the new sector is governed [101]. Divesting is a complex process. Its consequences have been difficult to foresee by policy makers in the past. The cases of bankruptcy and bail-out of utilities in California can be attributed in part to a partial openness of the industry and ill-designed legislation. On the one hand, only the wholesale market was open to competition obscuring price signals to the customers. In addition, the existing legislation had a cap on the retail price of power. All together created a weak setting extremely prone to negative manipulation.

In the open market, electricity is traded as a commodity despite its strategical nature. Typically an independent regulatory body is in charge of price controls. Generators and distributors have two main mechanism of marketing their product or service, respectively. One mechanism are bilateral contracts. This requires a generator and a distributor to set the terms and conditions such as price, location and time of electricity delivery. This first type of agreement is done months ahead of delivery. The second mechanism is the energy pool market or spot market (SM). The principal motivation is to allows both parties to fine-tune their positions. Exchanges of energy in the SM happen close to real time, typically 60 or 30 minutes before delivery. The tight time scheduling to dispatch makes the SM prone to high volatility. The SM operates as a merit-order dispatch or an auction based market. In merit-order the less expensive and must-run plants (e.g. nuclear plants) are dispatched first. The resulting price of electricity is determined by the marginal generators, that is, the last scheduled generators needed to cover the demand. In the auction based market, the closing price is the equilibrium price of the bids and ask submitted by generators and distributors, respectively.

The coordination of the SM is responsibility of an independent body often referred as the Independent System Operator (ISO) or Transmission System Operator (TSO). One of the most important objectives of the ISO is to maintain grid stability. The quality of power is measured by deviations from nominal voltage (110/220 V) and frequency (60/50 Hz). To maintain the power within acceptable limits the ISO has access to different markets. The SM is further atomized into several markets. Different time spans are the fundamental criteria behind the splitting. The most common markets are the Day-Ahead (DAM), Intra-Day (ID) and Balancing Markets (BM). In the DAM, parties can submit bids before closing time. This time varies among power exchanges, some examples are 10 am, 12 am or 3 pm [80]. Irrespectively of the closing time the bids are scheduled and executed during the next 24 hours. The Intra-Day market operates between the closure of the DAM and one hour before delivery. Lastly, the BM is open few minutes before physical dispatch. The ISO procures power in the BM to balances mismatches between real and forecast supply and demand. A less common market is the Capacity Market (CM). Generators bid idle capacity that is purchased by the ISO whenever fast response is needed to maintain the stability of the grid. The debate over trading capacity gravitates about inefficiencies and thus costs brought up by this type of market [98]. An alternative that fulfills the need of prompt reaction without sacrificing efficiency is a capacity reserve [32].

To circumvent the volatility of the SM generators and utilities can hedge their positions ahead of time. The electricity industry is required to trade the gross of the power volume through bilateral contracts. Hedging besides reducing uncertainty prevents arbitrage and speculative trading. Common contract designs include: Contracts for Differences, Forwards and Futures. Moreover energy traders can purchase financial instruments in the form of Options. In an Option contract the price electricity has two components. A reservation cost and execution price. The reservation cost, guarantees the utility company a volume of energy at a specific day and time. However it has the option, through the execution price, to partially or not make use of it [117].

The restructure of the Irish electricity sector introduced on November 1st 2007 created a single electricity market (SEM) for the ROI and Northern Ireland (NI). The Single Electricity Market Operator (SEMO), a joint venture between EirGrid and SONI[1] (the transmission operators on both countries, respectively), is responsible of wholesale trading. SEMO became one of the first to integrate two different jurisdictional spot markets [26].

In 2018 Ireland underwent another restructure of the energy market. The reform transitioned the SEM to the Integrated Single Electricity Market (I-SEM). It was planned to go live on May 2018 however I-SEM had to be postponed until October of the same year. The reform couples the Irish energy with pan-European electricity markets. Furthermore, it levels the ground for the electricity wholesalers. The I-SEM will impact renewable generators by moving to a market-based support. Rather than relying on REFIT[2] schemes. The new legislation requires generators and suppliers to forecast their production and load and to bid at the price at which they are prepared to buy and sell, bearing the responsibility of balancing their positions. The new market will increase competition and ease risk management through concentrating trading in the day-ahead, intra-day and balancing markets [21].

The regulatory changes have had a favorably impact on electricity end-customers. The Department of Communications, Climate Action and Environment has submitted its final decision on the PSO[3] Levy [27]. For the period 2018/2019, the tax changed from €92.28 to €41.76 a 55% decrease over the pre I-SEM value.

[1]System Operator Northern Ireland
[2]Renewable Energy Feed-in Tariff.
[3]Public Service Obligation

However this will encourage renewable electricity producers to revisit their trading strategies.

1.1.2 Renewable Energy

The significance of renewable energy stretches beyond the environmental aspect. The importance of renewables can be better understood under the light of the Energy Trilemma. The World Energy Council partitions energy sustainability in three quintessence pillars. Energy Security, the first pillar, is concern about the management of energy supply, reliability of the infrastructure and the capability of servicing demand needs. The second pillar is Energy Equity. It measures the extent to which a population can access and afford energy supply. The third pillar is a two-fold metric. It assess the efficiency of demand and supply and the substitution of carbon based generation with renewable sources.

The falling costs of renewable technologies contributed in 2017 to an estimated 2,195 GW of installed capacity. This record-breaking represents 26.5% of global electricity. 17 countries produced more than 90% of the electricity demand entirely from renewable sources [86]. Furthermore, in 2016, 9.8 million people were employed in the renewables sector a 1.1% increase over 2015. The countries leading the expansion of the sector are China and the United States [42].

A new record was established in 2017, 310 billion dollars were invested in renewables. This more than doubles the amount invested in fossil fuel generation and represents an increase of 4% over 2014. Commercial banks funded the vast majority of utility-scale new projects. Private equity and venture capital investment, however modest in comparison (only 3.4 billion in 2015), increased by 34% [85]. Google, for example, invested 2.5 billion dollars in renewable energy. Since 2007 it is carbon neutral and announced that in 2017 Google's operation will be supplied entirely by renewable energy [34]. In addition, the company signed a power purchase agreement for 536 MW of wind power. Its total procurement of renewable power amounts to 3.1 GW which is equivalent to the total Irish renewable capacity [86]. The large oil and gas companies, an industry that might seem as a natural competitor of renewable energy, are veering to the renewables. Companies like the Dutch Shell, the French Total and Norwegian Statoil are future proofing their revenues by expanding to the solar and wind sectors.

Ireland is introducing a new energy legal framework whereby more and fairer integration of wind energy into the market is possible and thus addressing the challenges of the Energy Trilemma. The Irish score is consistently improved, in 2017 it climbed to the 17th place out of 125 countries assessed [22]. In addition, it ranked as the country with the most added wind power relative to consumption and the 2nd largest for total wind power capacity per capita [86]. In 2015, 9.1% of the gross final consumption was supplied by renewables. This is a significant achievement given that in 2015 the electricity consumption recorded a 4.9% increase. More importantly, it secures the way towards closing the breach with the 16% target of contribution from renewable sources set for 2020. The use of renewables in 2015 meant 286 million euros less in fossil fuel imports whereas electricity generation increased to 27.3% of gross electricity consumption [39].

The blending of renewable energy into the grid requires substantial changes. For the most part, non-dispatchability of intermittent generation is the biggest concern. Several studies have proposed the need of a market for ancillary reserves to facilitate the integration of variable generation [30, 66, 69, 112]. However in the long-term it is not desirable to depend on ancillary reserves because of the distortion to the market signals and inefficiencies that it might provoke [32, 52, 55]. Instead storage and demand-side response can provide the necessary flexibility and circumvent the drawback of supply-side idle capacity [19, 77, 79].

Studies agree that adding renewable sources into the generation mix lowers the wholesale price of electricity. This is a direct consequence of the negligible marginal cost and thus the displacement of incumbent technologies [115]. Another factor are support schemes that coax renewable generators to submit zero or negative bids biasing market signals [107]. Despite the fact of lower average wholesale prices, the variance can increase in relation to the share of non-dispatchable sources [70, 116]. Utilities can avail of lower bulk prices by offering competing contracts to generators whereby attracting a bigger volume of end users. To accomplish this utilities need to hedge their procurement strategies. A hedged energy portfolio could include a share of renewable and fossil fuel sources. To determine the ratios of renewable and conventional to demand it is paramount to quantify the inherent risk and the impact upon profit creation.

The traditional approach to ease capital lending to investments in renewable capacity has been through payments guarantees. The security of cash flow assures the investors the repayment of the loans irrespective of the uncertainty prevailing in the sector. The legal framework behind is known as support schemes. Feed-in-Tariff and Feed-in-Premium are the most common examples of support schemes. The former scheme is also called market-independent, it consists of a fixed price payable to the producer for the power sold to the grid. The latter is market-dependent meaning that rather than giving a bilateral contract to the producer, as in the fixed scenario, the payment received mocks the spot price [23].

Taxpayers carry the burden of funding the support schemes. This means that the risk involved is socialized among the electricity customers. The purpose has been accomplished despite varying degrees regarding the specific technology [45]. However the impact of the supports is not merely the burden of new taxes but also the bias levied in the energy market. The market gets distorted by the deflationary signals send by artificially lowered power bids [19]. The challenge is to accomplish the integration of variable energy sources in a self-sustained manner such that external support is deemed redundant.

1.1.3 Wind Power

We can argue that long before human kind walked on the surface of the earth wind power was already shaping it. Wind is a direct consequence of the atmosphere and sun radiation. In a sense is a byproduct of solar energy. Temperature and pressure gradients create motion of atmospheric air molecules; this we call Wind.

Although the relationship between wind power and the human race is a continuum, the interest of the latter on the former has been cyclical. Researchers believe that more than 5000 years ago Egyptians where already harvesting wind power using linen sails [87]. Moving forward in time, the first appearance of inland exploitation of wind power is rather unclear and many legends exist. Nevertheless evidence confirms that windmills were in use around the 9th century in todays Iran and southern Afghanistan [4]. Persians converted wind into mechanical power to grind seeds and transport water to irrigate their fields.

A similar concept but a rather different structural design permeated Europe in the 12th century strengthening the Medieval industrial revolution. Leaping forward to the late 19th century, electricity was for the first time generated from wind. In 1888, Charles Brush constructed a 12 kW direct current wind generator in Cleveland, Ohio [49]. Despite its simplicity and low cost wind turbines did not get much attention during the twentieth century [15]. Instead electrification backed by fossil fuels concentrated the vast of the attention.

The debate about wind power in modern days should not surprise us. This has been a topic of controversy since its primal days. Holders of water rights in twelve century feudal Europe controlled the lives of their subjects. In England, the nobility and the clergy "owned" the rights to water. One way they exerted ominous control of commerce and society was by means of grinding revenues. The well established waterwheel mills was a privilege that peasants could not afford to possess however they could pay to use [87]. This setting sparked creativity in the middle class to challenge the water monopoly. The 13th century experienced a construction boom of wind mills and antagonistic disputes did not wait long to emerge.

The next milestone came from Sweden and Denmark more than a century after the first onshore wind power generator. In 1990, the Swedes installed the first offshore wind turbine. A year later the Danish company Elkraft[4] pioneered offshore wind farms [91]. Until its decommission in 2017[5] the farm was located in shallow waters 2 km from Vindeby's shore and consisted of 11, 450 kW, turbines.

Worldwide the year 2017 closed with more than 510 GW wind capacity installed and connected. This represents an increase of 10% with respect to 2016 [113]. Denmark set a new annual record in 2017 with 50% of the electricity generation coming from wind power. Worldwide the total financial investment increased 15% over the average of the last decade. The estimated quantity for 2017 is in excess of 100 billion US dollars [86].

The growth of wind industry between 2000 and 2011 was at a rate of 27%. On average every three years the installed capacity has been doubled [40]. Nameplate turbine capacity had a dramatic 172% increase in the latter years of last century. Rotor diameter and hub height, with average diameter of 99.4 meters and 82.7 meters high, experienced a 108% and 48% increase respectively [114].

An important driver to this figures is the falling cost of wind turbines. The International Renewable Energy Agency's 2018 report found a 37-56% decrease, depending on the market, with respect to the 2007-2010 peaks [43]. The levelized cost of electricity (LCOE) continues to decrease for wind capacity. Recent estimates of the LCOE for wind power place it lower than gas and nuclear power [9, 31]. The cost of onshore wind farms decreased from \$4,766/kW in 1983 to \$1,623/kW in 2014. The onshore wind global weighted average LCOE is estimated to decrease

[4] A predecessor of DONG Energy

[5] The concession was for 25 years. In 2017 DONG dismantled the farm. The spare parts are going to be reused and the blades given to DTU Risø as part of a research project.

26% by 2025 [3]. The appeal of investing in wind power is reflected in US NEMS[6] estimates for the difference between LCOE and LACE[7] (the levelized avoided cost of electricity) for plants entering service in 2022 [41].

Indirect Private investment is also spurring into the sector. In 2017, big technological companies such as Google, Amazon and Microsoft signed wind power agreements to light their business. The modernization to the legal framework is permitting the coupling of markets and jurisdictions thus allowing complex procurement of power to be possible. On December 2016, Google signed a 12 years long contract to purchase the entire wind electricity production of a new Norwegian wind park. The nameplate capacity of the 50 turbines wind farm is 160 MW. BlackRock, the world's largest investment management firm [124], provides the equity to finance the project. This power purchase agreement is only possible because of the integrated European energy markets. Google is capable of procuring the electricity from Norway and consuming it elsewhere in Europe.

The other most common energy scheme is the Microgrid. In this setting the load from a consumer or microcluster of consumers is served from self generation. In 2017, BMW deployed a 15 MW storage facility for its 4 10 MW turbines wind farm in Leipzig, Germany. Beside consuming the own generated electricity it supplies the grid with surplus generation during the plant's off-peak periods. From an economical perspective this creates a 3-sided decision challenge: At any given moment what is the most profitable way of using the wind power. That is, store, consume or offer it to the grid. This thesis contributes an answer to this conundrum.

The independent institution in charge of bringing a low carbon economy to the ROI is the Sustainable Energy Authority of Ireland (SEAI). The mission of the SEAI is to designs programs to increase awareness and engage the society

[6] United States National Energy Modeling System.

[7] Avoided cost removes the biased when comparing non-dispatchable and dispatchable technologies.

into transitioning to a more efficient and sustainable energy future. At the same time assesses and informs the Government about energy matters on the current performance and possible future status. In particular in Ireland wind power has the biggest share within the renewables. According to the SEAI 2016 report, wind generation represented 80% of the total renewable electricity generated. The country's installed capacity at the end of 2017 was more than 3 GW, an increase of 15% over the previous year. The report estimates that wind infrastructure contributed the most to the reduction of greenhouse gas emissions. The electricity generated from wind avoided 2,436 kilo tonnes of CO_2 emissions [38].

The top five countries for total wind power capacity per inhabitant, at the end of 2017, were Denmark, Ireland, Sweden, Germany and Portugal. In particular, Ireland integrated the most wind power capacity relative to its electricity demand [86]. By 2015 9.1% of the Irish gross final consumption was supplied by renewables, practically half way from the 2020 target of 16% [75]. Ireland has a prominent location with respect to Europe. Figure 1.1 presents potential wind power harvest of Europe and the outstanding potential of Ireland. In [94] Ryberg *et al.* estimate the Full Load Hours (FLH) metric for the EU countries. The FLH metric is of interest because it is negatively correlated to the LCOE. In the ranking Ireland has an outstanding place owing to its privileged position. The European average is 2560 FLH whereas Ireland's figure is 3949 FLH. In terms of LCOE, the estimated average for Europe is €0.665 per KWh; Ireland has the potential to generate wind power at €0.3 per KWh [94].

Despite the comforting figures mentioned above, in three modeled scenarios, the latest projection report of the SEAI states that the country might fail to reach the 2020 renewable energy integration and energy efficiency target [75].

The topic of this thesis is aimed to facilitate achieving the targets for renewable energy. It is focused on the contractual aspect of electricity procurement. More

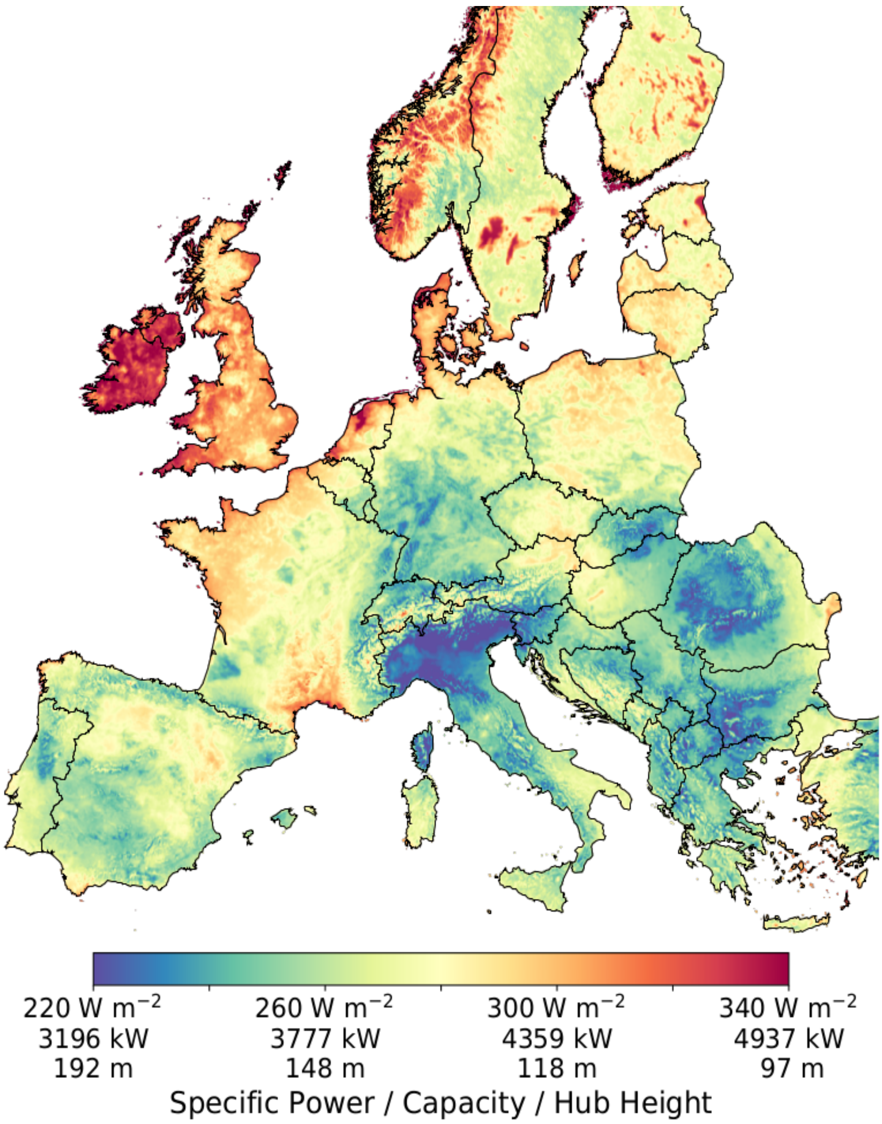


Fig. 1.1 Estimates of Wind turbine design across Europe [94].

specifically to avoid taxpayer support with a seamless integration of variable power into utilities portfolio.

1.1.4 Challenges

The preceding sections have presented a general overview of the current situation of renewables and energy markets. The text has made special emphasis on wind power and the figures pertaining to the Republic of Ireland. Although, the figures are promising, utilities still face new challenges to integrate renewables into their portfolios. A clear example is the modification of the electricity legislation in the ROI. For more than a decade utilities with power purchase agreements (PPA) with wind farms have had access to a support scheme that had guaranteed a steady income irrespective of market or weather conditions [28]; the so called REFIT[8] schemes and its predecessor RESE[9]. These schemes are no longer available.

In addition to the halt of the support, the I-SEM, a new market environment was introduced in Q4 2018. Among several changes, the new conditions require the renewable industry to be responsible of balancing their positions rather than relying on a support to cover up for lack of electricity supply. The current state of the art is far from fully meeting the new setting faced by Load Serving Entities (LSEs).[10] We envision that to increase wind penetration the properties of next generation wind energy trading should be self-sufficiency with respect to profit creation, autonomic trading and making part of the operation the power balancing responsibilities.

These properties signify important problems, specially for LSEs. This work presents solutions to these challenges. The remaining of this section list the challenges (**C1-C5**) addressed in this research.

[8]Renewable Energy Feed in Tariff.
[9]Renewable Energy Sourced Electricity.
[10]Load Serving Entities, Utilities or electricity retailers are used interchangeably throughout the document.

C1 Contract Offering

Electricity prices are prone to high volatility, on the other hand to account for the lack of electricity storage of scale, legislation of energy markets favor forward contracts over real-time trading. The long-term (LT) bilateral contracts offered by electricity retailers to wholesalers should be designed to take into account the competitiveness of other retailers as well as the variability in electricity generation by wind farms. Therefore, the hedged contract must optimize the trade-off between uncertainty and profit. The contract would then be a mix of conventional and renewable generation that balances the procurement trade-off.

C2 Heterogeneity

Electricity retailers can have a myriad of different specific needs. For example, the degree of risk aversion or customers with loads of different magnitudes. Also, the generators could require complex pricing strategies depending on the quantity of power delivered. Such heterogeneity may translate as non linearities in the competitive model. Moreover each party is self-interested and autonomous. Thus, the mechanism to design the LT contract should provide an answer irrespective of the heterogeneity of electricity retailers.

C3 Risk Exposure

The long-term contract offering necessarily depends on market and power generation statistics. The potential of estimates deviations, as a result of uncertainty, can negatively and significantly counteract the hedged strategy. A risk assessment could leverage the potential of LT contracts with renewable generators. Two important source of risk should be addressed: 1. Electricity market fluctuations and; 2. Renewable generation.

C4 Spot Market Trading

An integral hedged portfolio should include as part of the energy procurement a short-term trading strategy. Long-term contracts with wind power producers rely on weather forecast. Moreover, the power purchased also depends on the demand forecast. However accurate, there exist a considerable error that needs to be accounted for and acted upon. On the one hand the task is to quantitatively assess the risk for a given portfolio. The holder of the portfolio should be capable of defining a desired risk policy. On the other hand, real-time demand and supply mismatches should be balanced in the spot market. The decision making about position balancing has to be fast paced to contend with the high frequency trading in the intra-day market.

C5 Technology Coupling

Coupling different generation technologies helps to diversify the risk. A common example are wind and solar farms. Wind and solar energy can be negatively correlated, bringing them together smooths the generation output. Another approach are hybrid power plants in which a principal source of power is complemented with a storage system. In the specific case of wind energy, a coupled system not only serves to flattened the electricity produced but also to reduce spillage and curtailment due to off-peak demand. However the control of a coupled system is not a trivial task. In this thesis we concentrate only on a hybrid systems. The decisions involve determining how to best utilize the combined production of wind power and the complementary system. The design of the trading strategies should take into consideration the optimal management of the system such that it further contributes to minimize the procurement cost of the LSE.

1.2 Research Scope of the Thesis

This section discusses the scope of the research presented in this thesis. Section 1.2.1 presents the limitations of current integration methods of wind power in utilities' portfolios which is the focus of this thesis. Section 1.2.2 discusses the main objectives of the research, these are presented in the form of Research Questions. The work in this thesis is divided in two parts. The first part concentrates on the long-term perspective of electricity procuring by retailers. In particular, the focus is on designing strategies to allocate wind and conventional energy sources in a competitive market, that minimize procurement cost in the long term. The utilities are considered to be rational, self-interested, profit maximizers and non cooperative among them. This part of the thesis subdivides the procurement process in two tasks. First the design of a strategical contract for given market and wind site characteristics. And secondly a stochastic methodology to quantify the portfolio's risk.

The second part of the thesis focalizes on the short-term managing of electricity. An electricity trader can typically adjust its positions one hour before dispatch in order to avoid the more volatile markets and penalty fees. More specifically, in the second part the research focuses on the combined production of wind energy and an ancillary pumped system. The generation is either channeled within the system or traded externally in the electricity market. Market in this context, can be interpreted as an energy exchange or a microgrid.

The two parts of the research are entitled as follows:

P1 Long-term wind power contracts

P2 Short-term trading management

1.2.1 The Limitations

In the open-market environment, the stakeholders in the electricity supply chain strive to create profit. From the perspective of an LSE, there are a few ingredients that play a key role in making profit, such as, retaining and attracting customers. One basic rule to make this happen is offering a low cost product which in turn means procuring at even lower costs. Because of its negligible variable cost, wind power is a formidable means of procuring low cost electricity. However, in a support free market, the holders of variable energy contracts are exposed to high uncertainty about revenue inflows and potential hefty payments. Nevertheless, it is possible to hedge the uncertainty. In the following the lifecycle of electricity contracting is split in two timescales and presents the limitations therein.

Long-term wind power contracts. LSEs procure the vast majority of their electricity commitments through long-term contracts. This gives certitude about energy supply and price. In the pre-renewables era, volatility in energy markets was in general a direct consequence of fuel prices. Oil prices can be dramatically affected by a handful of factors, from the geological to the geopolitical. An energy retailer could reduce the effect of oil price swings by diversifying with renewables. However this may have adverse effects when the uncertainty in weather variability is not considered in the design of the energy contract. This limitation correlates with the challenge ***C1 Contract Offering***.

In addition to accounting for variability in electricity generation, another factor relevant to open markets is competitiveness. An LSE can face a bottleneck offering contracts or paying premiums to secure them. The main limitation is the access to partial information of the market participants. Thus, the designing of an LT contract must determine a best response strategy that takes into consideration the competitors own strategical decisions. The equilibrium strategy must guarantee that deviation from it would convey less optimal results to the market participants. This limitation also correlates with the challenge ***C1 Contract Offering***.

The heterogeneity among the LSEs can organically hinder the determination of the best response strategy. LSEs in a given market can compete for the same contract but could differ internally among themselves, for example market share. Therefore the contract designing methodology needs to be robust to incorporate competitors with different internal policies. The competitive model can be expressed as a non-linear coupled system. This limitation correlates with the challenge ***C2 Heterogeneity***.

Another factor that plays an import role in asset diversification is the policy towards risk. The likelihood of adverse outcomes needs to be quantified to enhance the reliability and provide certitude to the LSE about the LT contracts. Furthermore, the technique to evaluate the portfolio should be convergent to a solution regardless of the risk aversion of the holder. This limitation correlates with the challenge ***C3 Risk Exposure***.

Short-term trading and management. Complete certainty about future commitments is limited by the forecast error on weather and real-time market prices. To minimize, the negative consequences of failing to comply with the demand commitments, LSEs can make balancing trading in the spot market. In a perfect market, forward prices are an unbiased signal of prices in the spot market and as such can guide on the just-in-time position balancing. However, energy markets are far from being perfect. An estimate of future events can help to circumvent this limitation and balance the long positions of the LT contract. The time shift of the future events of interest is within close proximity. The short time difference between events decorrelates them from control states that affect mid-term scaling trends. This is a feature that can be exploited although it poses a difficulty. The time lapse between events in the spot markets implies taking actions at a high frequency. This limitation correlates with the challenge ***C4 Spot Market Trading***

The adverse impact of weather variability is not only limited to deficit generation. Excess production because of unaccounted weather or lower demand is also an overwhelming factor. Spillage and curtailment are the most common ways to handle surplus generation. This limitation can be used as an advantage if equipped with a storage device and a management system capable of orchestrating the flow of electricity. Furthermore it adds an extra element that can serve to minimize the spread between demand and supply. In addition, the decreasing cost of self generation and further openness of the electricity sector are fostering the development of decentralized microgrids in both rural and urban settings. The safe operation and optimal decision making can be limitations of managing the electricity generation and the trading within the microgrid. This correlates with the challenge ***C5 Technology Coupling***

1.2.2 The Objectives

The research was organized in three work packages. The second work package addresses the five questions of the research. There is a sequential flow from the first to the last question, nevertheless each of them can be understood individually. The remainder of this section presents the two parts of the research and the questions addressed by each part.

Long-term wind power contracts: The first part of the thesis presents a theoretical formulation that models the adversarial setting between two utility companies. This part of the research explores contract pricing with a wind power producer (WPP), the ratio of renewable energy to total demand and the portfolio risk. The utilities compete with each other by means of contract offering to the WPP. In addition to the partial information accessible to each utility, the adversarial setting describes the self-interest and non-cooperative characteristics of the utilities. The objectives of the first part of the work are expressed by the following Research Questions (RQ):

P1-RQ1 **Gaming equilibrium** *What is the energy portfolio of LSE companies procuring electricity from long-term contracts with conventional and wind power producers?* (Challenge C1)

P1-RQ2 **Heterogeneity** *How to find the equilibrium portfolio for multiple LSEs with heterogeneous demand?* (Challenge C2)

P1-RQ3 **Risk assessment** *How to generalize a methodology to determine the risk on hedged portfolios for different wind and market characteristics?* (Challenge C3)

Short-term trading and management: The second part of the thesis investigates on the intra-day trading and technology coupling. The intra-day market is characterized by fast and short-lived events. From the LSE point of view, the spot market serves to minimize the foreseen mismatches between supply and demand. Although the quandaries of the spot market there is the advantage of having access to more accurate weather and demand forecast, however for a short period of time. Similarly, combining uncorrelated technologies can further improve reducing the supply/demand spread. Thus, the LSE can avail of these opportunities to avoid exposure to the more volatile balancing market or penalty fees. This last part presents an implementation of a trading orchestration that exploits the previous features and manages the combined production of a hybrid power plant. The objectives of the second part of the work are expressed by the following Research Questions:

P2-RQ1 **Fast signaling** *Can a deep artificial intelligence model provide accurate signals for short-term procurement?* (Challenge C4)

P2-RQ2 **Agent trading and management** *How to automate the trading with the spot market and internal management of a hybrid power plant?* (Challenge C5)

1.3 Solution Method

This section presents the techniques employed to answer the research questions. The theoretical work has been verified numerically. The testbed simulations considers synthetic and real market and weather data. The latter has been retrieved from NordPool, one of the most relevant and growing power exchange pools in Europe.

1.3.1 Long-term wind power contracts

P1-RQ1 **Gaming equilibrium:** Markets around the globe are the result of behavioral economics. In all markets, with enough liquidity, we can see the price fluctuation of the assets. Uncertainty is a primal factor influencing an investor's decision to acquire or retain an asset. Energy markets are not oblivious of this reality. Is because of this reason that support schemes have been necessary to create momentum for renewable capacity investment. It is paramount, to increase integration of renewables efficiently, to find the way such that renewable sources are financially buoyant without external support. Long-term contracts can hedge fuel uncertainty and weather variability when designed to maximize the expected utility of the holder. To answer this question this work uses a game theoretical approach. The behavioral economics of designing an LT contract with a WPP is studied as a non-cooperative game.

Several methods for portfolio creation have been proposed [1, 5, 13, 56, 73], though they are designed without taking into account wind power or competitive environments. To propose a solution to this challenge this work employs a similar concept, that is, the conflict-of-interest between reliability and cost is analyzed as a procurement game. The mixed Nash equilibrium is understood as the solution portfolio to the procurement game. In the model, the Nash portfolio is the allocation strategy that maximizes the expected utility of the LSE.

P1-RQ2 **Heterogeneity:** The advent of the smart grid will increase the number of directly involved energy trading entities [10, 51, 88]. The direct participation of distributed stakeholders will create newer markets adding more demand heterogeneity.

This research question generalizes the procurement model defined in P1-RQ1 in a context of multiple players with heterogeneous characteristics. In addition to demand heterogeneity, power producers are considered to have a non-decreasing supply response. The coupled system with the added diversity also adds complexity to the model in P1-RQ1. Daskalakis *et* al. proved that computing a Nash Equilibrium approximative solution is PPAD-Complete[11] [25]. For this reason I developed a numerical algorithm instead of solving the model analytically. The two main features of the solution method are its freedom of customization and scalability. In summary, this part of the work designed the RGAn algorithm 3.1 to determine Nash equilibria portfolios for a densely interconnected network of LSEs.

P1-RQ3 **Risk assessment:** An LSE can face hefty costs if its supply and demand are unmatched. Mismatch costs serve to ensure the stability of the grid such that voltage and frequency remain at all times within the very tight ranges. Therefore system operators impose penalty fees or imbalance costs to maintain a safe operation of the distribution infrastructure. Energy traders can hedge exposure to the more volatile balancing markets if the ratio of renewable energy to total demand takes into consideration the hourly values of spot prices and wind generation.

[11] Polynomial Parity Arguments on Directed graphs

The method proposed to address this research question presents an approach to quantify the hourly dynamics of wind power and an energy market and the impact on long-term costs. In the literature there exist several techniques to model this types of dynamical systems. Typically time series is a common utilized technique [54], however they lack flexibility. Instead I use a stochastic approach because it can closely resemble the seasonality and mean reversion characteristics of electricity spot prices [16, 57]. Features, such as lack of storage of scale and grid stability make the energy market prone to sudden jumps of short duration. On the other hand I considered the autocorrelation of wind speed as a parameter of wind trajectories rather than a result. In summary, this part of the research developed a stochastic procurement model (SPM) for the risk assessment of electricity portfolios.

Two risk metrics complement the results of the SPM: Conditional Value-at-Risk (CVaR) and Excess Cost. CVaR is a consistent measure of risk in terms of the probability of high costs in a portfolio with Option assets [92]. Moreover CVaR is more robust than other risk metrics, for example its predecessor Value-at-Risk, because it quantitatively assays extreme events [6]. On the other hand, Excess Cost is the probability of exceeding a defined threshold. This features add flexibility to LSE to consider different risk policies. To bring the pieces together I implemented a Monte Carlo algorithm to test the SPM.

1.3.2 Short-term trading and management

P2-RQ1 **Fast Signaling:** The electricity spot market is an auction based exchange. Successful bidding requires setting the price of the ask or bid close and lower than the clearing price. However the clearing price is only known after the auction has finalized. Adding to this complexity, another challenge is the frequency of the auctions. The spot market in different exchanges could have various trading floors, the most common is the hourly floor [97, 106]. LSEs use this mechanism to flatten their supply and demand differences close to real-time.

This part of the research proposes a two layer decomposition of short-term trading. First a novel artificial intelligence model for anticipating SM prices. And data analytics to process the input data. The proximity of trading windows is the key factor exploited for the successful results. The analytics part extracts knowledge off the streams of the raw input data. The AI model uses this knowledge to create wisdom. The system predicts a sign change of the next clearing price with respect to the current one. In addition, creates a belief vector about the likelihood of the next clearing price belonging to a known cluster.

More specifically the analytics layer categorizes the most important features utilized by the AI model. This layers implements a pattern recognition algorithm to classify the raw values. The motivation behind this layer is to take into account the seasonality as a performance leverage. It aggregates the demand and price data into clusters of different scales. These include yearly, monthly and hourly clusters. The aim is to increases the accuracy of the prediction layer using the clustered data.

P2-RQ2 **Agent trading and management:** A fundamental challenge of smart grids is handling the sheer size of atomized trading. In the smart grid the vertical arrangement of the energy supply chain is going to be shaken to its bare foundations and transformed into a complex network of distributed interconnected prosumers. Agent trading can provide a solution to the overwhelming task of managing the many-to-many interactions of nodes in the decentralized network [37, 46].

This last part part of the research studies the management of a hybrid power plant (HPP). More specifically, the aggregated generation of wind and hydro power. The goal is to allocate in a cost-effective way the output of the HPP. At each instant, the best decision is determined by a) the current and foreseen market, b) weather and c) demand conditions. This work considered the following possible actions: 1. Offer surplus wind power on the SM; 2. Use the combined generation to satisfy demand and procure lack of generation on the SM; 3. Store wind energy as potential energy in the hydro plant and instead procure committed position on SM; 4. Sell hydro power on the SM; 5. Use stored power and procure the lack of power on the SM and; 6. Do nothing.

The short-term decision-making is automated with a reinforcement learning algorithm. An agent that consists of several instances of itself brings together the pieces of the work done in the second part. The agent maneuvers the electricity of the HPP in a cost effective way by means of furnishing the decision making with the necessary information from the predictions obtained in the previous research question.

1.3.3 Validation

Testing and validating the ideas presented has been a cornerstone concomitant all along this research. The models and algorithms developed have been validated with simulations. The numerical simulations have used both synthetic and real data. In both parts of the research we designed and developed the simulators used to test our models. The external dependencies have been carefully investigated and selected those proven to be robust and sound. In particular, the numerical simulations on P1-RQ3 incorporates an stochastic discretization C library [50]. On the other hand, the second part of the thesis uses well established and validated API's for data analytics and artificial intelligence [2, 65, 81].

Simulations on the first part of the research largely relies on C implementations whereas the second part adopts Python, a more versatile programming language for scientific computations. The gathering and pre-processing of data was automated with several tailor made Python scripts. All the real data comes from official but publicly available sources. The synthetic data was chosen so that it resembles real market conditions. Finally, to run the programs and store the results, a dedicated, although small, cloud computer was set up to host the simulators.

1.4 The Contribution

The primal drive of this work is to positively contribute to the advancement of diversifying energy assets. More succinctly, decarbonizing utilities with a risk controlled integration of renewable energy in their portfolios. I believe the results of my research can make one piece clearer the inclusion of the intermittent energy puzzle.

The following sub sections summarize the main achievements of the research. The results of both P1 and P2 are presented below, the tables 1.1 and 1.2 provide a map between the Research Questions, results and the published work. The latter is the output of the work done.

1.4.1 Long-term wind power contracts

P1-RQ1 **Gaming equilibrium:**

A1 The results of the first part of the work have Game theory as the modeling framework of the LSEs' trade-offs. The work modeled the decision-making involved in the process of designing a bilateral contract with a wind farm or a conventional power generator. Thus two strategies are considered: a) the low-risk but expensive conventional energy and b) wind energy which is characterized as less costlier but of higher risk. In addition, the involved parties are deemed rational, self-interested and profit maximizers. In this context, we introduced *indistinguishable players* as a new concept in Game theory.

A2 The expected result of the game model is the equilibrium point in which no player has an incentive to change strategy. Firstly the focus was on the case of single or "pure" strategies. I present a method for reducing the configuration space of equilibrium search for pure strategies. The asymptotic complexity is reduced from $O(2^n)$ to $O(n)$. The method is proven utilizing the concept of indistinguishable players in binary games and borrowing ideas from statistical physics.

P1-RQ1 **Heterogeneity:**

A3 The scope of the model was broadened by considering price heterogeneity. This means that rather than a flat cost per kWh, the price was considered to depend on demand. To incorporate the dependency of prices on demand, the work modified the pay-off matrix of the gaming model. In this context the mixed strategies Nash equilibrium solution is derived. The solution is utilized as a diversified energy portfolio. Mixed strategies can be understood as the utility's contracting policy of conventional and wind power.

A4 In solving the game model, I found a bargaining scheme for price negotiation. The analysis of the mixed strategies in the heterogeneous case lead to a wind energy price range that can be exploited by the LSE when offering long-term contract to wind power producers.

A5 The scope of model was further increased by adding demand heterogeneity among the LSEs. This added requirement also increased the complexity of the challenging task of determining the equilibrium of the game. I designed a tailor made algorithm to find the mixed strategies Nash equilibrium and thus the energy portfolio for each LSE. The solver combines two robust heuristics: the Genetic algorithm as search method and an annealed routine for determining if a candidate solution should be rejected or included in the gene pool.

P1-RQ3 **Risk assessment:**

A6 The stochastic procurement model (SPM) represents the real-time trading of the LSE in the spot market. The result is the theoretical basis of an integral stochastic model for the dynamics of electricity price and wind power. This duality is the main contributing aspect of this achievement. The relevant features that characterize power price paths are taken into consideration with the Ornstein-Uhlenbeck and Lévy processes. These features include short lived sudden jumps and trend inertia typical of spot market prices. Moreover, the work also models wind paths with a Brownian process with multiplicative noise. The drift and diffusion of the SDE are adapted so that the solution trajectories resemble the autocorrelation of a chosen wind distribution. In conjunction, the model convergences to an optimal portfolio irrespectively of the WPP characteristic autocorrelation decay rate.

A7 The SPM on its own provides little information with respect to undertaken risk. Thus, the model is assessed with two risk metrics: CVaR and a metric I designed which is termed Excess Cost. Both metrics complement each other. The former sheds light on the average tail events. The latter quantitatively evaluates the likelihood of a given portfolio incurring in high cost procurement. In the testbed the results show a 15% to 18% wind power integration.

Table 1.1 P1 Research Achievements

RQ	Challenge	Achievement	Presented	Appendix
P1-RQ1	C1	A1, A2, A3	IEEE ICRERA 2016	A
P1-RQ2	C2	A4, A5	IEEE ICSG 2017	B
P1-RQ3	C3	A6, A7	SPRINGER TESG 2018	C

1.4.2 Short-term trading and management

P2-RQ1 **Fast Signaling:**

A8 The second part of the research states the challenges of peer-to-peer and neighborhood-to-grid electricity exchange. The work then proposes an automated mechanism that is capable of interacting with several of the market components in synchronisation with the speed of events. The first constituent is the analytics instance. The motivation is that by applying some effort it is possible to retrieve "free" knowledge. The goal is then to find patterns in the streams of raw demand and electricity price data. The K-Means algorithm is used for pattern discovery. Those patterns or clusters provide the knowledge necessary to carry on further functionalities.

A9 The prediction of SM prices is a second instance of the automated trading. The leveraged property is the close proximity of events in short-term trading. The prediction instance is a recurrent deep neural net with a vertically stacked sequence-to-sequence architecture (DS2S). In this implementation, The Hidden layer represents the vertically stacked units. We use LSTM units [35] to capture the long-term temporal tendencies of mean-reverting energy prices [14]. The adaptability to foresee can improve the accuracy, in large sequential datasets, as compare to vanilla neural models [100].

P2-RQ2 **Agent trading and management:**

A10 The last part of the work aims to bring closer machine learning and energy trading with a decision-making agent. The agent wraps together the analytics and prediction instances. Our approach is the MAL, an holistic agent-based methodology to power supply management. The MAL is formed by a tiered framework to manage a hybrid energy system on behalf of a power producer. The three fundamental instances of the MAL are 1) A clustering algorithm to extract knowledge of the raw data; 2) A deep sequence-to-sequence recurrent neural network to forecast day-ahead prices; and 3) A multi-policy Q-learning algorithm for decision-making. The performance of the MAL is validated with data from NordPool.

Table 1.2 P2 Research Achievements

RQ	Challenge	Achievement	Presented	Appendix
P2-RQ1	C4	A8, A9	SMARTGREENS 2017 IEEE TSE	D E
P2-RQ2	C5	A10	IEEE TSE	E

1.4.3 Publications

The work and results of the research have been published in a number of research articles. The publications list include 5 peer-reviewed articles. Two have been published in journals, namely *IEEE Transactions on Sustainable Energy* and *Springer Technology and Economics of Smart Grids and Sustainable Energy*. The other three articles have been published in conference proceedings, namely *IEEE International Conference on Renewable Energy Research and Applications (ICRERA 2016)*, *IEEE International Istanbul Smart Grid and Cities Congress and Fair (ICSG 2017)* and the *INSTICC International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2017)*.

Chapter 2

State of the Art

The openness of the energy sector, interest in decreasing dependence on fossil fuels and the advent of the smart grid has attracted wide attention on possibilities to include bigger shares of renewable energy. This chapter presents the state-of-the-art (following the same order) of bilateral contracts, price modeling and autonomic trading.

2.0.4 Contract Offering

The openness of the energy sector has attracted the attention from the research community, for example, [5, 17, 18, 33, 53, 56, 68, 78, 93, 119, 121, 125]. These works implement behavioral theories to model the interactions or trade-offs among conflicting elements. The aim is to determine an equilibrium states that satisfies all the parties involved; this state is represented in the form of a binding contract.

High frequency and large amplitude fluctuations can occur in almost all commodity markets but in particular in the energy market. To constraint the occurrence of sudden escalations, energy legislation requires suppliers and retailers to engage in especial market instruments. These instruments are off-market agreements between producers and retailers. The specific name of these agreements are bilateral long-term contracts. In this work we consider the *Options* type of LT contracts. This means, the price of electricity has two components. A reservation cost and execution price. The reservation cost, guarantees the utility company a volume of energy at a specific day and time. However it has the option, through the execution price, to partially or not make use of it [117].

More specifically this research focuses on portfolio creation of a utility company (UC), the retailer, seeking to hedge its procurement cost by signing an LT contract with a wind power producer and a conventional generator, the producers [61]. The UC balances the real-time commitment mismatches in the spot market. In particular non cooperative Game theory is applied to model the trade-off between reliable but expensive conventional generation [125] and uncertain but cheap renewable power.

In the literature, Game theory (GT) is the *de facto* methodology to model conflict-of-interest problems. Also, in the field of energy contracting is commonly used to determine best trade-off strategies between risk and profit. The work [56] presents a game theoretic approach to energy trading among microgrids. In the analysis, surplus energy is offered and the microgrids necessitating energy submit purchase orders. The utility function of the seller expresses the trade-off between storing or selling surplus electricity. On the other hand, the buyers' *social welfare* is expresses as the price gap between energy from the national grid and from neighboring microgrids. The emphasis resides on studying the effect of various sellers and buyers upon the equilibrium energy price. In [121] the authors model the bargaining process between a GenCo (generating company) and an LSE. The work assumes full communication between both parties with cooperative GT. Moreover, it also considers the GenCo to have a secure and reliable source of fuel for electricity generation. The uncertainty in the studied problem is solely the spot price. The sense of this thesis differs from these works in the integration of wind energy and in particular also differs from [56] in considering the statistics of the market price.

Yi et al. analyze the contract price of power producers [119]. The competitiveness to attract consumers is modeled with Bayesian GT. The work assumes a quadratic cost function, that is, conventional generation only. Thus each generation company knows its own cost function but not the cost of its competitors. The optimization variable is the fix price of the contract. The heterogeneity of the system is modeled as a characteristic Type for each player. The risk uncertainty of procuring energy from the spot market is not considered to simplify the analysis. The Nash-equilibrium of the game is found using a standard genetic algorithm (GA). Convergence is reached when the value of the objective function reaches a steady state. However it is known that standard implementations of evolutionary algorithms suffer from premature convergence [67, 90]. In [60] we designed an improved version of the standard GA. A benefit of our implementations is faster existing local minimum solutions.

The work in [33] models a coalition of renewable sources. The objective of the coalition is to minimize the insufficiency of load supply by aggregating their electricity generation. The problem is to maximize the worst-case such that the renewable producers are incentivized to remain in the coalition. The authors use cooperative GT to model the coalition formation problem. However desirable this is, there is always the challenge of competitors; which is also desirable. An obstacle addressed by the authors is the intractability of the problem as the number of parties grows. They use Benders decomposition to divide the original problem into a master/follower iterative algorithm. In [60] we present an efficient algorithm to find the Nash equilibrium with the additional generality of considering demand heterogeneity of the LSEs.

A similar approach is presented in [17]. The authors propose to maximize the realized profit of the coalition rather than the average profit. The goal is to obtain a contract that is coalition-stable. This means that the distribution of profits among the coalition is equitable. A drawback of this contract design is the incurred cost, as loss of expected profit, that is needed to provide fairness in the distribution of equity. The members of the coalition are required to be in distant geographical locations to disregard correlation effects. This condition limits its applicability for participants in the same market in an adversarial setting.

In [53] the authors use EMCAS an agent based simulator to study the effects of demand elasticity and power price between GenCos and DemCos (demand companies). The authors conclude the need for further studies with increased market participants. This challenge is addressed in [60]. Furthermore, there is no adversarial consideration among the demand companies nor intermittent power generation. I considered these aspects are in my work.

Several distinct risks can affect the willingness of contract signing. The authors of [5] study the behavior of a producer and a retailer for different concession tactics. The tactics take into consideration the risk asymmetry and attitude of the agents. In the model, a parametric formulation accounts for both risks as arguments to an exponential function. However in reality determining the attitude towards risk involves the expectation about impact variables, for example, market prices and renewable generation.

2.0.5 Price of Energy in the Spot Market

The previous section commented on long-term bilateral contracts. The current section presents a literature review with regards to real-time trading. The need for a spot market arises from the fact that it is of paramount importance to keep the electric grid within safety operational levels. Thus close-to-delivery markets serve to smoothen the inherent variability of demand and supply.

Spot prices represent the clearing of a continuous or periodic double auction. Wholesalers and retailers submit bids and ask offers, respectively. The system operator determines the equilibrium point. Modeling and forecasting commodity prices in not a new problem nevertheless it prevails as a basin topic that attracts wide attention from the research community. The temporal problems make the case of electricity to stand out among other commodities. The lack of storage of scale increases the forecasting complexities in contrast to other marketable products. Besides the non storability, the energy dependence on endogenous components contribute to the spiky behavior seen in electricity prices. The openness has naturally fostered the creation of financial instruments with medium- and long-term horizons. These financial instruments (e.g., derivatives and futures) are intended to control price volatility however developing accurate forecast models over such horizons is a significant challenge for an energy trader. To diversify the risk, LSEs design electricity portfolios to control the exposure to uncertainty and assure, in a statistical sense, a positive profit over the portfolio horizon.

In [13] Boroumand et al., propose an intra-day strategy to hedge the risk of price volatility from a retailers perspective. In contrast to daily or longer horizon portfolios, an intra-day distributed portfolio is presented. The day is discretized into 8 blocks and a specific portfolio is allocated to each block. The intuition behind the intra-day discretization are the periodic fluctuations of demand observed within a day. The hedging portfolios can integrate 5 different contracts. In addition to physical deliveries the contracts can be derivatives such as forwards, call and put options. An optimization routine is used to determine the best allocation, per time block, of the five available contracts. Two risk metrics are optimized to determine the best portfolios. Value-at-Risk and Conditional Value-at-Risk are the risk measures implemented to assess a decade long data set of historic spot prices in the French energy market.

Skajaa et al. confirm the possibility of generating positive income with intraday trading for a WPP [96]. They use as case study the NordPool market. The study presents an algorithm that relies on logical and algebraic operations based on an out of sample evaluation of the trading strategies. To avoid evaluating the risk they use an strategy that underestimated the participation of the WPP on the market thus securing the trade at the historical price. In this respect, we relax this condition and instead incorporate a risk evaluation based on two complementary metrics.

[7] studies the offering strategies of a price-maker WPP in the spot market. The work presents an algorithmic decision process to decide the allocation of wind power. The authors use a large set of feasible scenarios to account for the uncertain quantities: market prices and wind power. The algorithm includes CVaR to assess the offering strategies and gauges the risk tolerance through a modulating factor. In contrast to a fix set of scenarios, our work [63] develops a generic stochastic differential model for the price and wind dynamics. Furthermore this thesis presents a more general case, that is, a price-taker WPP and conventional power.

Tushar et al. present a decentralized method to minimize penalties from demand deviations [102]. Consumers in a microgrid engage in self flattening the demand forecast for their energy requirements. The *give-and-take* is modeled with non-cooperative GT. The output is communicated to the microgrid operator; thereafter the operator produces or procures the power on behalf of the consumers. Close to real time, the consumers engage in a second round to close the gap between the initial request and the actual consumption. The authors consider a quadratic but static energy price function and thus no risk evaluation. In reality the uncertainty of the energy price is more complex this in turn makes risk assessment indispensable for a future-proof trading strategy.

Systems prone to rare events are characterized by fat-tailed distributions. The work of Hagfors et al., presents a simple but insightful analysis of extreme events on the German day-ahead electricity price. In this context, extreme events are considered as negative spot prices and the 1% most expensive of the sample. In their paper, they use a standard logit model to assess the relationship of several fundamental variables (e.g. coal price and expected demand) and rare events to predict, at same period of next day, extreme event occurrences [36].

Bello et al., propose a more complex method, for medium-term prediction, to account for rare events and thus the spiky nature of price time series. Fundamental analysis is limited in extracting higher-order moments of distribution functions. In [8], the analysis assumes electricity prices to follow a given market equilibrium model (MEQ). Possible scenarios are created by a two phase technique. The initial phase involves sampling the MEQ for several risk scenarios. The output of the first phase are the variables of interest, in this case the electricity price. In the second phase a Monte Carlo algorithm creates scenario combinations of the uncertain variables. The outcome of both phases serves to interpolate the results from phase one given the simulated scenarios of phase two. The output is analyzed by an econometric method to recalibrate the statistical results. The objective is to reshape the distribution near the tails to reflect more accurately the extreme events.

In contrast to [8], the paper of Li et al. attempts to model explicitly the unexpected price jump of average day-ahead electricity prices. The authors presented a bipartite approach to the spot price. On the one hand, the trend and seasonal behavior is modeled through a deterministic function. On the other hand, jumps and random fluctuations from the trend are modeled via a Cox-Ingersoll-Ross diffusion interspersed with time inhomogeneous Poisson compound process [57]. The deterministic function is constructed upon a trigonometric expansion to accommodate several seasonal time scales. The stochastic jumps rely on a random clock built from a Gamma process of a periodic activity rate. The activity rate is a piecewise linear activation function with yearly periodicity whereby winter and summer jumps can be easily concentrated. A principal advantage of the model is that not only the drift term but also the jump process contributes to the mean reversion of the spot prices.

A behavioral algorithm was used in [120]. Young et al., argue that a behavioral method is capable of providing meaningful insight for policy making. Moreover, they comment that changes, over time, of the underlying fundamentals are better portrayed by a behavioral approach than, e.g., a time series regression. The paper implements the reinforcement-learning algorithm MRE, a modified version of the Roth and Erev algorithm, to predict spot prices in the New Zealand electricity market. A drawback of the algorithm is the deficiency of immediate forecasting. The results shown are statistically accurate for a weekly time frame.

In [1], the authors analyzed the diversification problem of a large energy consumer (LEC). The allocation strategies are renewable energy, storage infrastructure, conventional generation and a demand response program (DRP). The diversification problem was formulated as a two stage stochastic energy procurement problem. In the first stage here-and-now decisions take place before the stochastic elements are known. The second stage, follows a wait-and-see strategy, after the realization of the stochastic variables are known. The LEC is subscribed to a Time-of-Use tariff; in this scheme the daily electricity price varies as a function of the time. The DRP is used to shift the load from peak hours to less expensive periods; although capped to a 15% of its demand. The uncertain variables are modeled through a set of scenarios. This limits the performance of the algorithm to adapt to different contexts e.g. in a competitive settings. Moreover, they demonstrate with 4 cases the capabilities of the model to lower procurement cost. The paper lacks an evaluation of the risk assumed by the LEC.

The work of Nie et al. [73] addresses some of the deficiencies in [1]. They approached a similar problem with an interval-stochastic risk management (ISRM) algorithm. The ISRM merges the two stage stochastic problem, interval-parameter programming (IPP) and risk analysis. In their work the uncertainty is characterized by a lower and upper bounds. Hence the uncertainty of fuel prices, demand and electricity generation is modeled as a set of intervals for three scenarios. The

ISRM is applied to minimize the overall cost of production and control the cost of a recourse strategy. More specifically, importing energy was considered as a recourse to fulfill the consumption demand. The risk metric is defined as the probability of surpassing a defined cost limit. A tacit monopsony is the framework of the setting; thus learning and adaption are redundant and not considered. The assumption of fixed intervals limits the performance in dynamic environments.

The uncorrelated dependency of past event from current and future wind speed realizations makes Markov chains a suitable methodology to model variable energy generation. The cost minimization problem of unit commitment with wind integration and transmission constraints is studied in [122]. The authors modeled wind generation as a Markov chain. However, to reduce the large number of Markov states and yet retain the possibility of extreme events, they combined the Markov-based approach with IPP. The hybrid model is a trade-off between complexity and conservativeness.

2.0.6 Autonomous Machine Energy Management

This section of the literature review presents the recent works of machine trading and management in the field of electricity markets. The supply chain of electricity is an ecosystem in which all members of society have an impact, even communities considered to be off-grid. The Interconnectivity, both physical and virtual, between regions and countries has increased the complexity of the energy market. In this context, keeping up to speed becomes ever more challenging. Fortunately, the breakthroughs in hardware capabilities and ICT have provided the possibility of full-fledged software agents. It is not far fetched to foresee a wholly ingrained *in-silico* electricity supply chain. The rest of this section presents and comments the relevant works.

Peters et al. in [82] developed an autonomous agent for trading in a retail market. The primarily focus was to evaluate the performance of different feature selection methods. The setting considered customers with fixed demand but varying degrees of rationality. They contrasted a manual feature selection against two unsupervised learning algorithms. The agent's learning is based in a finite Markov-Decision-Process (MDP). The authors implemented a SARSA algorithm to determine the best state to action map of the MDP. To analyze the performance of the agent they considered the fixed-rate tariff and traditional consumers.

The work of Radhakrishnan and Srinivasan [84] study the problem of efficiently allocating power from different sources. Every component of the system (e.g. loads, wind turbines, system operators, etc) is regarded as an agent. A fuzzy logic module takes care of the decision making of the storage device. The resulting usage is communicated to an optimizer agent whose task is to determine the minimum cost scheduling of conventional generators. The optimizer agent is an implementation of the Particle Swarm Optimization (PSO) algorithm. The objective function is the operating cost for each conventional unit; it is expressed as a convex function. The price of electricity is taken as a single 24 hours snapshot of the spot price. We overcome the scalability drawback of many agents with the MAL, a unique agent that reasons on different instances of itself.

Pinto *et al.* propose a solution to energy bidders in the wholesale market [83]. More succinctly, the paper analyses the problem of price forecasting in the Iberian energy markets. The price predictions are then passed to the Particle Swarm Optimization algorithm to determine the best allocation of resources in a federated portfolio. A feedforward neural network with one hidden layer and single node output layer is implemented as forecasting engine. The authors recommend the need to explore other topologies of neural networks that could improve the prediction performance. I address this issue with a vertically stacked sequential network of LSTM cells [64].

Similar to the previous work, Liu *et al.* [58] propose to predict market prices with a vanilla ANN. In addition to electricity prices, they also forecast wind power with a second ANN. The system modeled is a WPP with an energy storage system. The goal is to optimize the energy trading of the system with the grid. The authors use the locational marginal price (LMP) from the ERCOT[1] power exchange to train and validate the ANN. The proposed method is tested on two typical summer days. One day presents LMP spikes whereas the second case study is mostly smooth without LMP sudden escalations.

Quite often, in the field of agent modeling, a tacit requirement is to account for environments or states that are unknown a priori. With techniques such as Reinforcement Learning (RL) it is possible to make a map of the environment dynamically. In [95] and[111], the authors present an optimal control of a battery system such that the electricity consumption cost is minimized. The work exploits a cost free solar energy resource; the challenge is to manage the flows of energy from the grid to the battery. The charge/discharge control of the battery is optimized with a two step Q-Learning algorithm. In the first step an estimation of the control function is obtained. The result is plugged in the second step to update the value function. This procedure is possible because of the periodicity assumption. The authors consider that the electricity prices, solar generation and demand have a period of 24 hours. Although this might be arguable for the latter two variables, the prices of electricity are seldom periodic. In this thesis that assumption is relaxed [64].

Chowdhury et al. divide the energy supply problem in two subproblems [20]. Firstly, predicting clearing prices and secondly tariff offering. In the wholesale market, a reduced-error pruning tree empirically outperformed both an artificial neural network and a linear regression classification model. For the latter sub-problem, they followed a similar approach as [82]. The authors use Q-learning to

[1]Electric Reliability Council of Texas

determine the best policy in the finite MDP model. However, they considered a coarser action space in contrast to [82]; action space of the former is of rank three whereas the latter spans a further two. Similarly, the design does not includes renewable energy trading.

A more complex tariff structure is used in [24]. The tariff policy is based on the daily average consumption patterns. A fixed price is initially defined. This is followed by a linear weighted distribution of several trading blocks during the day. The results are Time-of Use (TOU) tariffs, this means that the price per kWh depends on the specific time of the day. Nevertheless, the authors do not consider the weekly consumption profiles, i.e., to distinguish from weekdays and weekends. The wholesale strategy is based on bidding according to a linear regression of previous clearing prices.

A problem to be address by smart cities is the need for peak capacity. The daily consumption pattern is characterized by peaks amongst valleys. This phenomenon gives rise to the need of ancillary markets. Basically generators bid spinning capacity that is prompt to meet the peak load. Demand side management can overcome this excess cost by offering TOU instead of only fixed-rate tariffs. In [104], the TOU tariff offering in retail markets is stated as an MDP problem. The authors proposed a lookahead policy optimization algorithm to solve the MDP.

The MDP with lookahead policy implemented by Urieli et al. is detailed in [105]. The two components of the wholesale strategy are the: Cost predictor and Bidding strategy. Forecasting of clearing prices is based on linear regression of bootstrap data. Moreover, the trained model is updated in real-time using the past 24 hours prediction errors. To hedge uncertainty, the bidding strategy is a combination of truthful and strategic bidding. The former is based on submitting bids with a limit price equal to the brokers imbalance fee. Whereas, the latter relies on the fact that bidding slightly higher than the clearing price is more likely to clear. Thus, the broker submits a set of 25 bids, one according to the truthful method and 24 strategic bids in an increasing ladder approach. However, the agent is not implemented to account for and procure energy from renewable sources.

In [108], Wang et al. trade in the wholesale market with a modified version of Tesauros's bidding algorithm (similar to [103]). The tariffs offered in the retail market follow the SARSA scheme as in [82]. They innovate the tariff offering by clustering costumers. Instead of considering all possible energy consumers as a single group they identify clusters and offer tailor-made tariffs. The clustering is based on the costumers' consumption patterns. The consumption patterns are extracted through a two-layered clustering algorithm. On the first layer, the variance of consumption is calculated as the variance of electricity usage during hour k for different days. The second layer takes the clusters from the first layer and segregates the consumers with respect to their usage gradient. Usage gradient is defined as the average energy consumption over different days for hour k. The intuition is that consumers have different levels of energy predictability according to the stability reflected on their consumption patterns [118].

Ozdemir and Unland [76] exploit the autocorrelation of market clearing prices with a reinforcement predictor. They find that a short-sighted ($\alpha = 0.8$) implementation has the smallest error. In their findings they comment on several key aspect to improve the accuracy of the predictions. The most relevant is to consider weather as an input variable. In addition to considering the weather forecast, the spot price prediction in this thesis capitalize on the authors findings. Rather than only considering recent past events the prediction model implements a neuron architecture with correlations of different time scales.

In [126] the authors use agents to study the demand response of a competitive system formed by commercial buildings, power generators, load serving entities and an independent system operator. The input data is based on past events whereas the neural-like network of the LSTM cells I use in the DS2S creates temporal dependencies of different timescales keeping track of short and long-term price drift trends.

The work [109] studies the selling and buying of energy to and from the smart grid. The authors consider the case of a smart building with generation and storage capacity. The agent's main features are the adaptive capability to mimic the counterpart's behavior and a model for eagerness of both parties. The adaptability is based on maximizing the benefits of reaching an agreement within a pre-defined time frame. In this context, eagerness is understood as the willingness to concede and reach an agreement. The solution to the maximization problem is done with the Particle Swarm Optimization algorithm. The analysis considers a predominantly deterministic and linear scenario. In this thesis I present a deep sequence-to-sequence neural network to account for the non-linearities of the market (the other party).

Chapter 3

Research Summary

This chapter presents the synopsis of the research findings. The content is divided in two sections. First, Section 3.1 presents the conclusions of the work. Followed by section 3.2 which comments on possible paths and future work that can extend the research presented in this thesis. The first part is a summary of the main findings. It contains an intuitive description. I have duplicated from the appendices some formulae, plots and algorithms that are relevant to help the text however the details can be found in the Appendices A-E. Appendix F is devoted entirely to technical details of the algorithms used in the previous appendices.

3.1 Conclusions

The main results of the work are stated as answers to the research questions presented in section 1.2.2.

P1-RQ1 Gaming equilibrium *What is the energy portfolio of LSE companies procuring electricity from long-term contracts with conventional and wind power producers?*

Conclusion: Competing companies servicing electricity consumers face the conundrum of securing the customers' demand at the lowest procurement cost. On the one hand there is cheap electricity from renewable sources however unreliable. On the other hand fossil-fuel electricity is reliable although more expensive. I formulated a game model for the procurement trade-off: $\mathcal{G} = \{\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}}\}$. The stakeholders are utility companies, conventional power generation, wind energy and the wholesale market. The pure strategies $\{\mathcal{S}_i\}_{i\in\mathcal{N}}$ available to each company comprise a low and high risk contract: `LR` and `HR` respectively. (3.1) models the cost of procuring energy from two types of power wholesalers: a fossil-fueled power plant (CG) and a wind farm (WPP). And balancing power mismatches at spot market prices (P_{SM}). P_{CG}, P_W represents the contract price with the conventional and wind power producers respectively. Each utility i is committed to serve its clients energy demand D_i. w_i is the power sourced from the WPP. The CG is consider a low risk source because of the possibility of dispatching at command hence it is termed the `LR` strategy. On the other hand the uncertainty inherent to wind power makes the WPP a riskier source hence this is the high risk (`HR`) strategy. The solution of the game is a hedged mix of both types of energy sources and the wholesale market [61].

$$u_i(s_i, \mathbf{s_{-i}}) = \begin{cases} -D_i P_{\text{CG}} & \text{if } s_i = \texttt{LR} \\ -\sum\limits_t (D_i - w_i^t)p^t - w_i^t P_w & \text{if } s_i = \texttt{HR}, \end{cases} \tag{3.1}$$

(3.2) is the payoff matrix of $\mathcal{G}$. U_1 and U_2 are the column and row player respectively. Each matrix element-pair $m^i_{jk}, i \in \mathcal{N}$ of (3.2) represents the costs of both UCs according to the strategies chosen. This is the cost to be paid by the UC depending on the strategy selected and the other UC's strategy. For example

$\mathbf{m^2_{2,1}}$ is the cost incurred by U_2 when U_2 plays `HR` and U_1 plays `LR`.

$$\begin{array}{cc} & \mathbf{U_1} \\ & \begin{array}{cc} \texttt{LR} & \texttt{HR} \end{array} \\ \mathbf{U_2} \begin{array}{c} \texttt{LR} \\ \texttt{HR} \end{array} & \begin{bmatrix} \mathbf{m^1_{1,1}},\ \mathbf{m^2_{1,1}} & \mathbf{m^1_{1,2}},\ \mathbf{m^2_{1,2}} \\ \mathbf{m^1_{2,1}},\ \mathbf{m^2_{2,1}} & \mathbf{m^1_{2,2}},\ \mathbf{m^2_{2,2}} \end{bmatrix} \end{array} \tag{3.2}$$

where

$$\begin{aligned} \mathbf{m^1_{1,1}} &= -D_{U_1} P_{\mathrm{CG}}, & \mathbf{m^2_{1,1}} &= -D_{U_2} P_{\mathrm{CG}}, \\ \mathbf{m^1_{1,2}} &= -(D_{U_1} - \mathbb{E}[w])\mathbb{E}[P_{\mathrm{SM}}] - \mathbb{E}[w]P_w, & \mathbf{m^2_{1,2}} &= -D_{U_2} P_{\mathrm{CG}}, \\ \mathbf{m^1_{2,1}} &= -D_{U_1} P_{\mathrm{CG}}, & \mathbf{m^2_{2,1}} &= -(D_{U_2} - \mathbb{E}[w])\mathbb{E}[P_{\mathrm{SM}}] - \mathbb{E}[w]P_w, \\ \mathbf{m^1_{2,2}} &= -\left(D_{U_1} - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\mathrm{SM}}] - \tfrac{\mathbb{E}[w]}{n}P_w, & \mathbf{m^2_{2,2}} &= -\left(D_{U_2} - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\mathrm{SM}}] - \tfrac{\mathbb{E}[w]}{n}P_w. \end{aligned}$$

Utilities need to determine the share of power to procure from the conventional and the renewable sources σ^{LR} and σ^{HR} respectively. The power allocation to either source can be expressed as the Nash equilibrium for mixed strategies: $\mathbf{p}_i^* = [1 - \sigma_i^{*\mathrm{HR}}, \sigma_i^{*\mathrm{HR}}]$; where $\mathbf{p}_i^*$ is the probability distribution over the pure strategies and $\sum \mathbf{p}_i^* = 1$.

The market setting is composed of two utilities -the next RQ addresses the problem of higher competition and heterogeneous demand. The analysis considers two cases. First, elastic energy prices. In the second scenario the price of electricity increases with demand. In the latter, the upper-right and lower-left elements of matrix (3.2) are modified to introduce price changes as a function of the number of buyers:

$$\begin{aligned} \mathbf{m^1_{1,1}} &= -D_1 P^+_{\mathrm{CG}}, & \mathbf{m^2_{1,1}} &= -D_2 P^+_{\mathrm{CG}}, \\ \mathbf{m^1_{2,2}} &= -\left(D_1 - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\mathrm{SM}}] - \tfrac{\mathbb{E}[w]}{n}P^+_w, & \mathbf{m^2_{2,2}} &= -\left(D_2 - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\mathrm{SM}}] - \tfrac{\mathbb{E}[w]}{n}P^+_w. \end{aligned}$$

Equation (3.3) is the portfolio for the case of price elasticity of energy. It is expressed in terms of the competitor's market share, conventional (P_{CG}) and renewable contract (P_w) prices, nameplate capacity of the wind farm ($\mathbb{E}[w]$) and expected market price ($\mathbb{E}[P_{\text{SM}}]$).

$$\sigma_i^{*\text{HR}} = 2\left[1 - \frac{D_{-\mathbf{i}}(\mathbb{E}[P_{\text{SM}}] - P_{\text{CG}})}{\mathbb{E}[w](\mathbb{E}[P_{\text{SM}}] - P_w)}\right]. \tag{3.3}$$

A higher competitive market could decrease the price elasticity of electricity. The aim here is to obtain the power allocation when price increases as demand grows. The analysis takes into consideration changes on the contract shares and not on the price functional. I use a parametric form in the payoff matrix to abstract the price dependency on demand. Eq. (3.4) is the best response portfolio for the scenario of inelastic LT contracts. P_{CG}^{+} and P_w^{+} represent the higher contract prices for conventional and wind power, respectively. A corollary of the previous result is a price window for the wind contract (3.5). For a given market there is a lower and upper bound. The LSE can avail of this price window for contract negotiations with the power producer. For this to hold, the utility's demand must be bigger than the expected wind power generation.

$$\sigma_i^{*\text{HR}} = \frac{D_{-\mathbf{i}}(P_{\text{CG}}^{+} - \mathbb{E}[P_{\text{SM}}]) + \mathbb{E}[w](\mathbb{E}[P_{\text{SM}}] - P_w)}{D_{-\mathbf{i}}(P_{\text{CG}}^{+} - P_{\text{CG}}) + \mathbb{E}[w](\frac{\mathbb{E}[P_{\text{SM}}]}{n} + \frac{P_w^{+}}{n} - P_w)}. \tag{3.4}$$

$$\begin{aligned} \kappa P_{\text{CG}} - \mathbb{E}[P_{\text{SM}}] \leq & P_w \leq \beta P_{\text{CG}} - (\beta - 1)\mathbb{E}[P_{\text{SM}}], \\ \kappa &\triangleq \frac{2\beta}{2\beta - 1}, \\ \beta &\triangleq \frac{D}{\mathbb{E}[w]} > 1. \end{aligned} \tag{3.5}$$

In current decentralized power generation the TSO uses Merit-order to dispatch power plants. This means that power producers submit power bids (quantity and price) to the TSO. The bids are sorted in terms of price in increasing order until the total network demand is fulfill. Figure 3.1 shows $\sigma^{*\text{HR}}$ for different P_w and P_{CG}. The renewable component of the portfolio is asymptotic as 1) P_w approaches $\mathbb{E}[P_{\text{SM}}]$ and 2) when P_{CG} equals $\mathbb{E}[P_{\text{SM}}]$. The integration of wind power increases with lower energy prices than the spot price and as the conventional energy price increases. In Figure 3.1b shows the opposite for contract prices higher than the SM price. To explain this phenomenon we need to recall the assumption that on average SM prices are higher than those of a price taker renewable source and correlated to conventional power (because of the Merit-order dispatch) the latter sets the marginal price of electricity.

P1-RQ2 Heterogeneity *How to find the equilibrium portfolio for multiple LSEs with heterogeneous demand?*

Conclusion: The complexity of the system of equations increases as more competing utilities participate in the market. For a 2-players game an analytical solution can be derived. Whereas as the number of players increases so does the degree of the system. In addition to the non-linearities the equations are coupled. We developed a tailor-made program (RGAn) to determine an approximate of the Nash equilibrium and hence the energy portfolios of the utility companies [60].

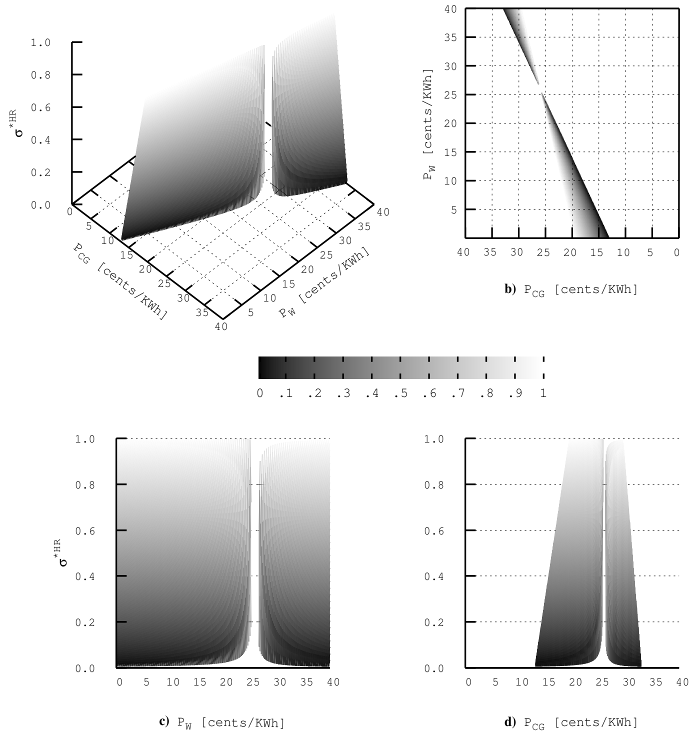


Fig. 3.1 Long-term contracting policy $\sigma_i^{*\mathrm{HR}}$ for different conventional and wind energy prices with given parameters: $P_{\mathrm{SM}} = 26$ cents/KWh, $D = 30$ MW and $\mathbb{E}[w] = 15$ MW.

The program is a recursive implementation of the Genetic Algorithm. The rejection method of the GA routine is enhanced with a criteria similar to the cooling of the Simulated Annealing algorithm. We benchmarked the performance of the portfolio solver with an implementation of the standard GA (SGA).

The RGAn pseudo code can be seen in Algorithm 3.1; Appendix F presents the details of the implementation. Four major novelties make the RGAn outperform the SGA. First, the BinaryTable. Secondly, the ObjFunEval. Thirdly, based on the Simulated Annealing algorithm, the RGAn accepts, with a control parameter, sub optimal genes in the chromosome pool. Lastly, the memory handling of the vectors *population* and *fitvector*.

BinaryTable, is a hash map. It indexes the number of players for every evaluation of the objective function hence making a **for** loop unnecessary. It is a quick way of knowing the total number of players choosing the same pure strategy and hence the price of the LT contract. It does this by indexing the combination of players willing to sign a contract with the LR or with the HR power source. ObjFunEval is the scheme used to evaluate the objective function. The tree is traversed recursively in a depth-first search manner, backtracking just one level before moving into unvisited nodes. This method reduces the computations in polynomial order. In the RGAn, the n-dimensional structure of game $\mathcal{G}$ is transformed into a 1-D structure. From the computational viewpoint, handling arrays instead of higher dimensions structures (e.g., cubes) is faster; although less human readable and more cumbersome to code. The acceptance probability, of non optimal offspring, is proportional to the exponential of the difference, Δ, of current objective function and the worst of the pool. The parameter T (Algorithm 3.1, line 40) controls the intensity ratio.

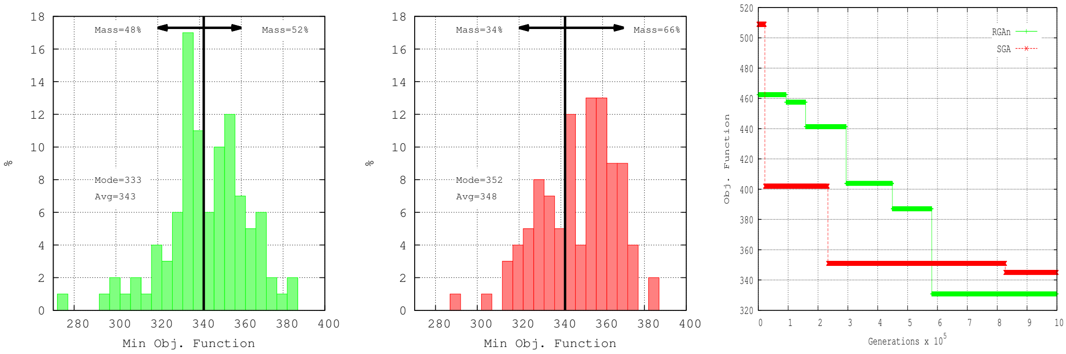
The equilibrium point is a distribution over the pure strategy set that in expectation has the same level of risk as a portfolio comprising of only the low risk strategy. The RGAn minimizes the risk deviation from the diversified portfolio with respect to low risk but costlier portfolio. Thus the objective function of the RGAn solver is to minimize the absolute value of the difference, for each load serving entity, between 1) the expected utility for choosing the low risk pure strategy and 2) the expected utility of choosing the high risk pure strategy; given all other players chosen strategies in both scenarios. For a player $i \in \mathcal{N}$ the expected utility of choosing the strategy `LR` is 1) the cost of procuring energy from the CG source multiplied by the weight it has in the portfolio taking into account other players also selecting this strategy plus 2) the cost of procuring energy also from the CG but multiplied by the corresponding weight in the portfolio taking into account the cardinality of the subset of $\mathcal{N}$ that selected the `HR` strategy. Then the expected utility of selecting the other pure strategy (i.e., `HR`) is calculated similarly as in the previous case however in this scenario the cost incurred by the LSE corresponds to procuring energy from the WPP; like before the proportions that constitute the portfolio are influenced by the decisions of the other players in $\mathcal{N}$. When this two expectation coincide the resulting mix is then the equilibrium diversified energy portfolio.

The testbed considers 10 utilities with heterogeneous demand. The results show improvement both on speed and quality of solution. The average of the Modes on both algorithms is used as pivot point to contrast the quality of the solutions. The distribution of the RGAn are less right heavy than the SGA. This is a desirable result since the left side solutions are closer to convergence. As a result, the RGAn left side is 14% heavier than the left side of the SGA.

Figure 3.2, shows histograms of 100 runs. It can be seen, on average a 1.5% improvement, although the probability mass, $P(\text{Min O.F.} < 342)$, of the RGAn is 40% higher than with the SGA. The rightmost plot shows the effect of enriching the population. The time spent in suboptimal solutions is shorter hence this is a mechanism for faster escaping of plateaus that translates as a more comprehensive exploring of the domain space within the same timespan.

Algorithm 3.1 Recursive Genetic Annealing Algorithm

```
define PBC2(·) ← periodic boundary conditions
procedure Initialize
    Struct par ← input params {T, stop, ···}
    population ← vector of length twice players
    population ← U(0, 1)
    fitvector ← fitness eval population
    goto BinaryTable(par)
end procedure
procedure BinaryTable(par)
    binarytable ← vector of length pow(2, players)
end procedure
function Selection(par)
    population ← sort
    parentA ← fittest population
    parentB ← random population
    worst ← less fittest population
    offspring ← crossover parentA, parentB
    offspring ← mutation offspring
    goto ObjFunEval(par, offspring, binarytable)
end function
function ObjFunEval(par, offspring, binarytable)
    leaf ← tree pointer
    n ← backtracking counter
    esc ← tree pointer
    dpl ← twice number of players
    for i ← 0, 2 do
        n ← PBC2(n+1,dpl)
        esc ← esc+1
        ObjFunEval(par, offspring, binarytable)
        leaf ← 1
        n ← n-1
        esc ← esc-1
    end for
    goto UpdatePopulation(par, offspring)
end function
function UpdatePopulation(par, offspringeval)
    Δ ← offspringeval-fitvector[worst]
    if offspringeval < fitvector[worst] then
        worst ← offspring
    else if U(0, 1) < exp(−Δ)/T then
        worst ← offspring
    end if
    while !stop do
        goto Selection
    end while
    Return population
end function
```



(a) RGAn. (b) SGA. (c) RGAn vav SGA

Fig. 3.2 **(a), (b)** Statistics of 100 runs of 1x10^6 generations each. **(c)** RGAn vis-á-vis SGA.

P1-RQ3 Risk assessment *How to generalize a methodology to determine the risk on hedged portfolios for different wind and market characteristics?*

Conclusion: This part of the research proposes the Stochastic Procurement model (SPM). A theoretical framework, beyond sufficient statistics, to evaluate the risk incurred in the energy portfolios. The methodology is divided in three parts: 1) A martingale model of the spot electricity price that comprises a Compound Poisson process; 2) A transformation to a given probability density function of a multiplicative Brownian motion process to model the wind speed dynamics; and 3) The metrics to estimate the risk of the energy portfolios.

Electricity can be thought of as a commodity however unlike other commodities like sugar, bulk electricity is hard to store for long periods of time. This fact makes wholesale prices experience sudden jumps and a mean reversion process. Thus the two distinct characteristics of the spot price are sudden short-lived price escalations and secondly mean-reversion. In the method, the first component incorporates these properties through a Lévy and Ornstein–Uhlenbeck processes respectively (3.6).

$$\Phi(t) = e^{-\gamma t}\Phi(0) + \gamma\mu_{sm}\int_0^t e^{-\gamma(t-s)}ds + \\ + \sigma_{sm}\int_0^t e^{-\gamma(t-s)}dB(s) + \sum_{j=N(t)+1}^{N(t+1)} \log(Y_j). \tag{3.6}$$

The second term in (3.6) models the mean reversion part. μ_{sm} is the local process trend. And γ is the rate towards the trend. The term $\sum_{j=N(t)+1}^{N(t+1)} \log(Y_j)$ represents the Compound Poisson process where The Y's are i.i.d. random variables that represent the magnitude of the jump. I use the martingale version of the Poisson process to remove trends in the price jumps, that is, to avoid predictability of the occurrence of the energy price escalation.

For the second part, the wind speed trajectories are modeled with a multiplicative Brownian SDE. I implemented Zárate-minano and Milano's method [123] to (3.7) with the Raleigh pdf. What the method does is to adapt the functions $\mu_w(\cdot)$ and $\sigma_w(\cdot)$ to the pdf. The aim is to include, in a general manner, the distribution and autocorrelation of wind speed statistics of any possible wind farm site. The first step is to transform the drift to the pdf. Then Zárate's method solves for the diffusion parts using the Fokker-Planck equation (partial differential equation that describes the time evolution of the probability density function).

$$dv(t) = \mu_w(v(t), t)dt + \sigma_w(v(t), t)dB(t) \tag{3.7}$$

As an example, for the Rayleigh distribution: $f(v) = \frac{2v}{\gamma^2}\exp[-(v/\gamma)^2]$ with autocorrelation decay rate α, the drift and diffusion are (3.8) and (3.9), respectively.

$$\mu_w(v(t)) = -\alpha\left(v(t) - \gamma\sqrt{\frac{\pi}{2}}\right), \tag{3.8}$$

$$\sigma_w(v(t)) = \sqrt{\frac{\alpha\gamma^2}{v(t)}\left[2v(t) + \gamma\sqrt{2\pi}\left(e^{\frac{v^2(t)}{2\gamma^2}}\operatorname{erfc}\left(\frac{v(t)}{\gamma\sqrt{2}}\right) - 1\right)\right]}. \tag{3.9}$$

Here we assume the *Option* type of contract. An *Option* gives the holder the possibility of fully or partially utilizing the reserved amount of energy. However this flexibility comes at price which is the fixed cost. The other price of the contract is the variable or execution cost. The holder pays a unit rate on the amount of energy executed from the contract with the power producer. Using (3.6) and (3.7) the cost of procuring electricity CEP is expressed as (3.1). The components are 1. ξ the minimum, at delivery time t, of d_w and $w(v)$, i.e., electricity contracted and available, respectively, bought at p_w, the WPP selling price; 2. execution and reservation costs, g and s respectively and the share d_c of electricity allocated to a CG; 3. x, the energy bought from the spot market at price p_{sm}; lastly, 4. depending on the wind power generation ζ, the LSE is subject to a penalty $\mathcal{P}$ for under fulfillment of the committed total demand D.

$$\mathrm{CEP}(t) = \xi p_w + d_c g + s(d_c) + x(t)p_{sm}(t) + \mathcal{P}\zeta p_{sm}(t) \tag{3.10}$$

where

$$D = d_w + d_c + x(t)$$

$$\xi = \min[d_w, w(v(t))]$$

$$\zeta = \begin{cases} 0 & \text{if } w(v(t-1)) < d_w \\ \max[D - w(v(t)) - d_c, 0] & \text{if } w(v(t-1)) > d_w \end{cases}$$

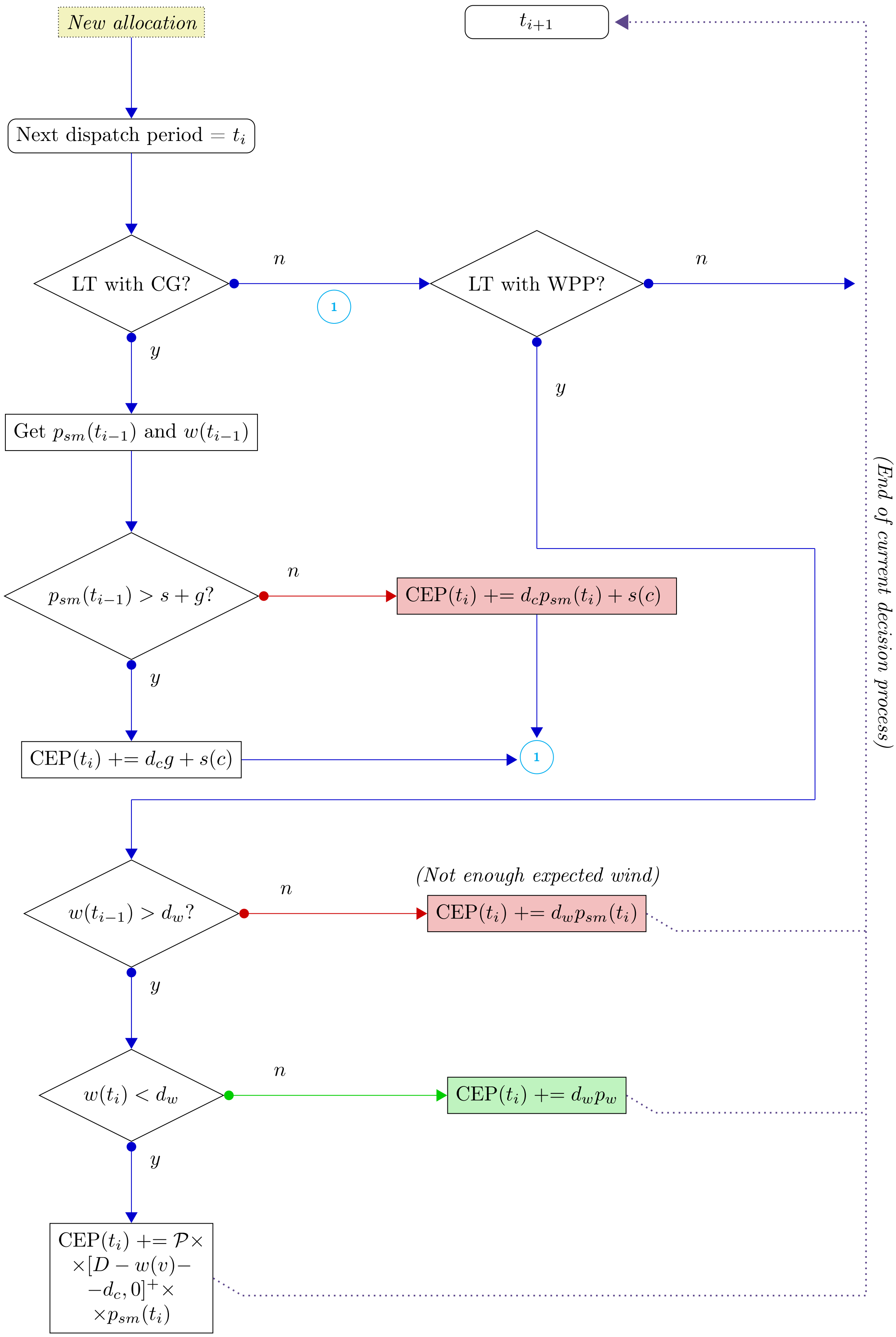
$$x(t) = \begin{cases} 0 & \text{if } p_{sm}(t-1) > s(d_c) + g \\ D - d_w & \text{if } p_{sm}(t-1) < s(d_c) + g \\ d_w & \text{if } w(v(t-1)) < d_w. \end{cases}$$

The LSE trading process is subject to the period before the next delivery time. This means that next period's executed conventional energy and real-time procurement have to be notified prior to dispatch time. This is motivated by the martingale property of market prices. Figure 3.2 shows the decision-making algorithm.

The stochasticity of the of price and wind dynamics could adversely impact the creation of profit. Thus, the portfolio is assessed with two risk metrics: CVaR and Excess Cost. CVaR evaluates the average tail events, in particular extreme events with a negative impact. Excess Cost evaluates the likelihood of a given portfolio incurring in high cost procurement.

The SPM is general in the sense that it provides a portfolio irrespective of the policy towards risk, and can be tuned to a market and wind site particular characteristics. This is translated as convergence to an optimal portfolio. To analyze the SPM I discretized eqs. (3.6) and (3.7) and implemented a Monte Carlo program. The experimental setup consisted of $D = 2$ MWh of total demand and contract prices $p_w = 18\$$ and $g = 24\$$ per MWh for wind and conventional power respectively.

Fig. 3.4 shows the expected cost of energy procurement $\mathbb{E}[\mathrm{CEP}(t)]$ for different electricity portfolios and distinct decay rates, α. The solid line represents a portfolio composed of solely conventional power. This divides the plot in two regions: diversified portfolios that are cheaper or costlier than one invested solely



Algorithm 3.2 Procurement algorithm. The energy portfolio is composed of real time trading in the exchange market and two bilateral contracts with a conventional and a renewable source.

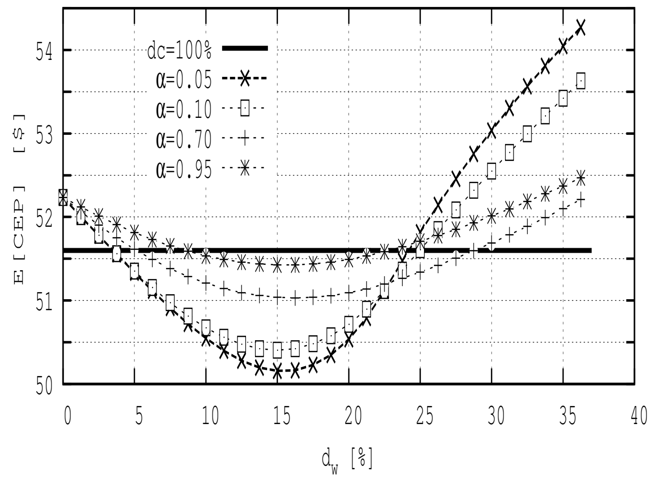


Fig. 3.4 Effect of α on the expected procurement cost for different d_w.

in conventional power. The diversification portfolios above the solid line are on average costlier because of the uncertainty in the wind power availability.

CVaR risk is the expected payable cost in the worst 10% and 5% cases ($\beta = 0.9$, 0.95). Fig. 3.5 shows the trade-off between expected cost and worst case scenario. In my simulation with synthetic data I found that the LSE should contract between 8% and 16% wind power from a WPP with an autocorrelation decay rate $\alpha = 0.7$ and nameplate capacity of 1.3MW.

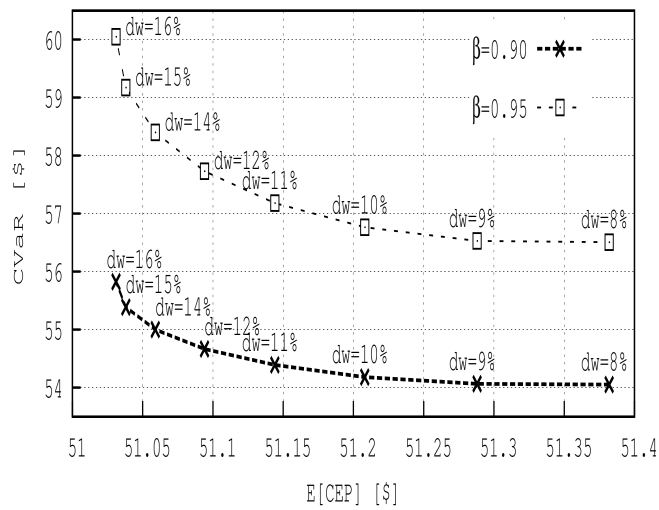


Fig. 3.5 Efficient frontier for different d_w. $\alpha = 0.7$ and two worst case scenarios.

P2-RQ1 Fast signaling *Can a deep artificial intelligence model provide accurate signals for short-term procurement?*

Conclusion: This question opens the second part of our research. The former RQs dealt with the long-term aspect of energy contracting. This last part is concern with the almost just-in-time condition of energy trading. The answer to this question is a solution to wholesale prices prediction.

The spot market is the preferred mechanism to balance supply and demand mismatches; the other option is paying hefty balancing fees. However it is prone to high volatility. To minimize trading cost by avoiding penalty fees decision-makers need fast and reliable price signals. Thus to predict the electricity price on the spot market I implemented a sequential network of long- short-term memory (LSTM) neurons. The gating architecture of the LSTM units provide persistence to the predicting model.

Other approaches, that lack the persistence mechanism, such as traditional neural networks or Markov models have unsatisfactory predictive performance. The feature is of special relevance for energy markets because of the sudden jumps and the reversion to trend that characterizes electricity spot prices.

The predictions are done with a deep sequence-to-sequence neural network of LSTMs (DS2S) [64]. Figure 3.7 presents the topology of the DS2S. It consists of serialized vertically stacked LSTM cells. The input sequence is the set of explanatory variables (e.g. demand forecast, previous cleared prices, power exchange with other regions, etc.). The output sequence contains the predicted prices for the next trading slots. The DS2S was tried on the NoordPool. The prediction capabilities were contrasted with a vanilla artificial neural network and a markovian-based prediction model. The predictive accuracy of the model successfully decreases the trading cost of a power trader over the other methods.

Figure 3.6 contrasts the performance of the DS2S with three different approaches. First, the yellow line represents the perfect information case, i.e.

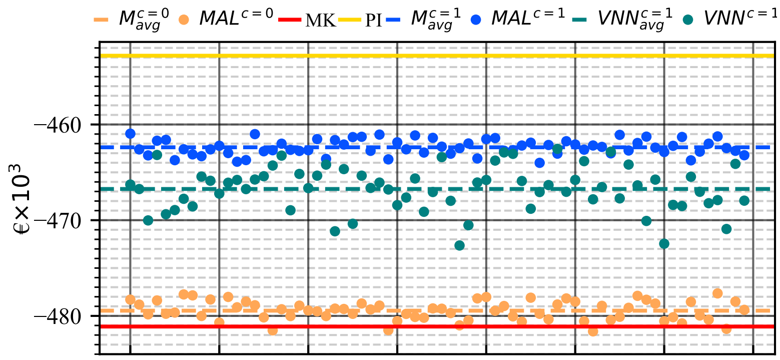
assuming complete knowledge of future conditions. Second, the red line is the result of markovian trading; it regards the current price to be independent of the past given the last event. Lastly, a vanilla feed-forward network (VNN).

Figure 3.8 shows the statistical contrast of the total energy trading (TET) cost with and without clustering, $c = 1$ and $c = 0$, respectively and a vanilla artificial neural network (VNN). The first and third quartiles and the minimum and maximum values of the agent $^{c=1}$ result in better performance than its counterparts. The variance of the DS2S is on average 28% lower than the agent with the VNN. Lastly the DS2S features a lower tendency to extreme outliers this is assayed through the kurtosis of the hourly costs. The kurtosis is 2.2 which is characteristic of a platykurtic distribution, that is, fewer extreme outliers.

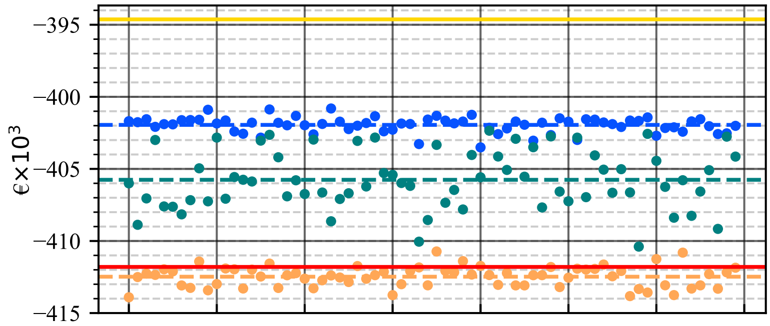
P2-RQ2 Agent trading and management *How to automate the trading with the spot market and internal management of a hybrid power plant?*

Conclusion: The integration of renewable sources of energy has been possible largely because of state support on private investment. Subsidies are the most common form of support. The support schemes directly translate into onerous levies on the consumer. The solution to this RQ paves the way for the integration of renewable source in subsides-free markets.

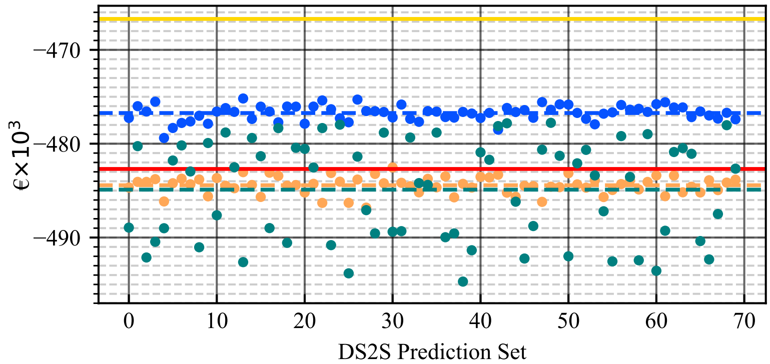
To reduce the dependency upon support renewable generators need accurate price signals and fast decision-making to compensate for the lack of dispatchability. To achieve this we designed the Meta Agent Learner (MAL) [64], an agent that incorporates data analysis, price prediction and resource management. The architecture of the agent is a tiered structure that comprises data analytics (DA), a novel AI model (DS2S) and reinforcement learning. Why Meta? the MAL is composed of different phases that we consider as agents themselves. Thus the state and action of the decision-making agent of the MAL is influenced by the beliefs of the other intra-agents. Those beliefs are, e.g., the wholesale price predictions



(a) June 2017.



(b) July 2017.



(c) August 2017.

Fig. 3.6[a] Comparison of the TET cost of the HWPP. Each plot shows the total cost for Perfect Information (PI), a Markovian trader (MK), the MAL and average ($M_{avg}^{c=x}$), and the VNN and average ($VNN_{avg}^{c=1}$). We also contrast the Analytics phase by switching it off and on, i.e., $x \in \{0, 1\}$ respectively.

[a] The two topmost graphs share the x axis scale of the lowest graph.

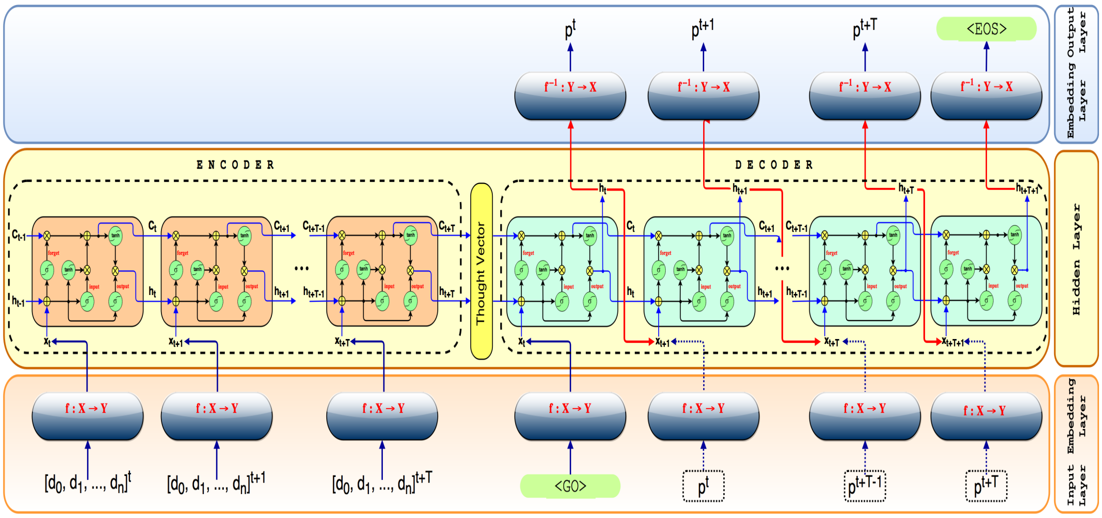
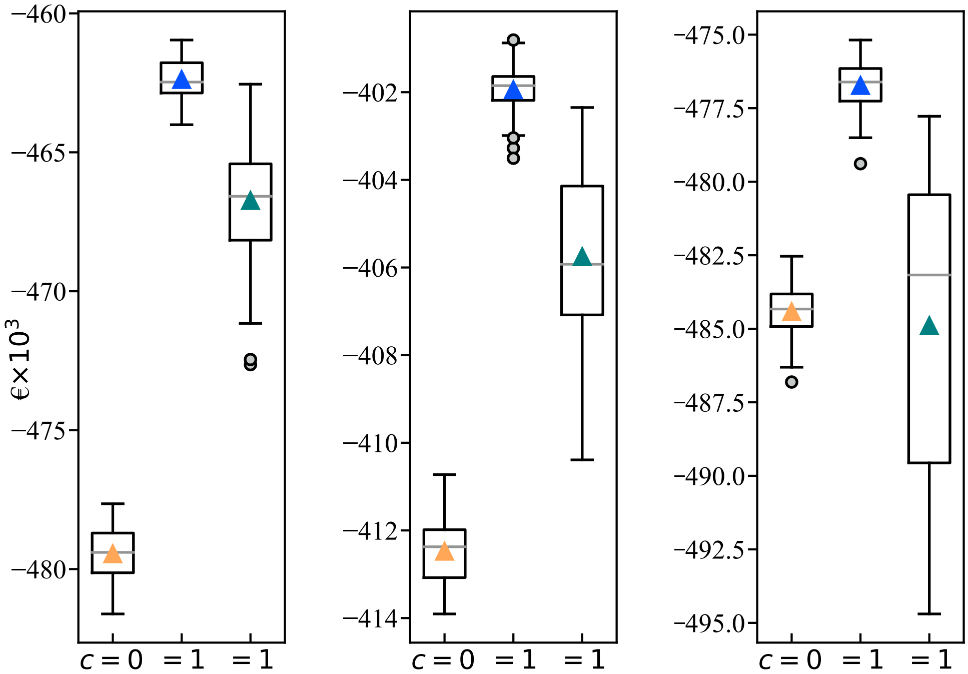


Fig. 3.7 Architecture of the DS2S.



(a) June 2017. (b) July 2017. (c) August 2017.

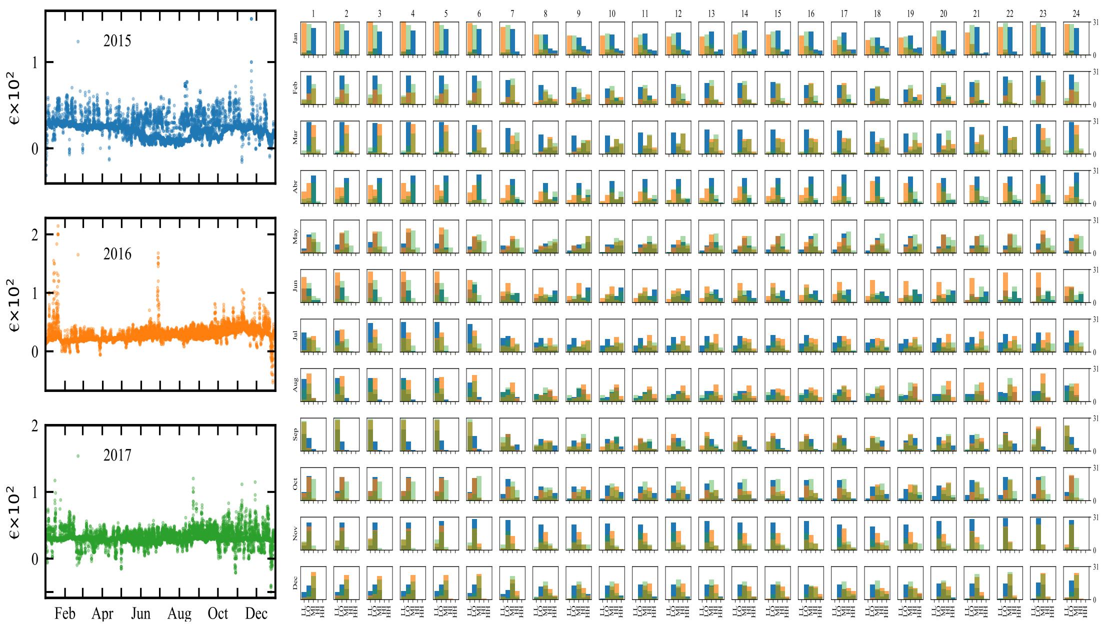
Fig. 3.8 Comparison of the DS2S and a vanilla ANN. Quartiles and mean of the TET cost with and without the Analytics phase, $c \in \{1, 0\}$ respectively for the DS2S.

made by the DS2S phase. Which in turn is influenced by another instance of the self: the Analytics phase.

The task of the data analysis part is to retrieve knowledge from the raw streams of market data. This is then conveyed to the DS2S, as presented in the previous RQ, the purpose is to predict future energy prices. The third phase of the MAL is the management of the power plant. This latter instance implements multi-policy Q-learning, it reasons upon the data analysis and price predictions for the decision-making concerning the trade of energy.

The MAL is validated with a price-taker hybrid wind farm (HWPP). The testbed comprises real market data from NordPool. Moreover, the wind generation and electricity demand correspond to percentages of factual data of the eastern Denmark (DK2). The performance of the MAL was contrasted with three traders: 1) An agent with access to future market data; 2) A markovian-based algorithm; and 3) An agent with a vanilla neural network. Furthermore, the performance of the MAL is presented when disregarding the data analytics instance.

The learning phase of the agent is the foundational Q-learning algorithm (QL) (3.11). In this research QL is compared with a more novel implementation of reinforcement learning: Dueling Double Network for Deep Q Learning with Prioritized Experience Replay (DDDQN). In [110] the authors benchmark the performance of DDDQN against other learning algorithms with a myriad of console games. The innovations of DDDQN proved advantageous in most of the reference games. The two novelties of this architecture are, firstly, a double network to estimate the value of the state and the advantage of the action, respectively. Secondly, the sampling process of the agent's memory weighs more SARSA memories that have more value to the agent and thus are replayed more often during training.



(a) (b)

Fig. 3.9 DK2 hourly electricity spot prices from 2015 to 2017. Fig. (a) energy spot price. Fig (b) K-means clusters. 5 clusters are used: Low-low (LL), Low (LO), Mid (MI), High (HI) and High-high (HH).

$$Q(s_t, a_t) \leftarrow (1-\alpha)Q(s_t, a_t) + \alpha[\mathcal{R}_t + \gamma \min_a Q(s_{t+1}, a)] \tag{3.11}$$

The backbone of the DA is an unsupervised clustering algorithm with an homotopic transformation of the temporal dimension. The added value of DA is manifested in both the demand and price data. Figure 3.6 shows the benefit of the clustering instance, represented by $MAL^{c=1}$, from the non-clustered data, $MAL^{c=0}$. Clustering significantly reduces the entropy and skewness. Figure 3.9 shows the raw electricity prices. The entropy and skewness prior to DA is 8.19 and 1.9 respectively. After processing the streams of data the resulting values are 1.5 and 0.3, respectively.

For the electricity prices the entropy decreased 82% and the skewness 84%. The overall trading cost of the HWPP is lower whit the MAL. The average monthly trading cost of July is 3% lower than without the DA and 2.4% than the markovian trader.

I utilized a boolean model so that the system is scalable and robust. Scalability from the perspective of the control. The Reward function of the Q learning phase is agnostic to any specifics of the HWPP system. The boolean model is also robust in that it can make quick decisions constantly in a highly volatile market, irrespective of the physical condition of the system. The reward function in (3.11) is expressed as a wait-and-see conjunctive function of the multiple policies controlled by the agent (3.12). The domains (3.13)-(3.14) of the indicators in (3.12) are containers of the agent's objectives.

$$\begin{aligned}\mathcal{R}_t(s,a) = \, & p_{ur}^t[S_t - \mathcal{D}_t]_- - p_{dr}^t[S_t - \mathcal{D}_t]_+ - w_1\varrho\Delta_F^t\varkappa \\ & - w_2 r_{up}^{t-1} - w_3\mathbb{1}_{\{r_{up}^{t-1} - r^{max} > 0\}} \\ & - [w_4\mathbb{1}_{\{\jmath_{hm}^t > 0\}} + w_5\jmath_{st}^t]\mathbb{1}_\xi \\ & - w_6\mathbb{1}_{\{\jmath_{hm}^t > 0\}}\mathbb{1}_\chi\end{aligned} \tag{3.12}$$

where

$$
\begin{aligned}
\Delta_E^t &= \jmath_{wf}^{\mathfrak{F},t} - \mathcal{D}_t^{\mathfrak{F}} \\
\Delta_F^t &= \Delta_E^t - \jmath_{st}^t + \jmath_{hm}^t \\
\xi &= \{\varrho < \overline{p}_{sm}(0:t-1) \wedge \Delta_E < 0 \wedge \overline{\Delta}_E(t:t+8) < 0\} && (3.13) \\
\chi &= \{\neg[p_{sm}(t-1) < \varrho \wedge \theta \wedge \varrho > \overline{p}_{sm}(0:t-1)] \mid \\
&\quad [\Delta_E(t) > \overline{\Delta}_E(t:t+8) \wedge r(t-1) < r_{up}^{th}] \wedge && (3.14) \\
&\quad \overline{\Delta}_E(t:t+8) < 0\} \\
\theta &= \begin{cases} 1 \text{ if } p_{sm}(t) > p_{sm}(t-1) \\ 0 \text{ otherwise.} \end{cases} && (3.15)
\end{aligned}
$$

The domain ξ compares ϱ against the average of the market and the surplus or lack of forecast energy Δ_E. χ checks 3 clauses: 1) Price prediction against current and averages and θ a boolean prediction of sign change of the difference between the current spot price and the next; 2) Compares the forecast energy difference with the average energy mismatch $\overline{\Delta}_E$ and the state of the pumped storage r and; 3) The expected energy imbalance. w_i are positive constants. $\overline{\Delta}_E(t:t+8)$ is an 8 hours rolling window of the average forecast of supply and demand differences.

In this setting the DDDQN did not provide the agent with a better performance. Despite the overhead and resource intensive computations the learning speed and test results perform worse than (3.11). In particular we find that the monthly trading cost of the HWPP is at best comparable to the results of the (3.11). However, and more importantly, the operation of the pumped storage is not completely reliable. DDDQN runs dry or overflows 3% and 1% respectively (Fig. 3.10). The novelties that have proven successful in other domain are not necessarily applicable to a more volatile, state and action rich problem, like the one at hand. Figure 3.11 contrast both realizations of Q-learning. It can be seen that (3.11)

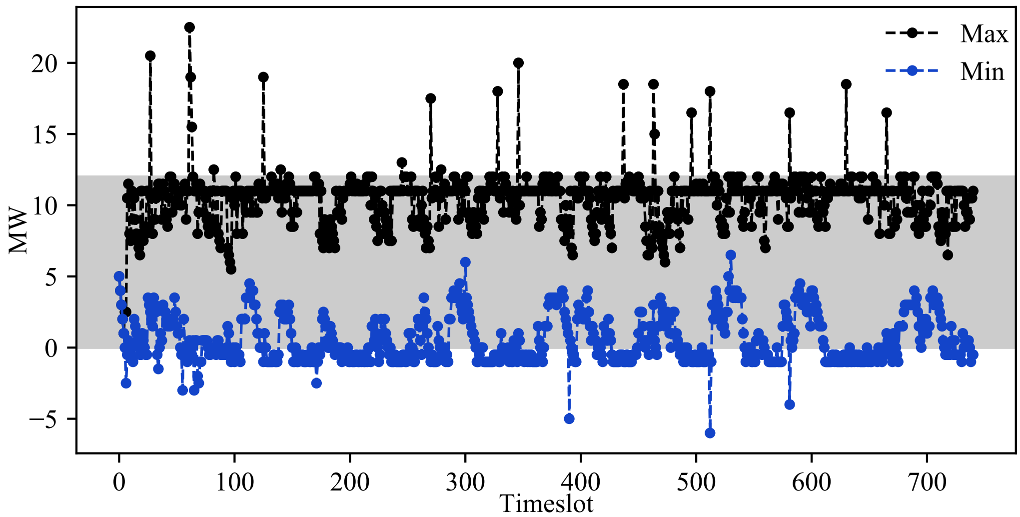


Fig. 3.10 Maximum charge and minimum discharge of the pumped storage by the DDDQN. The shaded area is the safe operational region.

converges faster to a better results than DDDQN. The initial spread is attributable to the anti-correlation memory sampling of DDDQN. In contrast to problems where there are actions with little or low significance with respect to the state of the system (e.g. racing cars in video game), in real-time control of energy flows this is seldom true. Hence the splitting of the network represents an overhead rather than a deeper insight to the agent. The simple yet robust reinforcement learning algorithm is better in managing the high frequency trading.

To summarize, Fig. 3.12 present the overall performance of the agent. The plots show the hourly costs and control of the HWPP, the wholesale price, demand, wind power, and hydro usage. The MAL learns a cost-effective charge/discharges of the hydro plant. It discharges the hydro plant when there is lack of wind power. The effect of the rolling time exploration (3.13) and (3.14) can be best observed when the agent holds hydro capacity and instead discharges when the spot price is disadvantageous. Although not perfect because of error estimates on future prices, the joint performance of the analytics, prediction and management phases achieves the best overall result. For example, the shaded areas highlight a discharge of the hydro plant to cover the lack of wind power. However, based on the predictions,

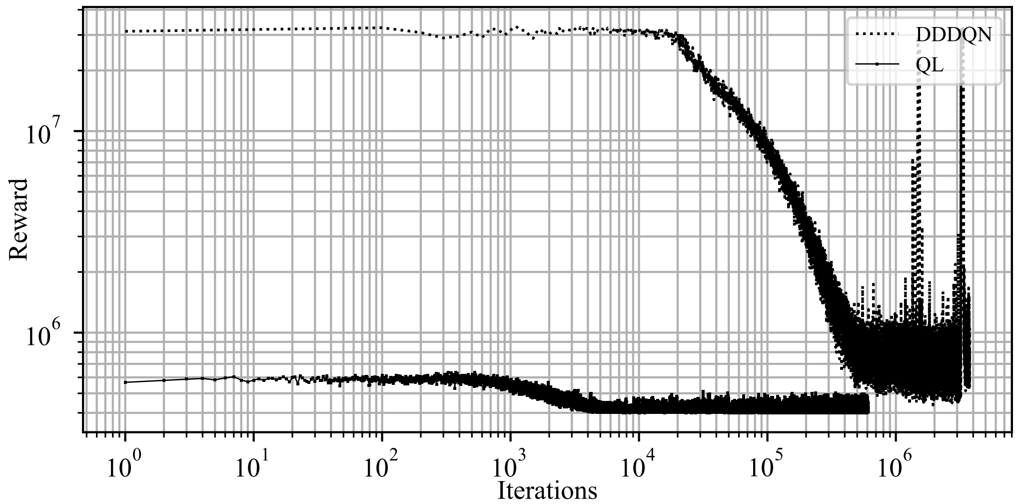


Fig. 3.11 Training of the QL and DDDQN.

holds on until a peak price. In addition, as can be seen in the left most shaded areas, the MAL prevents spillage and wind power curtailment by instead pumping water to the reservoir when the spot price is low or with surplus wind power.

The robustness of the control phase is tested with random outages of the wind farm and/or the hydro pumped storage. As a consequence of lack of internal energy generation, the results show an increase in the overall TPC as expected. However of more significance is the control of the hydro plant. In Fig. 3.13 we observe that the outages does not impact the management of the flows by either dry running or overflowing the reservoirs. In the shaded areas of the figure υ stands for wind power outage, ζ for a failure of the hydro plant and in λ both plants are out of service. In the first outage event, both plants are out for a period of 5 hrs. Followed by the hydro plant for 24 hrs. Lastly, in the third event the wind plant is out of service for 24 hrs.

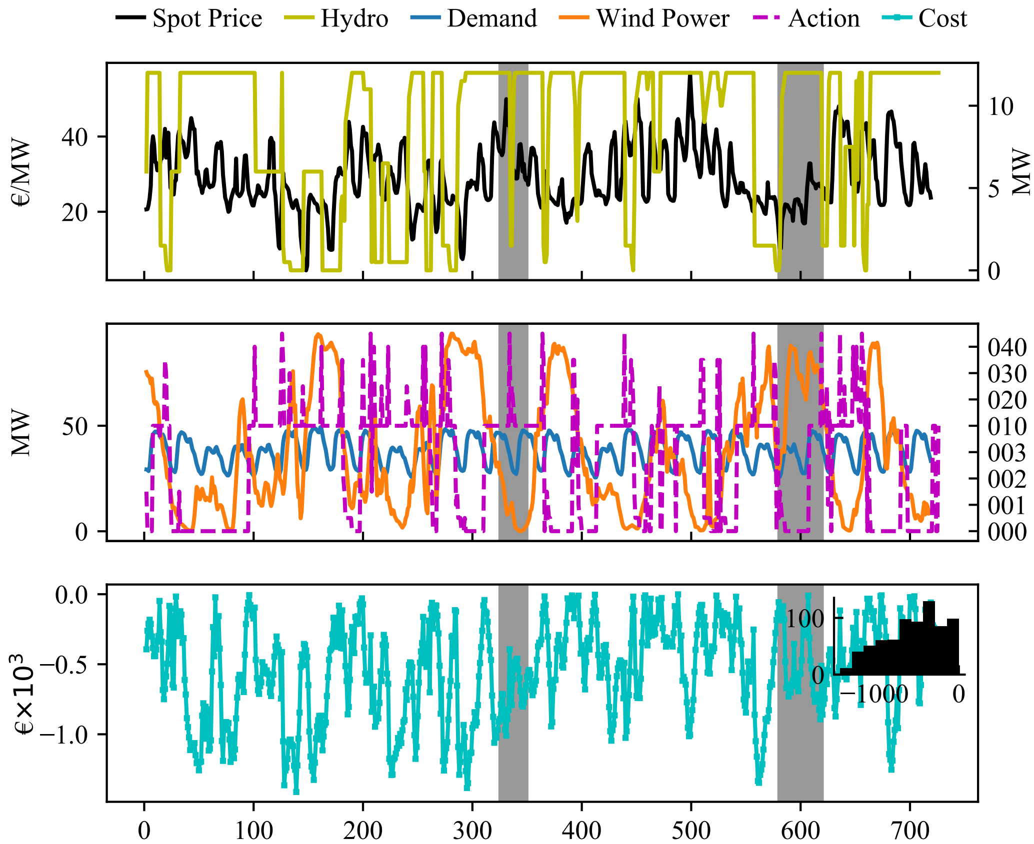


Fig. 3.12 Management of the HWPP for July 2017. The three plots share the x-axis scale.

3.2 Future Research

The work done can be extended to a more atomized and distributed market setting. The following presents several areas deemed interesting where this research can be continued.

Procurement from a mixture of wind farms The affordability to produce electricity is expanding. The methodology used to determine bilateral contracts can extend to a one-to-many or many-to-many scenario. This presents several appealing possibilities however challenging. Among those possibilities several stand out. The production of electricity either for selling purposes or surplus

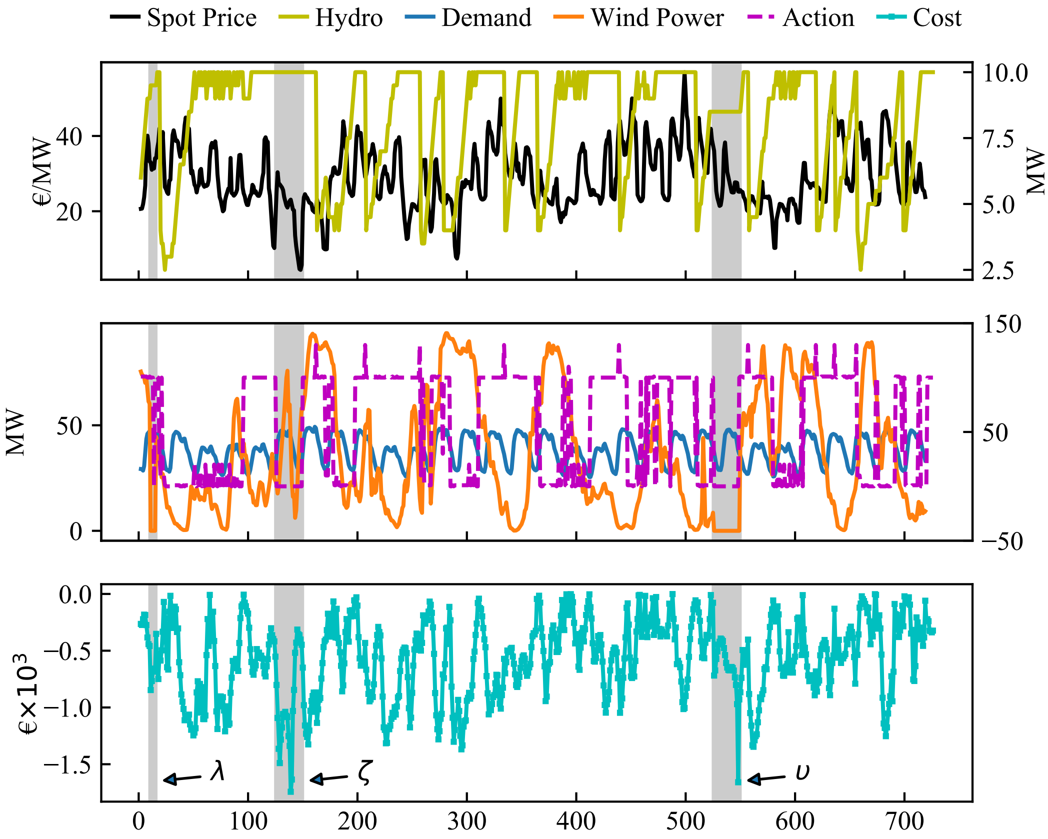


Fig. 3.13 Management of the HWPP with power outages for July 2017. υ and ζ are the time periods with wind or hydro outage respectively. In λ both plants are out of service. The three plots share the x-axis scale.

energy most likely would be in the low volume regime; in particular the latter. A many-to-many contract can maximize the utilization of electricity in a profitable way. The more distributed demand can be leveraged to accommodate the variable generation and thus counteract the lack of dispatchability of renewables.

This thesis studied bilateral contract for physical delivery. Future research can apply the gaming strategies for the case of contract as a financial instrument. A significant obstacle for a true smart grid is the connectivity between nodes. Thus a financial derivative can serve to guarantee an exchange of a physical quantity generetared elsewhere in the network. This becomes relevant in a setting that lacks the physical infrastructure of a fully connected and distributed network of consumers and producers. In [62] we present a futuristic idea: the wIsHood. It is an approach to the obstacle and describes the challenges to be addressed.

The payoff matrix in my game formulation can be extended with a mixture model for the demand distribution; benefiting from diverse demand patterns in different microgrids. In that way it could be possible to take into consideration multi-modal densities such that curtailment and more importantly spillage of variable generation is minimized.

Integration of regional energy exchanges The research path mentioned before can organically lead the way to creation of regional energy exchanges. In this scenario it is interesting to study the effects of loosely or negatively correlated markets. Although there might not be a physical market the collective trade among small sized communities could increase the heterogeneity of both supply and demand.

Another possibility is to include trade among traditional power markets on different continents and hemispheres. The potential benefit of such arrangement could have significant positive impact on the utilization of renewable sources and hence on the wholesale price of electricity. For instance, typically wind power is stronger during the night hours however in that same region the demand is typically at it lowest. Nevertheless the parts of the world where daytime is happening can be served of the wind power generated on the other side.

Besides the obvious physical challenges, there exist problems in the contract designing to be solved. The long-term prediction of electricity prices could become tangled. This would mean to include the coupling effects of interdependent markets. The diffusion coefficient in the jump-diffusion model can become a function of the other price model. This in turn would require a model to estimate the covariance dynamics among the coupled systems.

Non parametric probability densities Increased competition at the lowest level of the energy supply chain can lead to more tangled interactions among energy traders. To model this complexity, the payoff matrix can be enhanced in the game representation of the contract allocation. One possible way is to consider arbitrary non-parametric distributions. The relaxation of the payoff function of the players can incorporate an adaptation mechanism to changes in the trading environment. The modeling of heavily tangled trading markets can be approached with Hierarchical Topic Models. Topics represent distributions over possible states of the market. Then a given setting is characterized by a distribution over the topics.

Edge trading This concept includes the exchange of energy at the device level. A principal problem is the management of the system in real-time. Other challenges include privacy and scalability. Take for example a residential estate. Within a household smart devices should organize their use of power in a cost effective way. Within the estate households should coordinate to make efficient use of energy without trespassing each others privacy.

The agent developed in this thesis can be augmented to comprise a mechanism of estimating frequencies. This can then serve a scheduling engine in charge of switching on/off or tuning the devices. Moreover, in a hierarchical architecture the aggregated data can be submitted to a higher level agent in charge of managing the overall demand of the estate. The problems to solve by the upper level include signaling the lower level agents updates in the schedules, safeguard the operation of power generation and storage and contribute to the stability of the main grid.

Prognosis of low volume DER An aspect that could become a potential drawback in the push forward of the smart grid is asset maintenance. In this regard, further research has to be done to incorporate a prognosis of the operational conditions (e.g. mechanical, structural, electrical) of the distributed power plants. This is of significant importance for low volume prosumers. To incentivize investment on renewable infrastructure in the low volume regime it is paramount to provide the user with a reliability assessment of the e.g. solar panel-battery-inverter system. The consequences of not addressing this problem, that is using a run-to-fail strategy, might cause a wave of junk devices. This could have even worse outcomes if it happens before the return-on-investment timespan. Thus, a data analysis module for reliability can be integrated in the agent design. The prognosis should comprise the operational conditions of components like bearings, gearbox, generator armature's winding, blades and oil. Besides diagnosis the reliability of the equipment another problem to address is its overhaul scheduling to minimize the adverse impact on profit taking into consideration the maintenance cost.

Bibliography

[1] H. A. Aalami and S. Nojavan. Energy storage system and demand response program effects on stochastic energy procurement of large consumers considering renewable generation. *IET Generation, Transmission Distribution*, 10(1):107–114, Jul 2016.

[2] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. URL http://tensorflow.org/. Software available from tensorflow.org.

[3] U.S. Energy Information Administration. Annual Energy Outlook 2017. Technical report, Department of Energy, April 2017.

[4] A. Y. Al-Hassan. *Islamic Technology: An Illustrated History*. Cambridge University Press, 1992.

[5] H. Algarvio, F. Lopes, and J. Santana. Bilateral contracting in multi-agent energy markets: Forward contracts and risk management. In *Highlights of Practical Applications of Agents, Multi-Agent Systems, and Sustainability - The PAAMS Collection*, pages 260–269, Cham, 2015. Springer International Publishing.

[6] M. Asensio and J. Contreras. Stochastic unit commitment in isolated systems with renewable penetration under cvar assessment. *IEEE Transactions on Smart Grid*, 7(3):1356–1367, May 2016.

[7] L. Baringo and A. J. Conejo. Offering strategy of wind-power producer: A multi-stage risk-constrained approach. *IEEE Transactions on Power Systems*, 31(2):1420–1429, March 2016.

[8] A. Bello, D. W. Bunn, J. Reneses, and A. Muñoz. Medium-term probabilistic forecasting of electricity prices: A hybrid approach. *IEEE Transactions on Power Systems*, 32(1):334–343, Jan 2017.

[9] S. Bittlestone, A. Demurtas, K. F., and P. Kitson. Nuclear power in the UK. Technical report, Victoria,London, 2016.

[10] C. Block, J. Collins, and W. Ketter. Agent-based competitive simulation: Exploring future retail energy markets. In *Proceedings of the 12th International Conference on Electronic Commerce: Roadmap for the Future of Electronic Business*, ICEC '10, pages 68–77, New York, NY, USA, 2010. ACM.

[11] S. Blumsack. How the free market rocked the grid. *IEEE Spectrum*, December 2010.

[12] S. Borenstein, J. Bushnell, C. R. Knittel, and C. Wolfram. Inefficiencies and market power in financial arbitrage: A study of california's electricity markets*. *The Journal of Industrial Economics*, 56(2):347–378, 2008.

[13] R. Homayoun Boroumand, S. Goutte, S. Porcher, and T. Porcher. Hedging strategies in energy markets: The case of electricity retailers. *Energy Economics*, 51:503 – 509, 2015.

[14] D. W. Bunn, editor. *Modelling prices in competitive electricity markets*. John Wiley & Sons, West Sussex, England, 2004.

[15] T. Burton, N. Jenkins, D. Sharpe, and E. Bossanyi. *Wind Energy Handbook*. Wiley, 2011.

[16] A. Cartea and M. G. Figueroa. Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. *Applied Mathematical Finance*, 12(4):313–335, 2005.

[17] P. Chakraborty, E. Baeyens, P. P. Khargonekar, and K. Poolla. A cooperative game for the realized profit of an aggregation of renewable energy producers. In *2016 IEEE 55th Conference on Decision and Control (CDC)*, pages 5805–5812, Dec 2016.

[18] D. Chattopadhyay and T. Alpcan. Capacity and energy-only markets under high renewable penetration. *IEEE Transactions on Power Systems*, 31(3): 1692–1702, May 2016.

[19] J. P. Chaves-Avila, F. Banez-Chicharro, and A. Ramos. Impact of support schemes and market rules on renewable electricity generation and system operation: the spanish case. *IET Renewable Power Generation*, 11(3): 238–244, 2017.

[20] M. M. P. Chowdhury, R. Y. Folk, F. Fioretto, C. Kiekintveld, and W. Yeoh. Investigation on learning strategies for the spot broker in power tac. 2016.

[21] SEM Committee. Integrated Single Electricity Market (I-SEM) SEM Committee Decision on High Level Design. Ireland, September 2014.

[22] World Energy Council. World Energy Trilemma Report 2018. Technical report, London, UK, 2018.

[23] T. Couture and Y. Gagnon. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. *Energy Policy*, 38 (2):955 – 965, 2010.

[24] J. S. Cuevas, A. Y. R. González, M. P. Alonso, E. M. de Cote, and L. E. Sucar. Distributed energy procurement and management in smart environments. In *2015 IEEE First International Smart Cities Conference (ISC2)*, pages 1–6, Oct 2015.

[25] C. Daskalakis, P. W. Goldberg, and C. H. Papadimitriou. The complexity of computing a Nash equilibrium. *SIAM Journal on Computing*, 39(1):195–259, 2009.

[26] Climate Action Department of Communications and Environment. Renewable Electricity Support Scheme:Transitioning to I-SEM (Options Paper). Ireland, May 2017.

[27] Climate Action Department of Communications and Environment. Electricity Support Schemes I-SEM Arrangements (Decision Paper). June 2018.

[28] Energy Department of Communications and Natural Resources. A competition for electricity generation from biomass, hydro and wind. Technical report, Dublin, Ireland, 2013.

[29] P. Domah and M. G. Pollitt. The restructuring and privatisation of the electricity distribution and supply businesses in england and wales: a social cost-benefit analysis. *Fiscal Studies*, 22(1):107–146, 2001.

[30] A. M. Farid, B. Jiang, A. Muzhikyan, and K. Youcef-Toumi. The need for holistic enterprise control assessment methods for the future electricity grid. *Renewable and Sustainable Energy Reviews*, 56:669 – 685, 2016.

[31] Department for Business Energy and Industrial Strategy. Electricity generation costs. Technical report, London, 2016.

[32] Federal Ministry for Economic Affairs and Energy (BMWi). An electricity market for germany's energy transition, 2015.

[33] L. Freire, A. Street, D. A. Lima, and L. A. Barroso. A hybrid milp and benders decomposition approach to find the nucleolus quota allocation for a renewable energy portfolio. *IEEE Transactions on Power Systems*, 30(6): 3265–3275, Nov 2015.

[34] Google. Solving for sustainability. https://environment.google/approach/. Accessed: 2017-06-23.

[35] K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink, and J. Schmidhuber. Lstm: A search space odyssey. *IEEE Trans. on Neural Networks and Learning Systems*, 28(10):2222–2232, October 2017.

[36] L. I. Hagfors, H. H. Kamperud, F. Paraschiv, M. Prokopczuk, A. Sator, and S. Westgaard. Prediction of extreme price occurrences in the german day-ahead electricity market. *Quantitative Finance*, 16(12):1929–1948, 2016.

[37] H. He. Toward a smart grid: Integration of computational intelligence into power grid. In *The 2010 International Joint Conference on Neural Networks (IJCNN)*, pages 1–6, July 2010.

[38] M. Holland and M. Howley. Renewable Electricity in Ireland 2015. Technical report, Sustainable Energy Authority of Ireland, August 2016.

[39] M. Howley and M. Holland. Energy in Ireland 1990-2015. Technical report, Sustainable Energy Authority of Ireland, November 2016.

[40] IRENA. Wind Power. *Renewable Energy Technologies: Cost Analysis Series*, 1, June 2012.

[41] IRENA. The Power to Change: Solar and Wind Cost Reduction Potential to 2025. Technical report, International Renewable Energy Agency, Bonn, Germany, 2016.

[42] IRENA. Renewable Energy and Jobs - Annual Review 2017. Technical report, International Renewable Energy Agency, 2017.

[43] IRENA. Renewable power generation costs in 2017. 2018.

[44] D. Jacobson. Lloyd relaxation of voronoi diagrams. Wolfram Demonstrations Project, 2012. http://demonstrations.wolfram.com/LloydRelaxationOfVoronoiDiagrams/.

[45] S. Jenner, F. Groba, and J. Indvik. Assessing the strength and effectiveness of renewable electricity feed-in tariffs in european union countries. *Energy Policy*, 52:385 – 401, 2013.

[46] Z. Jiang, F. Li, W. Qiao, H. Sun, H. Wan, J. Wang, Y. Xia, Z. Xu, and P. Zhang. A vision of smart transmission grids. In *2009 IEEE Power Energy Soc. General. Meeting*, pages 1–10, July 2009.

[47] J. Johnson. Long History Of U.S. Energy Subsidies. https://cen.acs.org/articles/89/i51/Long-History-US-Energy-Subsidies.html. 22-03-17.

[48] P. L. Joskow. Lessons learned from electricity market liberalization. *Energy Journal*, pages 9–42, 2008.

[49] J. K. Kaldellis and D. Zafirakis. The wind energy (r)evolution: A short review of a long history. *Renewable Energy*, 36(7):1887 – 1901, 2011.

[50] N. J. Kasdin. Runge-kutta algorithm for the numerical integration of stochastic differential equations. *Journal of Guidance, Control, and Dynamics*, 18 (1):114–120, Jan-Feb 1995.

[51] W. Ketter, J. Collins, and M. de Weerdt. The 2017 Power Trading Agent Competition. *ERIM Report Series Reference No. ERS-2017-002-LIS*, February 2017.

[52] B. Kirby and E. Hirst. Allocating the costs of contingency reserves. *The Electricity Journal*, 16(10):39 – 47, 2003.

[53] G. Kneževic, S. Nikolovski, and P. Marić. Electricity spot market simulation involving bilateral contracts hedging. In *2011 8th International Conference on the European Energy Market (EEM)*, pages 122–127, May 2011.

[54] T. Kristiansen. A time series spot price forecast model for the Nord Pool market. *International Journal of Electrical Power & Energy Systems*, 61:20 – 26, 2014.

[55] I. Lampropoulos, J. Frunt, F. A. Nobel, A. Virag, P. P. J. van den Bosch, and W. L. Kling. Analysis of the market-based service provision for operating reserves in the netherlands. In *2012 9th International Conference on the European Energy Market*, pages 1–8, May 2012.

[56] J. Lee, J. Guo, J. K. Choi, and M. Zukerman. Distributed energy trading in microgrids: A game-theoretic model and its equilibrium analysis. *IEEE Transactions on Industrial Electronics*, 62(6):3524–3533, June 2015.

[57] L. Li, R. Mendoza-Arriaga, Z. Mo, and D. Mitchell. Modelling electricity prices: a time change approach. *Quantitative Finance*, 16(7):1089–1109, 2016.

[58] M. Liu, F. L. Quilumba, and W. Lee. Dispatch scheduling for a wind farm with hybrid energy storage based on wind and lmp forecasting. *IEEE Transactions on Industry Applications*, 51(3):1970–1977, May 2015.

[59] S. Lloyd. Least squares quantization in pcm. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982.

[60] G. Longoria and L. Shi. Nash-equilibrium electricity portfolios in the smart grid: A genetic annealing solution. In *2017 5th International Istanbul Smart Grid and Cities Congress and Fair (ICSG)*, pages 56–59, April 2017.

[61] G. Longoria, D. Jiang, A. Davy, and L. Shi. Wind energy allocation strategies for long-term contracts in open energy markets. In *2016 IEEE International Conference on Renewable Energy Research and Applications (ICRERA)*, pages 783–788, Nov 2016.

[62] G. Longoria, F. Akhtar, and L. Shi. Wireless power transmission in smart cities: The wishood - wireless smart neighborhood. In *Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems - Volume 1: SMARTGREENS*, pages 317–322. INSTICC, ScitePress, 2017.

[63] G. Longoria, A. Davy, and L. Shi. Ornstein-uhlenbeck-lévy electricity portfolios with wind energy contracting. *Technology and Economics of Smart Grids and Sustainable Energy*, 3(1):16, Nov 2018.

[64] G. Longoria, A. Davy, and L. Shi. Subsidies-free renewable energy trading: A meta agent approach. Submitted.

[65] P. Louridas and C. Ebert. Machine learning. *IEEE Software*, 33(5):110–115, Sept 2016.

[66] S. P. Meyn, P. Barooah, A. Bušić, Y. Chen, and J. Ehren. Ancillary service to the grid using intelligent deferrable loads. *IEEE Transactions on Automatic Control*, 60(11):2847–2862, Nov 2015.

[67] M. Mitchell. *An Introduction to Genetic Algorithms (Complex Adaptive Systems)*. MIT Press, 1998.

[68] A. Mondal and S. Misra. Game-theoretic energy trading network topology control for electric vehicles in mobile smart grid. *IET Networks*, 4(4):220–228, 2015.

[69] S. O. Muhanji, A. Muzhikyan, and A. M. Farid. Distributed control for distributed energy resources: Long-term challenges and lessons learned. *IEEE Access*, 6:32737–32753, 2018.

[70] T. Möbius and F. Müsgens. The effect of variable renewable energy sources on the volatility of wholesale electricity prices — a stylized full cost approach. In *2015 12th International Conference on the European Energy Market (EEM)*, pages 1–5, May 2015.

[71] D. Newbery. Electricity liberalisation in britain: The quest for a satisfactory wholesale market design. *The Energy Journal*, 26:43–70, 2005. ISSN 01956574, 19449089.

[72] D. M. Newbery and M. G. Pollitt. *The Restructuring and Privatization of the U.K. Electricity Supply-Was It Worth It?* Viewpoint: Public Policy for the Private Sector; Note No. 124. World Bank, Washington, DC, 1997.

[73] S. Nie, Y.P. Li, J. Liu, and C. Z. Huang. Risk management of energy system for identifying optimal power mix with financial-cost minimization and environmental-impact mitigation under uncertainty. *Energy Economics*, 61:313–329, 2017.

[74] Great Britain. Dept. of Energy. *Privatising Electricity: The Government's Proposals for the Privatisation of the Electricity Supply Industry in England and Wales*. Cm (Series) (Great Britain. Parliament). H.M. Stationery Office, 1988. ISBN 9780101032223.

[75] Sustainable Energy Authority of Ireland. Ireland's energy projections: Progress to targets, challenges and impacts. Technical report, Dublin, Ireland, 2018.

[76] S. Özdemir and R. Unland. The strategy and architecture of a winner broker in a renowned agent-based smart grid competition. *Web Intelligence*, 15(2): 165–183, 2017.

[77] C. O'Dwyer, L. Ryan, and D. Flynn. Efficient large-scale energy storage dispatch: Challenges in future high renewable systems. *IEEE Transactions on Power Systems*, 32(5):3439–3450, Sept 2017.

[78] S. Palamarchuk. Dynamic programming approach to the bilateral contract scheduling. *IET Generation, Transmission Distribution*, 4(2):211–220, February 2010.

[79] N. G. Paterakis, O. Erdin, A. G. Bakirtzis, and J. P. S. Catalo. Qualification and quantification of reserves in power systems under high wind generation penetration considering demand response. *IEEE Transactions on Sustainable Energy*, 6(1):88–103, Jan 2015.

[80] I. Pavić, M. Beus, H. Pandžić, T. Capuder, and I. Štritof. Electricity markets overview — market participation possibilities for renewable and distributed energy resources. In *2017 14th International Conference on the European Energy Market (EEM)*, pages 1–5, June 2017.

[81] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12: 2825–2830, 2011.

[82] M. Peters, W. Ketter, M. Saar-Tsechansky, and J. Collins. A reinforcement learning approach to autonomous decision-making in smart electricity markets. *Machine Learning*, 92:5–39, July 2013.

[83] T. Pinto, H. Morais, T. M. Sousa, T. Sousa, Z. Vale, I. Praça, R. Faia, and E. J. S. Pires. Adaptive portfolio optimization for multiple electricity markets participation. *IEEE Transactions on Neural Networks and Learning Systems*, 27(8):1720–1733, August 2016.

[84] B. M. Radhakrishnan and D. Srinivasan. A multi-agent based distributed energy management scheme for smart grid applications. *Energy*, 103:192 – 204, 2016.

[85] REN21. Renewables 2016 Global Status Report. Technical report, Renewable Energy Policy Network for the 21st Century, 2016.

[86] REN21. Renewables 2018 Global Status Report. Technical report, Renewable Energy Policy Network for the 21st Century, 2018.

[87] R. W. Righter. *Wind Energy in America: A History*. University of Oklahoma Press, 1996.

[88] P. Ringler, D. Keles, and W. Fichtner. Agent-based modelling and simulation of smart electricity grids and markets – a literature review. *Renewable and Sustainable Energy Reviews*, 57:205–215, 2016.

[89] C. Robinson. Electricity privatization in the united kingdom and its results. *Economic Planning Agency*, 60, 1995.

[90] M. Rocha and J. Neves. Preventing premature convergence to local optima in genetic algorithms via random offspring generation. In *Multiple Approaches to Intelligent Systems*, pages 127–136, Berlin, Heidelberg, 1999. Springer Berlin Heidelberg.

[91] M. Rock and L. Parsons. Offshore wind energy. *Environmental and Energy Study Institute*, 2010.

[92] R. T. Rockafellar and S. Uryasev. Optimization of conditional value-at-risk. *Journal of Risk*, 2:21–41, 2000.

[93] E. Roubik and H. Rudnick. Assessment of generators strategic behavior in long term supply contract auctions using portfolio concepts. In *2009 IEEE Bucharest PowerTech*, pages 1–7, June 2009.

[94] D.S. Ryberg, D.G. Caglayan, S. Schmitt, J. Linßen, D. Stolten, and M. Robinius. The future of european onshore wind energy potential: Detailed distribution and simulation of advanced turbine designs. *Preprints*, Dec 2018.

[95] G. Shi, D. Liu, and Q. Wei. Echo state network-based q-learning method for optimal battery control of offices combined with renewable energy. *IET Control Theory Apps.*, 11(7):915–922, 2017.

[96] A. Skajaa, K. Edlund, and J. M. Morales. Intraday trading of wind energy. *IEEE Transactions on Power Systems*, 30(6):3181–3189, Nov 2015.

[97] M. Song and M. Amelin. Purchase bidding strategy for a retailer with flexible demands in day-ahead electricity market. *IEEE Transactions on Power Systems*, 32(3):1839–1850, May 2017.

[98] K. Spees, S. A. Newell, and J. P. Pfeifenberger. Capacity markets—lessons learned from the first decade. *Economics of Energy and Environmental Policy*, 2(2):1–26, 2013.

[99] U. Stridbaek. *Lessons from liberalised electricity markets*. Organisation for Economic Co-operation and Development and International Energy Agency, Paris, 2005.

[100] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27*, pages 3104–3112. Curran Associates, Inc., 2014.

[101] S. Thomas. *The Privatization of the Electricity Supply Industry*. The British Electricity Experiment Privatization: the record, the issues, the lessons. Ed. J. Surrey. London: Earthscan, 1996.

[102] M. H. K. Tushar, A. W. Zeineddine, and C. Assi. Demand-side management by regulating charging and discharging of the ev, ess, and utilizing renewable energy. *IEEE Transactions on Industrial Informatics*, 14(1):117–126, Jan 2018.

[103] D. Urieli and P. Stone. Tactex'13: A champion adaptive power trading agent. In *Proceedings of the Twenty-Eighth Conference on Artificial Intelligence (AAAI 2014)*, July 2014.

[104] D. Urieli and P. Stone. Autonomous Electricity Trading using Time-Of-Use Tariffs in a Competitive Market. In *Proceedings of the 30th Conference on Artificial Intelligence (AAAI 2016)*, February 2016.

[105] D. Urieli and P. Stone. An mdp-based winning approach to autonomous power trading: Formalization and empirical analysis. In *Proceedings of the 15th International Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, May 2016.

[106] A. Valenciano, M. Bozorg, F. Sossan, and M. Paolone. An econometric model of the regulating power price for interconnected power systems: The case of the nord pool market. In *2018 15th International Conference on the European Energy Market (EEM)*, pages 1–5, June 2018.

[107] R. A. Verzijlbergh, L. J. De Vries, G. P. J. Dijkema, and P. M. Herder. Institutional challenges caused by the integration of renewable energy sources in the european electricity sector. *Renewable and Sustainable Energy Reviews*, 75:660 – 667, 2017.

[108] X. Wang, M. Zhang, F. Ren, and T. Ito. Gongbroker: A broker model for power trading in smart grid markets. In *2015 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, volume 2, pages 21–24, Dec 2015.

[109] Z. Wang and L. Wang. Adaptive negotiation agent for facilitating bi-directional energy trading between smart building and utility grid. *IEEE Transactions on Smart Grid*, 4(2):702–710, June 2013.

[110] Z. Wang, N. de Freitas, and M. Lanctot. Dueling network architectures for deep reinforcement learning. *CoRR*, abs/1511.06581, 2015.

[111] Q. Wei, G. Shi, R. Song, and Y. Liu. Adaptive dynamic programming-based optimal control scheme for energy storage systems with solar renewable energy. *IEEE Transactions on Industrial Electronics*, 64(7):5468–5478, July 2017.

[112] G. Wenzel, M. Negrete-Pincetic, D. E. Olivares, J. MacDonald, and D. S. Callaway. Real-time charging strategies for an electric vehicle aggregator to provide ancillary services. *IEEE Transactions on Smart Grid*, 9(5): 5141–5151, Sept 2018.

[113] A. Whiteman, H. Sohn, J. Esparrago, I. Arkhipova, and S. Elsayed. Renewable capacity statistics 2018. 2018.

[114] R. Wiser and M. Bolinger. 2014 Wind Technologies Market Report. Technical report, US Department of Energy, Oak Ridge, TN, August 2015.

[115] C.K. Woo, I. Horowitz, J. Moore, and A. Pacheco. The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy*, 39(7):3939 – 3944, 2011.

[116] D. Wozabal, C. Graf, and D. Hirschmann. The effect of intermittent renewables on the electricity price variance. *OR Spectrum*, 38(3):687–709, Jul 2016.

[117] D. J. Wu, P. Kleindorfer, and J. E. Zhang. Optimal bidding and contracting strategies in the deregulated electric power market: Part I. In *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*, pages 10 pp.–. IEEE, January 2000.

[118] W. Xishun, Z. Minjie, and R. Fenghui. A hybrid-learning based broker model for strategic power trading in smart grid markets. *Knowledge-Based Systems*, 119:142 – 151, 2017.

[119] T. Yi, L. Jing, W. Cheng, C. Ning, L. Xiaofeng, and G. Bingtuan. Game-theoretic optimization of bilateral contract transaction for generation companies and large consumers with incomplete information. *Entropy*, 19(6), 2017.

[120] D. Young, S. Poletti, and O. Browne. Can agent-based models forecast spot prices in electricity markets? Evidence from the New Zealand electricity market. *Energy Economics*, 45:419 – 434, 2014.

[121] N. Yu, L. Tesfatsion, and C. Liu. Financial bilateral contract negotiation in wholesale electricity markets using Nash bargaining theory. *IEEE Transactions on Power Systems*, 27(1):251–267, Feb 2012.

[122] Y. Yu, P. B. Luh, E. Litvinov, T. Zheng, J. Zhao, and F. Zhao. Grid integration of distributed wind generation: Hybrid markovian and interval unit commitment. *IEEE Transactions on Smart Grid*, 6(6):3061–3072, Nov 2015.

[123] R. Zárate-Miñano and F. Milano. Construction of sde-based wind speed models with exponential autocorrelation. ERC UCD, 2015. https://arxiv.org/abs/1511.02345.

[124] Zephyr. Google announces its first wind power transaction in norway. http://www.zephyr.no/wp-content/uploads/2017/03/Press_release_Google_Wind_Power_Norway__2_.pdf. Accessed: 2017-06-23.

[125] Q. Zhou, L. Tesfatsion, C. Liu, R. F. Chu, and W. Sun. A Nash approach to planning merchant transmission for renewable resource integration. *IEEE Transactions on Power Systems*, 28(3):2086–2100, Aug 2013.

[126] Z. Zhou, F. Zhao, and J. Wang. Agent-based electricity market simulation with demand response from commercial buildings. *IEEE Transactions on Smart Grid*, 2(4):580–588, Dec. 2011.

Appendix A

Wind Energy Allocation Strategies for Long-Term Contracts in Open Energy Markets

Wind Energy Allocation Strategies for Long-Term Contracts in Open Energy Markets

Genaro Longoria*, Dingde Jiang†, Alan Davy*, Lei Shi*

* Telecomunications Software and Systems Group † Northeastern University

* Waterford Institute of Technology † College of Information Science and Engineering

* Waterford, Ireland † Shenyang, China

* [fisrtletterfirstname][lastname]@tssg.org

† jiangdingde@ise.neu.edu.cn

***Abstract*—Electricity deregulation and the increase of renewable energy penetration are playing an important role in developed countries. In this work, a study of the decision-making process of energy traders is presented. We develop a theoretical solution for the sourcing trade-off, that a utility company faces when designing its long-term energy allocation strategy. The market mechanism of long-term contracts, where power producers and retailers engage, is presented and analyzed through a game theoretic approach. By introducing the concept of indistinguishable players and binary games, we construct a non-cooperative game. Nash equilibrium and Expected Utility theory are used to determine the optimal strategies for utility companies to minimize their purchasing costs. We devise an energy portfolio, for a utility company, to hedge against intermittent electricity production and secondly an energy price negotiation scheme for bilateral contracts with intermittent energy producers.**

***Keywords*—Binary games, non-cooperative games, indistinguishable players, energy market, long-term contracts.**

I. Introduction

The energy sector reformation is as yet a green field that has created a wide variety of research opportunities in the whole electricity supply chain. From generation, transmission/distribution, to storage and consumption, the openness of the electricity market and the slow but steady incorporation of emergent technologies are posing challenges upon governments, energy producers, retailers, industry and ultimately society.

Electricity, compared to until last century's early days, nowadays can be commercially converted from a wide variety of resources. The current trend towards green resources, such as wind, while being environmentally friendly are highly intermittent. Although weather forecast research provides statistical and phenomenological models for wind characterization and site development [1] uncertainty prevails. Intermittent generation, of renewable sources within the electric grid, is balanced through curtailment and storage, the former is typically the outcome of unexpected wind availability and/or low consumption time periods [2], [3]. Part of the energy storage research is targeted towards large energy capacities with low volume storage infrastructure and its impact on power systems [4]. Besides the effort required for its physical inclusion in the grid, the so called green resources, given their intermittent nature and the risk associated, add strain to the already complex energy exchange markets [5]. Profit creation, by means of energy trading, needs to incorporate strategies, at a faster pace, to cope not only with competitive parties but also with increasing supply side uncertainty, so as to balance expensive reliable sources with clean, less costlier but variable energy.

Bilateral contracts, under the presence of intermittent resources, are still a not fully understood mechanism, to the extent of the quantitative impact that weather variability has on procurement costs. Palamarchuk [6] and references therein analyze different aspects of typical medium and long-term contracts (LT), Scharff and Amelin [5] give a survey of modern electricity market-design across the European Union. Morales *et al.* [7] study the problem of wind energy trading in day-ahead markets. An approach to the problem of bilateral contracts by large consumers is studied in [8]; they develop a linear programming model to minimize the risk associated to the spot market. The conflict-of-interest problem of portfolio creation and energy prices schemes in forward markets have not been determined by means of a game theoretic approach.

This paper provides an answer to the problem of energy allocation of utility companies (UC), through bilateral contracts, among conventional and renewable power producers. It also contributes to the pricing negotiation strategies of UCs venturing in long-term contracts with intermittent energy generators.

We use Game theory (GT) to analyze the contracting policies between energy buyers and sellers. The sellers class is formed by conventional generators (CG) and wind power producers (WPP). Buyers are utility companies. All parties are assumed rational, self-interested and profit maximizers. GT's framework is used to determine decision-making criteria and energy price negotiation ranges. We focus on the trade-offs that utility companies face when allocating their electricity share among both types of energy sources.

The contributions we present in this paper are three principal results. Firstly, a methodology for many players games matrix representation, we then make use of statistical physics to introduce two concepts in GT's jargon: indistinguishable players and binary games which are used to derive an equilibrium search space order reduction.

Secondly, we derive a long-term energy share allocation

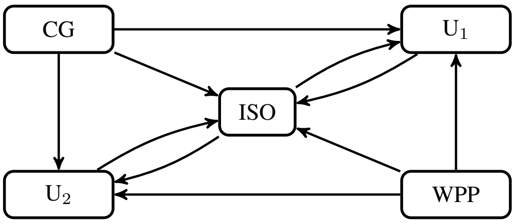


Figure 1. Energy flow between generators and retailers in a deregulated market. Power producers can sell their electricity via forward contracts or in the energy exchange market. Likewise, utility companies can procure and sell their committed electricity share.

criteria between renewable sources and fossil-fuel generators. In this context, the electricity market is used as a fulcrum. This result serves utility companies to hedge against the risk of wind uncertainty by not procuring its entire demand from an expensive source.

Lastly, we define a price negotiation scheme, based on known world state-of-affairs, for bilateral contracts between WPPs and UCs. Along with GT we use Expected Utility Theory -not to be confused with utility company- to obtain equilibrium strategies where no participant performs better by unilaterally deviating from its strategy

The reminder of the paper is organized as follows. In section II we present the marketplace scenario, energy traders interactions and our model. Section III states the problem from a game theoretical approach. The solution to the game is developed in section IV, we begin by introducing the concepts of indistinguishable players and binary games and the implication of them from a general game theoretic point of view. Then we derive the game's solutions in pure and mixed strategies for fixed and demand varying energy prices. In Section V we analyze the mixed strategy solution found for homogeneous prices. Based on it we present the energy allocation portfolio and the wind energy price range for contract negotiations between a WPP and a UC. Finally, in section VI we conclude with a general overview of the work done and the main results obtained.

II. Model

An open energy market is built upon private electricity producers, utilities and an Independent Service Operator (ISO). In conjunction, they give rise to the Spot Market (SM). The ISO has three key responsibilities: 1) maintain safe operation levels over the transmission and distribution lines; 2) balance real–time supply and demand differences; 3) determine equilibrium prices for unit of energy exchanged during each period of the trading day. Electricity producers span among a few different kinds of fossil fuels and renewable resources; they can deliver large volumes of energy which is bought by UCs to serve their demand commitments.

The interactions among the game players and the ISO is depicted in Figure 1. The arrows symbolize the direction of energy flow which might be from a producer to a UC, from the ISO to the UC and so on. The UC might buy energy from the power pool in such cases when the real wind energy output does not match the quantity agreed in the LT. We consider the electricity distribution lines are operated by the ISO such that the energy sold by any UC is delivered, to the end customer, via the ISO.

Given the fluctuating nature of the sector, to stabilize electricity prices and avoid arbitrage exploitation, open energy markets favor forward contracts over real-time energy trading. We construct a model for smart bilateral procuring policies by UCs. We consider that each UC has a reliable demand forecast D prior to the trading day and the Long-term contract (LT) signing. Every period of time during the trading day is t and i stands for each of the UCs.

The energy demand D_i of UC$_i$ is sourced from a LT with a CG and/or a WPP. Typically, forward contracts between UC and CG are in the form of *options*. This means that the energy price is composed of reservation and execution costs. We represented them by s and g respectively [9]. The reservation cost, guarantees the UC an amount of energy Q during the trading day at a specific period of time with the option, through the execution price, to partially or not make use of it. The electricity purchased in the SM will depend on the wind conditions on the trading day and the spot market price compared to the execution price for the CG.

The procurement policy of a UC can be formulated as $Q_i = \sigma_i D_i$, $w_i = (1-\sigma_i)D_i$ and $D_i = Q_i + w_i$. Where Q_i and w_i are the energy contracted with a CG and WPP respectively, $\sigma_i \in [0,1]$ is a probability distribution. It is interpreted as a measure of the risk-level preference of UC$_i$. The wind energy price agreed on between a WPP and a UC is P_w; since the WPP has negligible variable cost we assume $P_w < (s+g)$. Π_i^t is the cost of procurement of a UC. It can be expressed as:

$$\Pi_i^t = sQ_i^t + gq_i^t + p^t x_i^t + P_w w_i^t \tag{1}$$

$$D_i^t = q_i^t + x_i^t + w_i^t \tag{2}$$

$$x_i^t = \begin{cases} D_i^t - (w_i^t + q_i^t) & \text{if } p^t > s+g \\ D_i^t - w_i^t & \text{if } p^t < s+g. \end{cases} \tag{3}$$

Subject to the following assumptions: $W_{\max} < \sum D_i$, $Q_{\max} > \sum D_i$, $X_{\text{SM}} \gg \sum D_i$, $Q_i \geq \sum q_i^t$. The maximum installed power output of the wind farm is denoted by $W_{\max}$, X_{SM} is the energy traded in the SM during a trading day and $Q_{\max}$ is the installed capacity of the CG. The instantaneous output delivered by the WPP and executed energy from the CG are w^t and q^t respectively. The last inequality reflects the fact that not all the reserved conventional generated energy Q_i might be used by UC$_i$ on the trading day.

III. Problem Statement

In this section we analyze the decision-making of two UCs engaging in the process to sign a bilateral long-term contract with a WPP or a CG. Each UC can choose a low-risk but expensive energy source like a conventional producer or seek a better price deal with a less costlier and uncertain renewable source. The risk is translated into higher procurement cost of energy deficits bought at SM prices. We use a Game theoretic approach to determine the outcomes of the different possible interactions of the set of actions available to the UCs. The problem can be studied as a non-cooperative game in normal form, $\mathcal{G} = \{\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}}\}$ which consist of 1) the involved parties or players in the set $\mathcal{N}$, with n the number of elements; 2) the strategies or actions available to each player $s_i \in \mathcal{S}_i$; 3) a measure u_i of each player's gain or loss for any action taken by the players in $\mathcal{N}$ known as utility function. In game $\mathcal{G}$ the set of players $\mathcal{N} = \{U_1, U_2\}$, their utility function consists of the cost of energy procured to fulfill their customers electricity demand denoted by D_i for $i \in \mathcal{N}$. The strategy set is composed of either a low risk or high risk contract denoted as `LR` and `HR` respectively.

$$u_i(s_i, \mathbf{s_{-i}}) = \begin{cases} -D_i P_{\text{CG}} & \text{if } s_i = \texttt{LR} \\ -\sum\limits_t (D_i - w_i^t)p^t - w_i^t P_w & \text{if } s_i = \texttt{HR}, \end{cases}$$

where $P_{\text{CG}} = s + g$ and each player's $u_i(\cdot)$ is a function of its own strategy s_i and the actions $\mathbf{s_{-i}}$ taken by all other players[1]. The amount of power output, from the WPP, available in the future is uncertain at the time of signing the contract. We assume the wind speed's strength at any time follows or can be approximated by a priori probability distribution function (pdf) or can be approximated by a known pdf. It has been argued that wind speed distribution can be approximated through the Weibull or Rayleigh distribution functions [1], [10]. For instance, in the latter case $f(w) = \frac{2w}{c^2} e^{-(\frac{w}{c})^2}$, where c is the scale parameter. Then the expected value or average wind power production is $\mathbb{E}[w] = \int_{-\infty}^{\infty} w f(w) = \frac{c}{2}\pi$. Although, the expected power output can be estimated, any unbalance during the trading day must be compensated with real-time procurement. This brings another source of uncertainty into play: SM electricity prices. They are the result of supply and demand forces and the corresponding energy bidding from wholesalers and retailers. Although sometimes it may present a favorable price it is characterized by it high volatility.

In the following, we assume the pdf of the WPP's output and SM price are common knowledge to all players, hence the expected values for an arbitrary time period T are $\sum p^t/T = \mathbb{E}[P_{\text{SM}}]$ and $\sum w^t/T = \mathbb{E}[w]$. We also consider the expected wind energy production is distributed equally among the members of $\mathcal{N}$ thus when n UCs choose the `HR` strategy the volume of electricity procured from the WPP is $\mathbb{E}[w]/n$.

The matrix pay-off representation of game $\mathcal{G}$ is shown in (4); the column and row player are U_1 and U_2 respectively. Every matrix element-pair $m^i_{jk}, i \in \mathcal{N}$ of (4) represents the costs of both UCs according to the strategies chosen.

$$\begin{array}{ccc} & & \mathbf{U_1} \\ & & \begin{array}{cc} \texttt{LR} & \texttt{HR} \end{array} \\ \mathbf{U_2} & \begin{array}{c} \texttt{LR} \\ \texttt{HR} \end{array} & \begin{bmatrix} \mathbf{m^1_{1,1}},\ \mathbf{m^2_{1,1}} & \mathbf{m^1_{1,2}},\ \mathbf{m^2_{1,2}} \\ \mathbf{m^1_{2,1}},\ \mathbf{m^2_{2,1}} & \mathbf{m^1_{2,2}},\ \mathbf{m^2_{2,2}} \end{bmatrix} \end{array} \tag{4}$$

[1]The '$-\mathbf{i}$' notation stands for all elements of a given set other than i.

where

$$\begin{aligned} \mathbf{m^1_{1,1}} &= -D_{U_1} P_{\text{CG}}, & \mathbf{m^2_{1,1}} &= -D_{U_2} P_{\text{CG}}, \\ \mathbf{m^1_{1,2}} &= -(D_{U_1} - \mathbb{E}[w])\mathbb{E}[P_{\text{SM}}] - \mathbb{E}[w]P_w, & \mathbf{m^2_{1,2}} &= -D_{U_2} P_{\text{CG}}, \\ \mathbf{m^1_{2,1}} &= -D_{U_1} P_{\text{CG}}, & \mathbf{m^2_{2,1}} &= -(D_{U_2} - \mathbb{E}[w])\mathbb{E}[P_{\text{SM}}] - \mathbb{E}[w]P_w, \\ \mathbf{m^1_{2,2}} &= -\left(D_{U_1} - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\text{SM}}] - \tfrac{\mathbb{E}[w]}{n} P_w, & \mathbf{m^2_{2,2}} &= -\left(D_{U_2} - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\text{SM}}] - \tfrac{\mathbb{E}[w]}{n} P_w. \end{aligned}$$

Each player makes its decision independently seeking to minimize the procurement costs taking into account the possible actions of the other player. To solve the non-cooperative game $\mathcal{G}$ we find Nash equilibrium (NE) strategies where no player has an incentive to unilaterally deviate from this state searching to decrease its overall cost. A vector s^* is a NE strategy profile if equation (5) is satisfied [11]:

$$u_i(s_i^*, \mathbf{s}^*_{-i}) \le u_i(s_i, \mathbf{s}^*_{-i}), \quad \forall s_i \in \mathcal{S}_i, i \in \mathcal{N}. \tag{5}$$

To determine the NE strategies we use Expected Utility theory and John Nash's 1951 theorem [12] that states that every finite n-player game has at least one strategic equilibrium solution. We begin by presenting the concept of mixed strategies. Let $\mathcal{P}_m$ be a set of probabilities for each s_i such that:

$$\mathcal{P}_m = \{\mathbf{p} = (p_1, \ldots, p_m) \mid p_j \ge 0 \text{ for } j = 1, ..., m \text{ and } \sum_1^m p_j = 1\}.$$

Let m_i be the number of pure strategies in s_i then for player $i \in \mathcal{N}$ the vector $\mathbf{p}_i = (p^i_1, p^i_2, ..., p^i_m)$ is the probability distribution over his pure strategy set s_i. Moreover since there is no cooperation among UCs the joint probability distribution is the product of each player's $\mathbf{p}_i$, then under mixed strategies the expected utility of player i becomes:

$$\mathbb{E}[u_i] \triangleq v_i(\mathbf{p}_1, \ldots, \mathbf{p}_n) = \sum_{j_1=1}^{m_1} \cdots \sum_{j_n=1}^{m_n} p^1_{j_1} \cdots p^n_{j_n} u_i(\mathbf{s}). \tag{6}$$

It follows readily from the previous definition of player's i expected pay-off (6) that the mixed strategy equivalent of condition (5) can be defined as:

$$v_i(\mathbf{p}^*_1, \ldots, \mathbf{p}^*_i, \ldots, \mathbf{p}^*_n) \le v_i(\mathbf{p}^*_1, \ldots, \mathbf{p}_i, \ldots, \mathbf{p}^*_n) \tag{7}$$

where $\mathbf{p}^*_i$ is player's i best response, mixed strategy Nash equilibrium solution to the other players' mixed strategy profiles. If condition (7) holds there is no motivation for player i to seek lower procurement cost by deviating from its equilibrium strategy.

IV. Game Solution

In this section we use the mathematical results of GT, briefly described previously, to determine the equilibrium strategies for two utility companies. The set of possible actions to each UC is formed by a reliable low-risk contract with a CG or a less expensive and uncertain contract with a WPP. We consider the WPP as a price taker, the most common case in current energy markets [13]. This is partly a consequence of current renewable generation installed capacities compared to coal or gas-fired generator plants. If both UCs source energy from the WPP we assume that its output will be distributed equally.

In the next subsection, we present the equilibrium solutions for homogeneous followed by the general case of heterogeneous energy prices, in pure and mixed strategies. The intuition behind a mixed strategy solution is that of energy portfolios diversification; which we discuss in next section.

Before going further, we present a method to decrease the search space and hence the computational time to find equilibrium strategies under certain circumstances.

Any two person game can be depicted by a 2D structure as we did in matrix (4) as more players are incorporated the dimensionality increases proportionally such that a three person game would be a 3D matrix or cube, a four person game can be understood as a collection of 3D structures within a 1D structure, i.e., a vector of cubes, in the case of 5 players we will have a matrix of cubes followed by a cube of cubes and so on and so forth.

Equilibrium search is a computational resource intensive process. In particular, if the game consists of two possible pure strategies, any configuration in the $n-$dimensional space can be represented by a binary number, then the total number of strategy profiles and hence the exploration space for an equilibrium search algorithm is 2^n, where n is the number of elements in the set of players $\mathcal{N}$.

Theorem 1 (Pure strategy equilibrium search space in a binary non-cooperative game with indistinguishable players): For any non-cooperative binary game with n indistinguishable players the configuration space for equilibrium search in pure strategies is $\mathcal{O}(n)$.

Proof: Indistinguishable players are competing, self-interested and profit maximizers, just as any other player. Nonetheless, they are different from other classes in that they share a similar internal structure among the members, e.g., pay-off matrix, such that any element of $\mathcal{N}$ is interchangeable. We define a binary non-cooperative game as the interaction between non-communicating players with two possible strategies each. We define Ω as the set of all possible strategy permutations. In a binary game the number of elements in Ω is 2^n. Now, let us define

$$\omega_k = \left\{ s_1, \dots, s_n \middle| \sum_i^n s_i = \mathrm{B} \right\} \subseteq \Omega,$$

where $\mathrm{B} = \{x \in \mathbb{Z} \mid 0 \le x \le n\}$ because of the binary nature of the game and k is the number of players whose strategy is the same. The elements of ω_k are those profiles in which the mix of strategies chosen is held constant. The number of different ω_k, with their elements adding the same amount, is the number of possible combinations, i.e., $n\mathbf{C}k = \frac{n!}{k!(n-k)!}$ and $\sum_k n\mathbf{C}k = 2^n$, which is the upper bound. Now, for indistinguishable players their utilities within a $k-$group are just ordered differently, for equilibrium search the order is non-relevant whereas only the magnitude of the utility function is of interest. Hence, this search method only seeks and compares at the $k-$layer and $k = [0, \dots, n]$, so that the search space for a given algorithm is $\mathcal{O}(n)$. ∎

A. Homogeneous Energy Prices

In this section, we derive equilibrium solutions for fixed contracting electricity prices. That is, the price per unit of electricity, from both the CG and the WPP, remains constant independently of the number of utilities willing to sign a LT with any of them. This scenario is expected whenever the WPP is considered to be a price taker, the current situation in present energy markets. On the other hand, the CG might keep its price fixed, independently of the demand, in order to be attractive to potential buyers in a highly competitive market.

1) Nash Equilibrium in Pure Strategies: In game $\mathcal{G}$, the utilities' procurement costs come from three different sources: CG, WPP and the SM. Given the nature of the three energy wholesalers, the unique Nash equilibrium in pure strategies is the $[\mathtt{HR}, \mathtt{HR}]$ strategy profile: both UCs should procure energy from the WPP and the intraday unbalances from the spot market.

There is a maximum number x, of utility companies procuring from the WPP, that would make indifferent the next UC from signing a long-term contract with a CG or a renewable energy generator. In this general case, the indifference point is determined by equating the pay-off of each strategy in game $\mathcal{G}$:

$$\begin{aligned} -DP_{\text{CG}} &= -(D - \frac{\mathbb{E}[w]}{x})\mathbb{E}[P_{\text{SM}}] - \frac{\mathbb{E}[w]}{x}P_w \\ x &= \frac{\mathbb{E}[w]}{D}\frac{\mathbb{E}[P_{\text{SM}}] - P_w}{\mathbb{E}[P_{\text{SM}}] - P_{\text{CG}}}. \end{aligned} \tag{8}$$

For a current or foreseeable state of the world and hence an estimation of SM electricity prices along with the wind farm site characteristics, equation (8) tells us the maximum number of similar UCs that can be allocated by a WPP (or various wind farms as long as the total average output is $\mathbb{E}[w]$) without any of them willing to change strategy.

Equation (8) can be understood as a threshold or critical value at which a UC is equally likely pursuing to sign a long-term contract with either the CG or the WPP, since there is no longer an incentive to procure its demand from a less expensive but unreliable source.

2) Nash Equilibrium in Mixed Strategies: To solve the strategic game $\mathcal{G}$ we first determine the expected utility for a single UC regardless of the action chosen by the other UC. Using equation (6) with $\mathbf{p}_i = [p_i^1 = \sigma_i^{\text{LR}}, p_i^2 = \sigma_i^{\text{HR}}]$,

$$\mathbb{E}[u_2^{\text{LR}}] = \sigma_1^{\text{LR}}(-D_2P_{\text{CG}}) + \sigma_1^{\text{HR}}(-D_2P_{\text{CG}}) \tag{9}$$

$$\begin{aligned} \mathbb{E}[u_2^{\text{HR}}] &= \sigma_1^{\text{LR}}\{-(D_2 - \mathbb{E}[w])\mathbb{E}[P_{\text{SM}}] - \mathbb{E}[w]P_w\} + \\ &+ \sigma_1^{\text{HR}}\{-(D_2 - \frac{\mathbb{E}[w]}{n})\mathbb{E}[P_{\text{SM}}] - \frac{\mathbb{E}[w]}{n}P_w\}, \end{aligned} \tag{10}$$

where we have set 1 and 2 instead of U_1 and U_2 respectively to simplify notation. Equating (9) and (10) with $\sigma_i^{\text{LR}} + \sigma_i^{\text{HR}} = 1$ and $n = 2$ yields:

$$\sigma_1^{*\text{HR}} = 2\left[1 - \frac{D_2(\mathbb{E}[P_{\text{SM}}] - P_{\text{CG}})}{\mathbb{E}[w](\mathbb{E}[P_{\text{SM}}] - P_w)}\right]. \tag{11}$$

We have determined the NE mixed strategy solution of game $\mathcal{G}$ given by the vector $\mathbf{p}_i^* = [1 - \sigma_i^{*\text{HR}}, \sigma_i^{*\text{HR}}]$ which is also the best trade-off for the UC between both types of power producers. In section V we will examine the properties inherent in this probability distribution.

B. Heterogeneous Energy Prices

The general case of price dependency on demand is prone to arise in low competitive energy markets. To study this case the upper-right and lower-left elements of matrix (4) are modified to introduce price changes as a function of the number of buyers. We are not interested in the dependency structure of the price itself nor on its value but on the outcomes it might have from a strategic decision-making standpoint. Thus, when both utilities choose the same pure strategy, the price per unit of energy they face under a bilateral contract is P^+_{CG} or P^+_w which are costlier than its homogeneous counterparts, i.e., $P^+_{\text{CG}} > P_{\text{CG}}$ and $P^+_w > P_w$, then:

$$\begin{aligned} \mathbf{m^1_{1,1}} &= -D_1 P^+_{\text{CG}}, & \mathbf{m^2_{1,1}} &= -D_2 P^+_{\text{CG}}, \\ \mathbf{m^1_{2,2}} &= -\left(D_1 - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\text{SM}}] - \tfrac{\mathbb{E}[w]}{n}P^+_w, & \mathbf{m^2_{2,2}} &= -\left(D_2 - \tfrac{\mathbb{E}[w]}{n}\right)\mathbb{E}[P_{\text{SM}}] - \tfrac{\mathbb{E}[w]}{n}P^+_w. \end{aligned}$$

1) Nash Equilibrium in Pure Strategies: In the modified version of the non-cooperative game $\mathcal{G}$, given the costs of the three possible sources of electricity and as long as equation (12) holds true, it is straight forward to show that the NE in pure strategies remains $[\texttt{HR}, \texttt{HR}]$. Equation (12) states that the difference between the utility's demand and the wind availability should be so that the overall procurement cost are kept below the price of the conventional producer.

$$D_i - \frac{\mathbb{E}[w]}{n} > \frac{D_i P_{\text{CG}} - \frac{\mathbb{E}[w]}{n} P^+_w}{\mathbb{E}[P_{\text{SM}}]}. \qquad (12)$$

Both utilities should procure energy from the WPP and use the energy exchange pool, i.e. the SM, to balance real-time differences from demand and wind availability.

2) Nash Equilibrium in Mixed Strategies: The procedure used in section IV-A2 of this paper to determine NE strategies with homogeneous prices is applied to the case of price as a function of demand. Using the expected utility of any player the desired equilibrium is:

$$\sigma_1^{*\text{HR}} = \frac{D_2(P^+_{\text{CG}} - \mathbb{E}[P_{\text{SM}}]) + \mathbb{E}[w](\mathbb{E}[P_{\text{SM}}] - P_w)}{D_2(P^+_{\text{CG}} - P_{\text{CG}}) + \mathbb{E}[w](\frac{\mathbb{E}[P_{\text{SM}}]}{n} + \frac{P^+_w}{n} - P_w)}, \qquad (13)$$

where, as noted earlier, the strategy profile for each player is given by the vector $\mathbf{p}^*_i = [1 - \sigma_i^{*\text{HR}}, \sigma_i^{*\text{HR}}]$. Equation (13) has a more complex structure than equation (11) which requires the UC to know beforehand the pricing scheme used by the CG and the WPP. Although not a trivial task, utility companies can obtain estimates of those elements from previous negotiations or perform simulations for different price scenarios.

V. Solution Analysis

In this section we analyze the homogeneous case. The solutions found in the previous section will be the base to pin down certain fundamental characteristics of the wind and the energy market price probability distribution functions considered in game $\mathcal{G}$. First, we present an example to graphically explore $\sigma^{*\text{HR}}$. Figure 2 shows a graphical representation of a $\sigma^{*\text{HR}}$ realization as a function of P_w and P_{CG}. It is clear the asymptotic characteristic as P_w approaches $\mathbb{E}[P_{\text{SM}}]$ from either side. Meanwhile, if P_{CG} equals $\mathbb{E}[P_{\text{SM}}]$ the probability distribution attains non plausible results. For energy prices, below the spot market price, the probability of a HR contract increases as the energy cost from a CG increases. Above the spot market price the opposite is true (see Figure 2b), this contradiction can be explained by the assumption that on average spot market prices are higher than those of a WPP and similar to a CG.

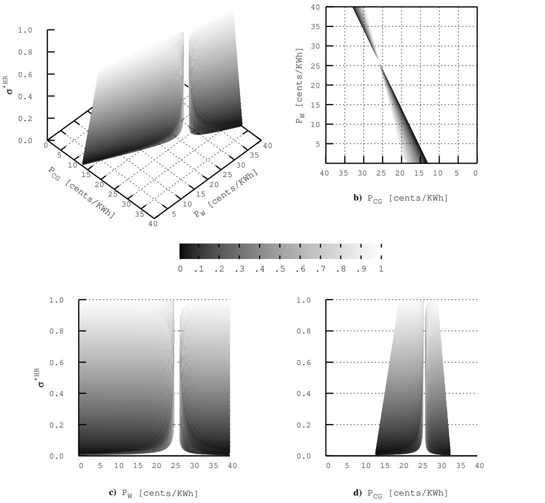


Figure 2. Long-term contracting policy $\sigma_i^{*\text{HR}}$ for different conventional and wind energy prices with given parameters: $P_{\text{SM}} = 26$ cents/KWh, $D = 30$ MW and $\mathbb{E}[w] = 15$ MW.

Since σ_1 is the probability distribution over the pure strategies s_1 of U_1 then equation (11) is restricted such that

$$1 \leq \frac{2D_2(\mathbb{E}[P_{\text{SM}}] - P_{\text{CG}})}{\mathbb{E}[w](\mathbb{E}[P_{\text{SM}}] - P_w)} \leq 2. \qquad (14)$$

To determine the relationship between the SM, CG and WPP energy prices, we can analyze the $\texttt{LHS}$ and $\texttt{RHS}$ inequalities in (14) in two different scenarios: 1) $\mathbb{E}[w] = D$; 2) $\mathbb{E}[w] < D$. Furthermore, we also consider both UC to be same-sized such that their committed demand are $D_1 = D_2 = D$. It follows readily what the first scenario implies for the price difference:

$$\texttt{LHS} \Rightarrow 2P_{\text{CG}} - P_w \leq \mathbb{E}[P_{\text{SM}}] \qquad (15)$$

$$\texttt{RHS} \Rightarrow P_{\text{CG}} \geq P_w \qquad (16)$$

Equation (16) correctly portraits real energy price differences among fossil-fuels and renewable energy sources: the latter has negligible marginal costs once it starts operating while the former is always dependent of, e.g., coal prices. On the other hand, and by virtue of the previous statement, equation (15) states that the expected cost of procuring energy during real-time trading is higher than that of a CG and a WPP.

Finally the last scenario bounds the energy price from the utility company's standpoint that is willing to pay in a long term-contract with a renewable power producer.

Theorem 2 (Utility company renewable energy source contracting policy): The long-term bilateral contract energy price P_w from a wind power producer for a utility company with demand larger than the expected wind energy production, i.e., $\mathbb{E}[w] < D$, is

$$\kappa P_{\text{CG}} - \mathbb{E}[P_{\text{SM}}] \leq P_w \leq \beta P_{\text{CG}} - (\beta - 1)\mathbb{E}[P_{\text{SM}}].$$

Proof: Given game $\mathcal{G}$ and its mixed-strategy Nash equilibrium profile $[\sigma_i^{\text{LR}}, \sigma_i^{\text{HR}}]$ for $i \in \mathcal{N}$, then from the self-imposed condition (14) it follows that

$$\texttt{LHS} \Rightarrow \frac{2\beta P_{\text{CG}} - P_w}{2\beta - 1} \leq \mathbb{E}[P_{\text{SM}}] \tag{17}$$

$$\texttt{RHS} \Rightarrow \frac{\beta P_{\text{CG}} - P_w}{\beta - 1} \geq \mathbb{E}[P_{\text{SM}}], \tag{18}$$

$$\beta \triangleq \frac{D}{\mathbb{E}[w]} > 1.$$

From equations (17) and (18), it is derived the lower and upper bounds of the electricity price for a UC negotiating strategy in a two-sided contract with a WPP,

$$\kappa P_{\text{CG}} - \mathbb{E}[P_{\text{SM}}] \leq P_w \leq \beta P_{\text{CG}} - (\beta - 1)\mathbb{E}[P_{\text{SM}}], \tag{19}$$

where κ is defined as:

$$\kappa \triangleq \frac{2\beta}{2\beta - 1}$$

■

A utility's planning department, that is envisaging a venture of a bilateral agreement with an intermittent resource of energy, can be served by equation (19) to determine energy prices. Equation (19) and available data, such as the wind farm location and hence its wind harvest distribution, conventional generators energy prices and energy market conditions, set the electricity contracting price range for the utility. It can be understood as a quantitative best-price negotiation scheme for a new long-term contract with a renewable energy wholesaler.

VI. Conclusions

The competitive interactions between utility companies and power producers has been presented. A non-cooperative game was constructed to analyze the strategic decision environment in which electricity wholesalers and retailers trade energy.

The concept of indistinguishable player and binary games were introduced. We proposed a reduction configuration space method for pure strategies equilibrium search in indistinguishable-player binary games. The methodology decreases the search space form exponential to linear, i.e., $\mathcal{O}(2^n)$ to $\mathcal{O}(n)$.

In this framework, we derived Nash equilibrium solutions for pure and mixed strategies. The former defined the critical number of utility companies allocated by the same source of renewable energy; at this threshold it is indifferent to sign a long-term contract with a conventional generator or a wind power producer. The latter is an energy portfolio creation methodology, for two competing indistinguishable utilities, to hedge against intermittent output of renewable energy sources. It is provided by determining the contracting amount of energy from conventional expensive sources and low-cost but unreliable renewable electricity generators. Finally, we presented a renewable energy price window for bilateral contracting among utility companies and green power producers.

Work ahead is aimed at studying non similar rationale utility companies energy portfolios. The equations describing the problem are non-linear and coupled, we will build a stochastic solver and contrast the numerical results with respect to the present theoretical work.

References

[1] Z. O. Olaofe and K. A. Folly, "Wind energy analysis based on turbine and developed site power curves: A case-study of darling city," *Renewable Energy*, vol. 53, pp. 306–318, May 2013.

[2] J. McKenna and M. Thomson, "Impact of wind curtailment and storage on the irish power system 2020 renewable electricity targets: A free open-source electricity system balancing and market (esbm) model," in *Renewable Power Generation Conference (RPG 2014), 3rd*. IET, September 2014, pp. 1–6.

[3] D. Arnone, M. Bertoncini, A. Rossi, F. D'Errico, C. García-Santiago, D. Moneta, and C. D'Orinzi, "An ict-based energy management system to integrate renewable energy and storage for grid balancing," in *Proceedings of the Fourth International Conference on Future Energy Systems*. ACM, May 2013, pp. 259–260.

[4] B. J. Donnellan, D. J. Vowles, and W. L. Soong, "A review of energy storage and its application in power systems," in *Power Engineering Conference (AUPEC), 2015 Australasian Universities*. IEEE, September 2015, pp. 1–6.

[5] R. Scharff and M. Amelin, "A study of electricity market design for systems with high wind power penetration," in *Energy Market (EEM), 2011 8th International Conference on the European*. IEEE, May 2011, pp. 614–612.

[6] S. Palamarchuk, "Bilateral contract correction and cancellation in the competitive electricity markets," in *PowerTech, 2009 IEEE Bucharest*. IEEE, June 2009, pp. 1–5.

[7] J. M. Morales, A. J. Conejo, and J. Pérez-Ruiz, "Short-term trading for a wind power producer," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 554–564, February 2010.

[8] A. J. Conejo, J. J. Fernandez-Gonzalez, and N. Alguacil, "Energy procurement for large consumers in electricity markets," *IEE Proceedings - Generation, Transmission and Distribution*, vol. 152, no. 3, pp. 357–364, May 2005.

[9] D. J. Wu, P. Kleindorfer, and J. E. Zhang, "Optimal bidding and contracting strategies in the deregulated electric power market.1," in *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*. IEEE, January 2000, pp. 10 pp.–.

[10] I. Arik, Y. M. Kantar, I. Usta, and I. Yenilmez, "Evaluation of robust estimation methods in estimating weibull parameters for wind energy application," in *Proceedings of the The International Conference on Engineering & MIS 2015*. ACM, September 2015, pp. 33:1–33:6.

[11] T. Basar and G. J. Olsder, *Dynamic Noncooperative Game Theory*. New York: New York: Academic Press, 1982.

[12] J. Nash, "Non-cooperative games," *Annals of Mathematics*, vol. 54, no. 2, pp. 286–295, September 1951.

[13] G. B. Shrestha and Q. Songbo, "A study on the optimal participation of wind generator in electricity market," in *Power Systems Conference and Exposition (PSCE), 2011 IEEE/PES*. IEEE, March 2011, pp. 1–6.

Appendix B

Nash-Equilibrium Electricity Portfolios In the Smart Grid: A Genetic Annealing Solution

Nash-Equilibrium Electricity Portfolios In the Smart Grid: A Genetic Annealing Solution

Genaro Longoria, Lei Shi
Telecommunications Systems and Software Group
Waterford Institute of Technology
Carriganore, Co. Waterford, Ireland
{glongoria, lshi}@tssg.org

***Abstract*—To leverage the potential of bilateral contracts in the smart grid, we address the conflict-of-interest problem of designing energy portfolios. From the viewpoint of competing Utility companies, we present a game theoretical formulation for contract offering with integration of wind energy. We propose a heuristic algorithm, the Recursive Genetic Annealing algorithm (RGAn), to find the Nash-Equilibrium solution, that is, the best trade-off between cost and uncertainty. To hedge the portfolios, we model the decision making process as a non-cooperative game. Expected Utility theory is used to define the minimum cost energy mix. We show the RGAn outperforms the genetic algorithm.**

***Keywords*—Contract management, Genetic Annealing Algorithm, Non-cooperative game.**

I. Introduction

Renewable technology, carbon taxes and climate awareness are steering electricity generation and consumption towards intermittent resources [1], [2]. The procurement planning of Utility companies has become more complex with the increased green energy integration. In this paper, our goal is to present smart negotiation strategies between producers and electricity retailers. We study the problem of energy contracting from the perspective of a Utility company (UC).

We use non-cooperative game theory to determine the contract offering strategies from Utility companies to power producers. We consider power producers to be a Conventional Generator (CG) (i.e., a fossil-fuel fired plant) and a Wind Power Producer (WPP). In this setting utility companies trade energy in the spot market to balance negative differences between power delivered from contracts and the smart city demand. The price negotiation, from the viewpoint of the electricity producers, is subject to supply and demand, this means that the price per kilowatt-hour becomes more expensive as more UCs offer contracts to the same power producer.

The problem of bilateral contracts has been approached, in the vast majority of studies, for a single entity [3], [4], [5], [6], [7]. For instance, Conejo *et al.* analyzed a large consumer, they develop a linear programming model to minimize the risk associated to the spot market [7]. Competing contracting is analyzed in the work of Wu *et al.*, they presented a game theoretic approach to the portfolio creation for multi energy wholesalers and buyers [8] . Whereas, Peng *et al.* [9], with a similar theoretic background, determine the equilibrium contracting electricity price. Khoussi *et al.*, proposed a game formulation for energy trading on the intraday market [10]. In this work, on the other hand, we model long-term contracting. To move forward the state-of-the-art, we bridge the gap between the theoretical framework and the solution process. We present an optimization algorithm to portfolio hedging for competing Utility companies.

II. Problem Statement

To avoid unbounded volatility of energy prices, and to account for the lack of electricity storage of scale, deregulated energy markets favor forward contracts over real-time trading [11]. This benefits price stability in an arbitrage-free framework [12]. A long-term contract with a CG is in the form of *options*. This means that the owner of the contract has the option to fully or partially execute the amount contracted. This type of contract specifies a fixed and a variable costs [13].

The procurement problem of multiple UCs competing to sign bilateral long-term contracts is twofold. Firstly, to determine the ratios of renewable and conventional energy to total demand that minimize the procurement cost. Secondly, the energy portfolio will serve to hedge against wind and market uncertainty. The decision-making process is carried on without cooperation, although coalitions might form as a byproduct. Conventional energy, although expensive has a lower risk compared to a renewable source. In this setting, weather variability impacts the procurement cost in two ways: purchasing energy differences at SM prices and penalty fees for under fulfillment of energy commitments.

The amount of wind power generation can be approximated by a probability mass function. During dispatch, shortages of energy are balanced with real-time trading in the spot market. In this respect, we assume the probability mass function of wind speed availability, at the wind farm, and SM volatility are common knowledge to all UCs.

III. Model

We formulate a game theoretic model for energy contracting by self-interested and competing UCs. The players in the procurement game are Utility companies. The strategies are contract offerings to electricity wholesalers. The goal is to determine the offering strategy and hence the energy portfolio

978-1-5090-5938-6/17/$31.00

that minimizes their procurement costs and hedges against weather and market uncertainty. In the open market setting, UCs can buy electricity in the SM. In our model, this depends on wind conditions and spot market price.

The UC portfolio can be formulated in terms of the total demand D and two diversification coefficients, σ and β. Thus, the energy sourced from a CG is $Q_i = \sigma_i D_i$ and the energy contracted to a WPP is $w_i = \beta_i D_i$. The total demand is $D_i = Q_i + w_i$. The contract price for wind power is P_w. To account for the negligible variable cost of the WPP we consider $P_w < P_{CG}$. The cost of procurement of UC_i, Π_i^t, is shown in (1). The energy balance for each UC is shown in (2). The intraday adjustments, x_i^t, are expressed in (3).

$$\Pi_i^t = sQ_i^t + gq_i^t + p^t x_i^t + P_w w_i^t \quad (1)$$
$$D_i^t = q_i^t + x_i^t + w_i^t \quad (2)$$
$$x_i^t = \begin{cases} D_i^t - (w_i^t + q_i^t) & \text{if } p^t > s + g \\ D_i^t - w_i^t & \text{if } p^t < s + g. \end{cases} \quad (3)$$

where p^t is the spot market price at time t. The fix and variable costs of the contract with the CG are s and g respectively. The real energy delivered by the WPP is w^t. The energy executed from the CG contract is q^t. The expected values of wind power and market price, for a time period T, are $\sum p^t/T = \mathbb{E}[P_{\text{SM}}]$ and $\sum w^t/T = \mathbb{E}[w]$, respectively.

The normal form of the non-cooperative game is expressed as $\mathcal{G} = \{\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}}\}$ which consist of 1) the set of players $\mathcal{N}$, where n is the number of UCs; 2) the strategies of each player $s_i \in \mathcal{S}_i$; 3) the payoff function u_i of each player for any action taken by the players in $\mathcal{N}$. The payoff function consists of the total expected cost of energy procurement. The strategy set is composed of low and high risk contracts LR and HR respectively.

$$u_i(s_i, \mathbf{s_{-i}}) = \begin{cases} -D_i P_{\text{CG}} & \text{if } s_i = \texttt{LR} \\ -\sum\limits_t (D_i - w_i^t)p^t - w_i^t P_w & \text{if } s_i = \texttt{HR}, \end{cases}$$

The payoff function $u_i(\cdot)$ couples player i strategy s_i and the decisions $\mathbf{s_{-i}}$ of all other players.

To determine the Nash-Equilibrium portfolio we state the game in terms of mixed strategies. We define $\mathcal{P}_m$ to be a randomization of each player's set of strategies:

$$\mathcal{P}_m = \{\mathbf{p} = (p_1, \ldots, p_m) \mid p_j \geq 0 \text{ for } j = 1, ..., m \text{ and } \sum_1^m p_j = 1\}.$$

The number of pure strategies in s_i for player $i \in \mathcal{N}$ is m_i. We can now define the vector $\mathbf{p}_i = (p_1^i, p_2^i, ..., p_m^i)$ as the probability distribution over his pure strategy set s_i. In this market setting, there is no *a priori* coalitions among UCs. Hence, the joint probability distribution is given by the product of each player's $\mathbf{p}_i$. Equation (4), is the expected utility of player i in the mixed strategy formulation.

$$\mathbb{E}[u_i] \triangleq v_i(\mathbf{p}_1, \ldots, \mathbf{p}_n) = \sum_{j_1=1}^{m_1} \cdots \sum_{j_n=1}^{m_n} p_{j_1}^1 \cdots p_{j_n}^n u_i(\mathbf{s}). \quad (4)$$

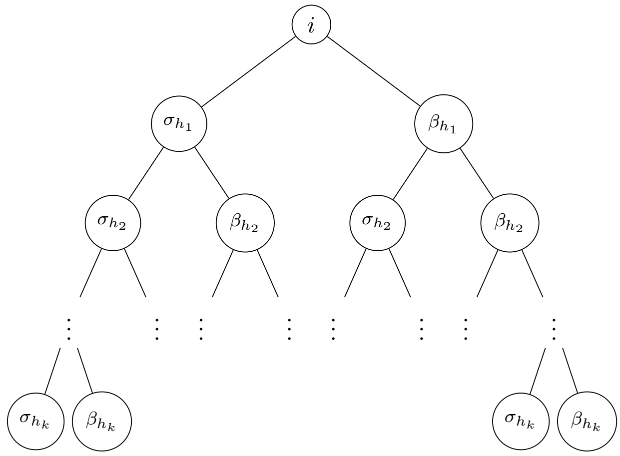


Figure 1: The joint probability of players' pure strategies is recursively computed using a binary tree structure. The inner nodes represent the pure strategies of the players in set $-\mathbf{i}$, i.e., all other players in $\mathcal{N}$ but i.

Lastly, using (4), the Nash-Equilibrium condition for mixed strategies is defined as:

$$v_i(\mathbf{p}_1^*, \ldots, \mathbf{p}_i^*, \ldots, \mathbf{p}_n^*) \leq v_i(\mathbf{p}_1^*, \ldots, \mathbf{p}_i, \ldots, \mathbf{p}_n^*). \quad (5)$$

The best response of player i, to the other players' mixed strategy profiles, is $\mathbf{p}_i^*$. Equation (5), represent a system of non linear coupled equations. The solution to (5) is the equilibrium portfolio, such that, there is no incentive for player UC i to deceitfully seek lower procurement cost by deviating from its equilibrium strategy [14]. The increase or decrease of the equilibrium share implies higher exposure to risk and thus higher cost on the long term.

IV. Recursive Genetic Annealing Algorithm

The Nash-Equilibrium scheme leads to a system of non-linear coupled equations. The complexity of the system grows exponentially with the number of players. As the number of interested UCs increases, the task of finding a NE solution algebraically becomes non feasible. We use a heuristic to estimate the equilibrium point of the game. In this work, we developed a Recursive Genetic Annealed algorithm (RGAn) to solve the optimization non-linear coupled problem.

The pure strategies of each player are arranged in a binary tree. The RGAn traverses the tree only on the none visited nodes. Then the RGAn algorithm evaluates the objective function fitness once a complete root-to-leaf path is completed. An schematic representation of the binary tree can be seen in Fig. 1. The root node represent each player of game $\mathcal{G}$. The inner nodes represent the low-risk (σ) and high-risk (β) strategies of all other players, where $h = \{-\mathbf{i}\}$, i.e, the set of all other players but i.

The RGAn pseudo code can be seen in Algorithm 1. Four major novelties make the RGAn better than the standard genetic algorithm (SGA). Firstly, the BinaryTable. Secondly,

Table I: RGAn and SGA Performance Comparison

Algorithm	Time	<Min O.F.>	Min O.F.	Generations
RGAn	9m 26.587s	343	331	58,1175
SGA	11m 33.819s	348	345	82,6751

Algorithm 1 Recursive Genetic Annealing Algorithm

```
1: define PBC2(·) ← periodic boundary conditions
2: procedure INITIALIZE
3:     STRUCT par ← input params {T, stop, ···}
4:     population ← vector of length twice players
5:     population ← U(0, 1)
6:     fitvector ← fitness eval population
7:     goto BINARYTABLE(par)
8: end procedure
9: procedure BINARYTABLE(par)
10:    binarytable ← vector of length pow(2, players)
11: end procedure
12: function SELECTION(par)
13:    population ← sort
14:    parentA ← fittest population
15:    parentB ← random population
16:    worst ← less fittest population
17:    offspring ← crossover parentA, parentB
18:    offspring ← mutation offspring
19:    goto OBJFUNEVAL(par, offspring, binarytable)
20: end function
21: function OBJFUNEVAL(par, offspring, binarytable)
22:    leaf ← tree pointer
23:    n ← backtracking counter
24:    esc ← tree pointer
25:    dpl ← twice number of players
26:    for i ← 0, 2 do
27:        n ← PBC2(n+1,dpl)
28:        esc ← esc+1
29:        OBJFUNEVAL(par, offspring, binarytable)
30:        leaf ← 1
31:        n ← n-1
32:        esc ← esc-1
33:    end for
34:    goto UPDATEPOPULATION(par, offspring)
35: end function
36: function UPDATEPOPULATION(par, offspringeval)
37:    Δ ← offspringeval-fitvector[worst]
38:    if offspringeval < fitvector[worst] then
39:        worst ← offspring
40:    else if U(0, 1) < exp(−Δ)/T then
41:        worst ← offspring
42:    end if
43:    while !stop do
44:        goto SELECTION
45:    end while
46:    Return population
47: end function
```

the OBJFUNEVAL. Thirdly, based on the Simulated Annealing algorithm, the RGAn accepts, with a control parameter, sub optimal chromosomes into the population pool. Lastly, the memory handling of the vectors *population* and *fitvector*.

BINARYTABLE, is a hash map. It indexes the number of players for every evaluation of the objective function hence making a **for** loop unnecessary. OBJFUNEVAL, traverses the tree recursively in a depth-first search manner, backtracking just one level before moving into unvisited nodes. This method reduces the computations in polynomial order. In the RGAn, the n-dimensional structure of game $\mathcal{G}$ is transformed into a 1-D structure. From the computational viewpoint, handling arrays instead of higher dimensions structures (e.g., cubes) is faster; although less human readable and more cumbersome to code. The acceptance probability, of non optimal offspring, is proportional to the exponential of the difference, Δ, of current objective function and the worst of the pool. The parameter *T*, controls the intensity ratio (see Algorithm 1, line 40).

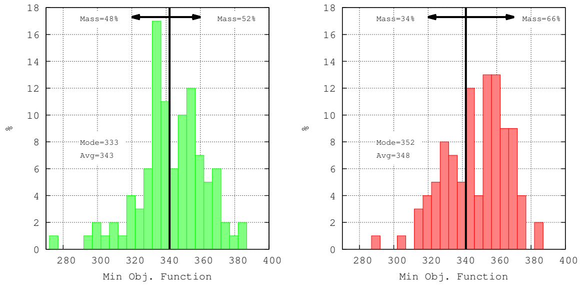
V. RESULTS

In this section we compare the performance of our algorithm with a SGA. Then, we present the results of the RGAn implementation of the proposed electricity mix allocation model. In our testbed, we considered 10 Utility companies. We assumed the UCs have a heterogeneous energy demand. We considered, without loss of generality, that the contract price, either with the CG or the WPP, increases linearly with demand. However, without effort and major modifications this can be modified for other cases.

We coded the RGAn algorithm and the SGA in *C* language. The programs were tested for 1x10^6 generations and executed on Ubuntu-14.04-trusty-server-x86_64 with 16 GB RAM and 2.6 GHz QuadCore Intel Xeon E312xx (Sandy Bridge).

Table I, presents the KPIs of the algorithms for a single and the average of 100 runs. Figure 2, shows the histograms of 100 runs. It can be seen, on average a 1.5% improvements. Nevertheless, the probability mass, to the left of 342, of the RGAn is 14% higher than the SGA. The algorithms were designed to solve game $\mathcal{G}$, i.e., a system of non linear coupled equations. The goal is to determine $\mathbf{p}_i^*$, such that the objective function is zero. For some scenarios this might be not feasible, although a close approximation suffices to design the best energy mix for each UC.

In Fig. 3 we present comparative results of the standard genetic algorithm and the RGAn. It can be seen that performance improvement is twofold. The RGAn ouperforms in time the finding of a solution to minimize the objective function. The best solution was found near the 6x10^5th generation while the SGA reaches its solution after approximately 8x10^5 generations. Furthermore, it can also be seen that the RGAn minimum value is better than SGA best result. The improvement is explained from to the blend of the genetic and simulated annealing algorithms. The acceptance of “bad” chromosomes enriches the population pool. Thus, the RGAn performs a more exhaustive search of the solution domain.



(a) RGAn (b) SGA

Figure 2: Statistics of 100 runs of $1x10^6$ generations each.

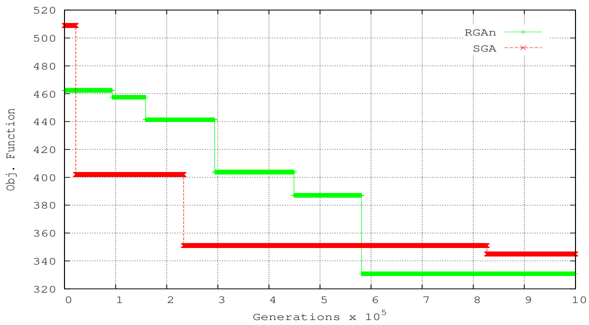


Figure 3: Performance of RGAn and SGA for 10 UCs with heterogeneous demand and linear supply-demand price response.

Table II: RGAn Diversification Strategy

Utility	% Conventional	% Renewable	Demand [MW]
0	36.4	63.6	44.0
1	42.1	57.9	40.2
2	43.5	56.5	36.4
3	54.2	45.8	32.6
4	76.3	23.7	28.8
5	83.3	16.7	25.0
6	99.5	0.50	21.2
7	99.7	0.30	17.4
8	76.0	24.0	13.6
9	97.9	2.10	9.8

This can be seen in the time decrease (i.e., plateaus length) in less optimal phases.

The Nash-Equilibrium solutions of the RGAn algorithm are shown in Table II. The contracting strategies, for the wind farm and energy market considered, are the Utilities best response in the non-cooperative setting. The energy mix serves each Utility company to minimize procurement costs and hedge against uncertainty.

VI. Conclusions

The problem of bilateral long-term contract offering in the smart grid was analyzed. Utility companies offer contracts to power producers to hedge against price volatility. To model the energy allocation of competing UCs we formulated a non-cooperative game. The Nash-Equilibrium of the game, defined the energy mix such that no UC would have an incentive to deceitfully deviate from the contracting scheme.

The game is expressed as a system of coupled equations. We proposed an algorithm to efficiently determine the Nash-Equilibrium portfolio. The results of our approach and the contrast to standard genetic algorithm were presented. The testbed considered 10 UCs with heterogeneous demand and a linear supply-demand price response from electricity producers. The Recursive Genetic Annealing algorithm outperforms, both in speed and quality of solution, the traditional genetic scheme.

The framework presented is general. It considers conventional and renewable energy sources. The model and the RNAn algorithm are flexible and scalable. The former, in the sense that, changes on risk policies and market designs are readily implementable. The latter, e.g., foreseen energy storage in smart cities can be incorporated. The proposed approach, can serve a Utility company to define its best energy mix among other UCs offering competing contracts to energy producers.

References

[1] F. Pazheri, M. Othman, and N. Malik, "A review on global renewable electricity scenario," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 835–845, Mar 2014.

[2] L. Sharifi, F. Freitag, and L. Veiga, "Envisioning cloud of energy," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov 2015, pp. 229–234.

[3] M. Chen and R. Xiaohong, "Research on strategy of purchasing electricity for large electricity consumers based on cvar," in *Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on*, Aug 2011, pp. 5760–5764.

[4] H. A. Aalami and S. Nojavan, "Energy storage system and demand response program effects on stochastic energy procurement of large consumers considering renewable generation," *IET Generation, Transmission Distribution*, vol. 10, no. 1, pp. 107–114, Jul 2016.

[5] M. B. J. Jimenez and A. C. Nerves, "Optimal allocation of spot market and bilateral contract transactions through quantity declaration adjustments," in *2013 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, Dec 2013, pp. 1–6.

[6] S. Palamarchuk, "Bilateral contract correction and cancellation in the competitive electricity markets," in *PowerTech, 2009 IEEE Bucharest*. IEEE, Jun 2009, pp. 1–5.

[7] A. J. Conejo, J. J. Fernandez-Gonzalez, and N. Alguacil, "Energy procurement for large consumers in electricity markets," *IEE Proc. - Gen., Tran. and Distribution*, vol. 152, no. 3, pp. 357–364, May 2005.

[8] D. J. Wu, P. Kleindorfer, and J. E. Zhang, "Optimal bidding and contracting strategies in the deregulated electric power market: Part II," in *System Sciences, 2001. Proceedings of the 34th Annual Hawaii International Conference on*. IEEE, Jan 2001, pp. 1–10.

[9] W. Peng, W. Yan-Hong, Y. Hua-Chun, and H. Ren-Mu, "Bayes equilibrium on negotiation means transaction of the power market long-term contract," in *Power System Technology, 2002. Proceedings. PowerCon 2002. International Conference on*, vol. 3, 2002, pp. 1814–1818.

[10] S. Khoussi, H. Bilil, and G. Aniba, "Optimal time of use of renewable electricity pricing: Three-player games model," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov 2015, pp. 199–204.

[11] S. Borenstein, "The trouble with electricity markets: Understanding california's restructuring disaster," *Journal of Economic Perspectives*, vol. 16, no. 1, pp. 191–211, Jan 2002.

[12] F. E. Beth, J. S. Benth, and S. Koekebakker, *Stochastic Modelling of Electricity and Related Markets*. Singapore: World Scientific, 2008.

[13] J. Nair, S. Adlakha, and A. Wierman, "Energy procurement strategies in the presence of intermittent sources," *SIGMETRICS Perform. Eval. Rev.*, vol. 42, no. 1, pp. 85–97, Jun 2014.

[14] T. Basar and G. J. Olsder, *Dynamic Noncooperative Game Theory*. New York: New York: Academic Press, 1982.

Appendix C

Wireless Power Transmission in Smart Cities: The wIshood Wireless Smart Neighborhood

Wireless Power Transmission in Smart Cities: The wIshood
Wireless Smart Neighborhood

Genaro Longoria, Fayaz Akhtar and Lei Shi
Telecommunications Systems and Software Group, Waterford Institute of Technology, Carriganore, Co. Waterford, Ireland
{glongoria, fakhtar, lshi}@tssg.org

Keywords: Control Engineering, Scheduling, Smart City, Smart Neighborhood, Wireless Power Transmission, wIshood.

Abstract: Wireless power transmission (WPT) of scale is the next step in power electronics. In this paper, we propose the Wireless Smart Neighborhood (wIshood). The idea presented serves smart city planners and developers to consider the future societal impacts of current and expected technological advancement. The wIshood merges ICT, IoT, CC, SDN and WPT to propose a solution to foster the creation and growth of the building blocks of modern societies. We outline the architecture and challenges of wireless smart neighborhoods. The wIshood is a solution to electricity congestion and deployment costs of transmission and distribution infrastructure.

1 INTRODUCTION

In the recent past, city planners have been busy resolving the best trade-off among mobility, green zones and residential and commercial expansion. To address these conflict-of-interest problems, technological breakthroughs will be fundamental for future smart city planning. At a careful but steady pace, modern cities are embracing the information and communication developments. Products and services, from technological innovations, will become ubiquitous in future smart cities. From rural to urban, industrial to residential and the overlap, Wireless Power Transmission (WPT), the Internet of things (IoT) and Information and Communication Technologies (ICT) will become a cornerstone in the design of new and growth of human settlements.

The evolution towards smart environments is being welcomed by society. Nowadays it is commonplace for cities to be equipped with free WiFi hotspots, real-time traffic information and safety surveillance, to mention a few. In this respect, creativity driven and farsighted governments are playing a crucial role to speedup the technological evolution of the city. For example, *Pervasive Nation*, a public funded initiative, is empowering academia and entrepreneurs to develop and implement an IoT testbed of scale in Dublin city (PervasiveNation, 2016). With the ever-increasing services and cloud connectivity, IoT devices are set to pervade all aspects of our daily lives. Thereby revolutionizing a broad range of applications in a variety of domains, such as healthcare, home automation, transportation, intelligent energy management and smart grids (Bellavista et al., 2013).

Neighborhoods form an important building block of every city. Nevertheless, presently they have a passive rather than active role in the progress of the city. In a top-down manner, technology is percolating into neighborhoods. In smart cities, legislation is requiring a change of old practices towards an efficient use of resources. Nevertheless, electricity distribution still relies on cables for its delivery.

In this paper we propose the wireless smart neighborhood: The wIshood[1]. The novelty of the wIshood is that households use WPT for electricity supply. The energy is wirelessly supplied from a local renewable power station (RPS). Although, still in an early stage, wireless power transmission is gaining momentum. Both, industry and academia know that WPT will be the solution to a variety of problems. With WPT, the wIshood has three major advantages to positively contribute to the smart city. Firstly, the increase of renewable electricity integration decreases fossil-fuels dependence. Secondly, city growth will have a lesser impact on the distribution and transmission capacity. Lastly, the wIshood will promote industrial investment by reducing transmission congestions hence lowering marginal energy prices. The wIshood exploits the edge cloud paradigm. The distributed architecture supports heterogeneous IoT devices, scheduling, information, processing and control of energy supply and demand for households.

[1] Pronounced as *wiz-hood*

The reminder of the paper is organized as follows. In section 2, we do a brief outline of related literature. In section 3, we present the architecture of the wIshood. In section 4, we outline the challenges to be addressed by the research community. Lastly, section 5 summarizes the work presented.

2 RELATED LITERATURE

The Smart city is a green field for research. Although, there are ingenious attempts of materializing some of the conceptual designs, technological progress is constantly and at a faster pace widening the possibilities. For the reader interested in a survey of Smart City architectures, Kyriazopoulou recently presented a thorough literature review on the topic (Kyriazopoulou, 2015).

The work of Akcin *et al.*, describes passive and active solutions to problems associated with population expansion and urbanization. Among the active methods, they comment on improving traffic flow with road-side sensors. On the passive approach, e.g., they presented a Swedish study on natural ventilation of cities to reduce the power for cooling buildings (Akcin et al., 2016).

Reducing the peak-to-average ratio (PAR), hence balancing the load curve, is one of the main goals of demand side management (Cakmak and Altas, 2016), (Yoon et al., 2014), (Liu et al., 2014), (Zhu et al., 2015). For instance, Cakmak and Altas, developed an Cuckoo search algorithm (CSA) to address the problem of appliance scheduling in a neighborhood. The approach is oriented to increase the efficiency of electricity supply and demand. The algorithm minimizes the objective function of the tradeoff of shiftable loads scheduling and consumer satisfaction by means of financial benefits. They showed the CSA scheduling reduced the PAR from 3.27 to 2.53 (Cakmak and Altas, 2016).

Smart metering of electricity, in smart homes, was described in the work of Pingle *et al.* They used an Arduino mote to gather data from the IoT equipped appliance. The raw data, in amperes, was processed in the cloud to output watts and finally sent to the user's mobile phone. They commented on the implications and advantages for the end user of real time information on energy bill savings (Pingle et al., 2016).

Presently, the four most common technologies for wireless power transmission are: 1. Electromagnetic radiation; 2. Inductive coupling; 3. Magnetic resonant coupling; and 4. Acoustic waves (Shinohara, 2014). Antennas alignment is one of the major concerns in WPT applications. A Planar Archimedean Coil was proposed to overcome misalignment between transmitter and receiver (Feenaghty and Dahle, 2016). Imura *et al.*, summarized the WPT requirements for electric vehicles (EV) charging in Japan. They described a road infrastructure for WPT to provide a solution to the problem of long-distance traveling with EV (Imura et al., 2016). Recently, Jian *et al.*, presented a proof of concept of WPT with inductive coupling. In their laboratory setup, they wireless transfered electricity from a renewable source to a load with a pivoting antenna (Jian et al., 2016). Although, long distance WPT over free space is feasible (Ma et al., 2016), WPT over long distances among obstacle rich environments is currently a topic of research.

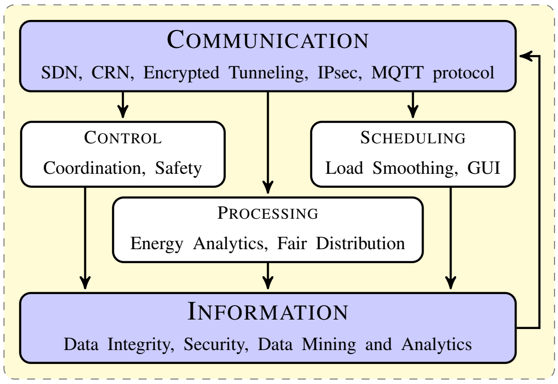


Figure 1: Layered architecture of the wIshood.

3 ARCHITECTURE

The layered architecture of the wIshood is shown in Fig. 1. It is composed of five layers: scheduling, information, communication, processing and control. Each household has IoT deployments of metering sensors, actuators, appliances and power switches. The functions of the IoT devices is to provide the hardware for data collection and communication. Machine learning and control theory will serve as the foundations of the Processing layer (Tobar et al., 2014). Finally, the control layer manages the energy distribution infrastructure; which is composed of the RPS transmitter antenna and the households' receiver antennas.

3.1 Communication

The fundamental task of the Communication layer is to ensure that the two way transfer of data from heterogeneous IoT motes and the edge-cloud is done in an efficient and secure way. We propose a Software Defined Network (SDN) and Cognitive Radio

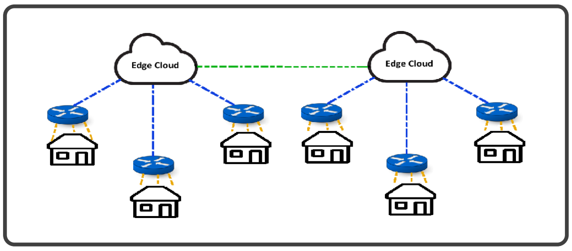


Figure 2: Communications are between IoT to gateways, gateways to edge-clouds and between edge-clouds.

Networks (Khan et al., 2016) to manage and transfer data from gateways (e.g., switches and routers) at each household to the edge-cloud; where the processing and decision making takes place.

The control of the queueing networks is done with a Lyapunov optimization algorithm (Samarakoon et al., 2016). To account for bandwidth bottlenecks and latency we adopt the Message Queue Telemetry Transport protocol (Jo and Jin, 2015). Figure 2, represents a high level communication view of the architecture. The data generated by the smart houses, RPS, weather forecast module and storage is channelled through gateways to the edge-cloud. *IPsec* tunneling is the cryptographic protocol of the communications network.

3.2 Information

The acquisition of the sheer amount of high-speed data, constantly generated from smart homes, is a significant task upon storage and analysis (Beckel et al., 2014). The Information layer resides in the edge-cloud, we adopt the integrated IoT Big Data Analytics framework (Bashir and Gill, 2016).

The principal functionality is to make the data accessible to the Scheduling, Processing and Control layers. A major task is to assure data integrity and security. At this layer, a first phase of data mining is implemented to eliminate redundant and non useful values. Thus, reducing the strain upon and bandwidth required by the Communication layer.

The stored data is fetched by the algorithms in the Processing phase. Figure 3, shows the flow of information among the IoT devices, cloud, Processing and Control layers. Dashed lines symbolize the WSN; red lines, power transmission and black lines, wired communication.

3.3 Scheduling

The scheduling layer positively exploits the flexibility of load shifting. The work of Liu *et al.*, categorized appliances as: 1. Shiftable; 2. Throttleable; and 3. Essential (Liu et al., 2014). Appliances such as dishwashers and laundry machines can be assigned a time slot to run. HVAC (heating, ventilation and air condition), although have rigid operation periods, are flexible to power adjustments within predefined ranges. A graphical user interface (GUI) is implemented for individuals to submit their desired scheduling of shiftable and operation ranges for throttleable devices. The output of the Scheduling layer is sent to the Processing layer (see §3.4). The latter analyzes the available resources and the energy demand. In case of mismatches, alternative scheduling arrangements are feedback to the households.

3.4 Processing

The processing layer, addresses the competing necessities of each household, proposes alternative scenarios to conflict-of-interest problems and determines tradeoff solutions between divergent goals. The functions of this layer are to perform the energy analytics and provide feedback when supply cannot meet demand. We use a ”divide and conquer” methodology to approach the non-linearity, uncertainty and highly coupled interactions in the wIshood.

The input, is the data from the information layer. Feedback is sent back to the scheduling layer. The processing unit integrates demand side management, energy generation and storage to optimize energy dispatch to the neighborhood. This layer provides a solution to the task of fair distribution of a scarce resource in a heterogeneous demand environment. To address this challenge, the functionalities of the processing layer include machine learning, optimization and forecasting algorithms.

A Kohonen self-organized network is used to reduces the dimensionality of the data. Then a Hidden Markov Model serves to classify the massive amount of sensor data; to be gathered and transfered by the IoT infrastructure. The HMM function is to determine clusters and patterns in the data. The output of the HMM is sent to the optimization module (OM).

The functions of the OM, are twofold: 1. Minimize the cost function of the wIshood energy distribution; and 2. Operate the RPS and storage infrastructure. The cost function takes into account individuals satisfaction, energy availability, weather forecast and storage levels. The feedback to the scheduling layer is the output of the optimization module. The algorithm is composed of two phases: 1. Optimization with given and foreseen conditions; and 2. Search of alternative scheduling scenarios whenever the demand surpasses the local supply. The feedback is sent back to the household individuals to accept the proposed changes or proceed with the original scenario; albeit requiring to buy electricity from elsewhere, e.g. the national grid. The latter functionality of the OM is to operate the RPS excess energy generation. This is done mainly through management of the centralized and distributed storage devices.

The weather forecast module objective is to provide support to the OM tasks. It is composed of two parallel processes. Firstly, an artificial neural network (ANN) algorithm performs fast, real-time and on-demand estimations of short-term (i.e., hours to a couple of days) weather conditions. Secondly, the forecast layer is connected to a national weather forecast system. This second process provides the necessary information for decision-making of long-range (i.e, weekly) estimates.

3.5 Control

The control layer principal tasks are: 1. Coordinate the commands sent from the processing layer; and 2. Guarantee the safety operation of the RPS, electricity distribution and storage infrastructure. The control layer receives input from the processing and communication layers. The output is the dispatch of energy from the RPS and central storage to the households appliances, storage facilities, centralized storage and into the national grid.

The backbone of the control layer are Adaptive Robust Control Theory and Kalman filtering. The design of the controller takes into account the uncertain events occurring in the wIshood, e.g., trucks blocking wireless communication or infrastructure failure. The metering devices constantly update the controller of the electricity distributed over the wIshood. The Kalman filter is a final preprocessing phase of the metering data before the control adapts to the changes of the environment.

4 CHALLENGES

The wIshood ecosystem (see Fig. 3) poses a myriad of challenges to be addressed by the research community. In the following we mention a few of the vast possibilities and from different domains of expertise.

4.1 Wireless Power Transmission

Electricity transmission of domestic scale is by far the most complex aspect to be addressed. Although successful attempts of long distance WPT have been accomplished, they have been based on a free space environment (Ma et al., 2016). WPT attenuation is due mainly to obstacles between source and destination and atmospheric losses. Frequency spectrum can be selected to minimize the latter although it should also take into account interference with existing communication bands (Imura et al., 2016).

The design of transmitter and receiver coupling systems is highly dependent of the material of the core. Presently, the core is made of composite ferrite materials such as Mn-Zn and Ni-Zn. The former is mostly employed because of its electric properties. Nevertheless, a mayor concern of core manufacture is scalability. Firstly, ferrite material are brittle and prone to breakdown as size increases. Secondly, the high permittivity of Mn-Zn leads to intense electric fields in discontinuities. Thus, arching or discharge occurs even in the presence of high dielectric materials. Lastly, frequency selection has a direct impact upon the permittivity of the ferrite material and hence the ability to guide the electric flux (McLean and Sutton, 2016).

4.2 Heterogeneous IoT

It is common to employ IoT motes from a variety of vendors. Hence, the data gathered, from these devices, cannot be used directly and must be converted into a standard form. Moreover, employing IoT in large sets can also result in spectrum scarcity. IoTs often employ unlicensed spectrum. To account for band saturation smart IoT should have cognitive capabilities i.e., dynamically switch between different frequencies.

Efficient bandwidth allocation techniques are of paramount importance (Khan et al., 2016). Dense deployment of IoT motes in a specific area can result in severe bandwidth constraints. This is due to the fact that IoT motes are, at a high-speed, continuously transmitting data to a shared infrastructure and using same unlicensed spectral bands. Bandwidth allocation, to the massive number of devices, poses stringent constraints to current communication protocols.

4.3 Security

The lessons learned from recent IoT hacks makes security of utmost importance. Coordinating security mechanisms (e.g., software updates, malware detection and identity management) present real constraints in highly federated environments. Security orchestration in the wIshood must incorporates threats aware mechanisms from IoT but also from cloud computing and SDN perspective.

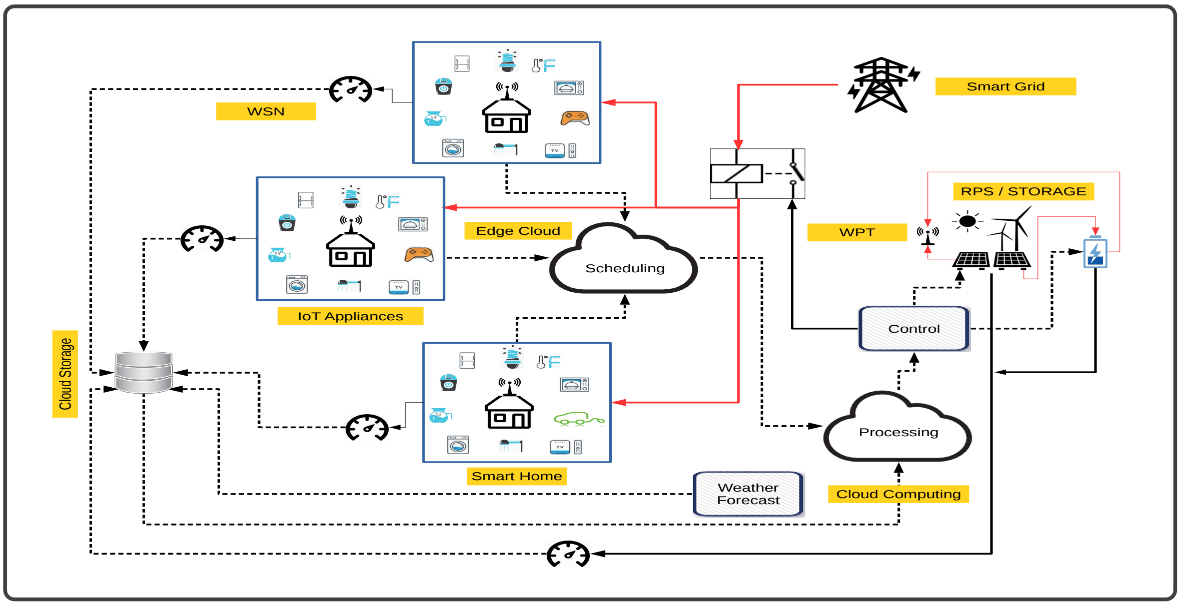


Figure 3: Topology of the wIshood's architecture. It is formed by the scheduling, information, communication, processing and control layers. The RPS supplies energy to the households using WPT technology.

4.4 Energy-Harvesting-Aware Robust Protocols

To efficiently exploit energy sources, robust communication protocols are also vital. Although such protocols have been thoroughly explored for conventional energy-harvesting sensor networks, they cannot be adopted for smart homes because of its unique challenges. Exclusive communication protocols and standards must be designed (Hou et al., 2016) for commercialization of reliable and customizable implementations.

4.5 Efficient Power Management

Scavenged energy requires effective power management among household appliances. We considered two cases 1. Energy generated by RPS is less than real-time demand; and 2. Power production is greater than demand. Thus, to address these scenarios, efficient utilization and fair distribution of energy algorithms need to be designed.

In the former, the energy should be fairly distributed among the households. A key aspect of power orchestration is the time allocation for running different appliances. For any excess power requirements the energy could be obtained from the smart grid (see Fig. 3). In the second scenario, if the energy produced is more than required, the excess energy could be stored for later use or re-routed toward other areas, e.g., sold to the smart grid. Thus, research effort should go into coupling wake-up scheduling schemes with harvesting schemes to ensure quality of service requirements.

Apart from dispatch specific issues, energy trading with third parties must be taken into consideration. This implies a *Credits* scheme for energy trading between neighborhoods in different periods of time. The dispatch algorithm should also take into account the best time for selling electricity to the smart grid.

4.6 Appliances Management

A principal challenge of the processing layer is to provide an optimized schedule of energy consumption. The cost function of the optimization algorithm will also take into consideration the users defined parameters for the shiftable, throttleable or essential appliances. The unsupervised learning algorithm proposes better scheduling based on previous data and recent consumption trends. The complexities of the non-linearities among IoT devices, household preferences and uncertainties call for adaptable models, faster learning and optimization algorithms.

5 CONCLUSIONS

This work presented a new framework of future smart neighborhoods, the wIshood. The wIshood advances the state-of-the-art of smart cities with an infrastructure for wireless transmission of electricity for residential needs. Within the wIshood, the energy is generated, stored and dispatched to the households. We envision, an intensive deployment of IoT devices, cloud computing and a wireless power transmission of scale. This paper outlined the architectural foundation and algorithms to address the challenges of such an ecosystem.

Future work intends to simulate components of the wIshood architecture. We plan to develop two algorithms. Firstly, a reduction of household data to stream to the Information layer. Secondly, a Recurrent Neural Network for energy demand forecasting.

REFERENCES

Akcin, M., Kaygusuz, A., Karabiber, A., Alagoz, S., Alagoz, B. B., and Keles, C. (2016). Opportunities for energy efficiency in smart cities. In *4th Int. Istanbul Smart Grid Cong. and Fair (ICSG)*, pages 1–5.

Bashir, M. R. and Gill, A. Q. (2016). Towards an iot big data analytics framework: Smart buildings systems. In *2016 IEEE 18th Int. Conf. on High Performance Computing and Comms; IEEE 14th Int. Conf. on Smart City; IEEE 2nd Int. Conf. on Data Science and Systems (HPCC/SmartCity/DSS)*, pages 1325–1332.

Beckel, C., Kleiminger, W., Cicchetti, R., Staake, T., and Santini, S. (2014). The eco data set and the performance of non-intrusive load monitoring algorithms. In *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings*, BuildSys '14, pages 80–89, New York, NY, USA. ACM.

Bellavista, P., Cardone, G., Corradi, A., and Foschini, L. (2013). Convergence of manet and wsn in iot urban scenarios. *IEEE Sensors Jounral*, 13(10):3558–3567.

Cakmak, R. and Altas, I. H. (2016). Scheduling of domestic shiftable loads via cuckoo search optimization algorithm. In *2016 4th International Istanbul Smart Grid Congress and Fair (ICSG)*, pages 1–4.

Feenaghty, M. and Dahle, R. (2016). A compact and high quality factor archimedean coil geometry for wireless power transfer. In *2016 IEEE Wireless Power Transfer Conference (WPTC)*, pages 1–3.

Hou, L., Zhao, S., Xiong, X., Zheng, K., Chatzimisios, P., Hossain, M. S., and Chen, W. (2016). Internet of things cloud: Architecture and implementation. *IEEE Communications Magazine*, 54(12):32–39.

Imura, T., Yasuda, T., Oshima, K., Nayuki, T., Sato, M., and Oshima, A. (2016). Wireless power transfer for electric vehicle at the kilohertz band. *IEEJ Trans. on Electrical and Electronic Engineering*, 11:S91–S99.

Jian, M. S., Fang, Y. C., Tong, R. W., and Lin, Y. H. (2016). Wireless green energy power transmission system based on assembly method and pivoting antenna module. In *2016 International Conference on Applied System Innovation (ICASI)*, pages 1–4.

Jo, H. C. and Jin, H. W. (2015). Adaptive periodic communication over mqtt for large-scale cyber-physical systems. In *2015 IEEE 3rd Int. Conf. on Cyber-Physical Systems, Networks, and Applications*, pages 66–69.

Khan, A. A., Rehmani, M. H., and Rachedi, A. (2016). When cognitive radio meets the internet of things? In *2016 Int. Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 469–474.

Kyriazopoulou, C. (2015). Smart city technologies and architectures: A literature review. In *2015 International Conference on Smart Cities and Green ICT Systems (SMARTGREENS)*, pages 1–12.

Liu, Y., Yuen, C., Huang, S., Hassan, N. U., Wang, X., and Xie, S. (2014). Peak-to-average ratio constrained demand-side management with consumer's preference in residential smart grid. *IEEE Journal of Selected Topics in Signal Processing*, 8(6):1084–1097.

Ma, H., Li, X., Sun, L., Xu, H., and Yang, L. (2016). Design of high-efficiency microwave wireless power transmission system. *Microwave and Optical Technology Letters*, 58(7):1704–1707.

McLean, J. and Sutton, R. (2016). Electric field breakdown in wireless power transfer systems due to ferrite dielectric polarizability. In *2016 IEEE Wireless Power Transfer Conference (WPTC)*, pages 1–4.

PervasiveNation (2016). Ireland's Internet of Things Testbed. https://connectcentre.ie/pervasive-nation/. Accessed: 19-Dec-2016.

Pingle, Y., Dalvi, S. N., Chaudhari, S. R., and Bhatkar, P. (2016). Electricity measuring iot device. In *2016 3rd Int. Conf. on Computing for Sustainable Global Development (INDIACom)*, pages 1423–1426.

Samarakoon, S., Bennis, M., Saad, W., Debbah, M., and Latva-aho, M. (2016). Ultra dense small cell networks: Turning density into energy efficiency. *IEEE J. Sel. Areas Commun.*, 34(5):1267–1280.

Shinohara, N. (2014). *Wireless Power Transfer via Radiowaves*. Wiley, New Jersey.

Tobar, A. C., Banna, H. U., and Koch-Ciobotaru, C. (2014). Scope of electrical distribution system architecture considering the integration of renewable energy in large and small scale. In *IEEE PES Innovative Smart Grid Technologies, Europe*, pages 1–7.

Yoon, J. H., Baldick, R., and Novoselac, A. (2014). Dynamic demand response controller based on real-time retail price for residential buildings. *IEEE Transactions on Smart Grid*, 5(1):121–129.

Zhu, L., Yan, Z., Lee, W. J., Yang, X., Fu, Y., and Cao, W. (2015). Direct load control in microgrids to enhance the performance of integrated resources planning. *IEEE Trans. Ind. Appl.*, 51(5):3553–3560.

Appendix D

Ornstein-Uhlenbeck-Lévy Electricity Portfolios with Wind Energy Contracting: A Theoretical Approach

Ornstein–Uhlenbeck-Lévy Electricity Portfolios with Wind Energy Contracting: A Theoretical Approach

Genaro Longoria, Alan Davy, Lei Shi
Telecommunications Systems and Software Group - Waterford Institute of Technology
Carriganore, Co. Waterford, Ireland

***Abstract*—To leverage the potential of integrating renewable sources into electricity portfolios we address the risk and cost trade-off. From the perspective of a Load Serving Entity (LSE), we present the theoretical implications of energy allocation from two type of markets: bilateral long-term contracts and real-time trading. We present the mathematical formulation of a stochastic procurement model (SPM) of purchasing energy on both markets and from two different sources: wind energy and conventional generation. We approach the unexpected jumps of spot market prices with a mean-reverting Lévy process. The wind energy availability is modeled with a multiplicative Brownian process transformed to a Rayleigh probability density function. We present the efficient frontier and a user defined risk level metric. The SPM is tested numerically. We determine the ratios of wind and conventional to total demand and the risk associated. This work serves an LSE in designing its energy diversification.**

***Index Terms*—Contract management, Electricity portfolio, Renewable energy sources, Risk analysis, Strategic planning.**

I. Introduction

Rising carbon taxes, climate awareness and technology breakthroughs, among others, had influenced the surge of intermittent resources integration into the electricity supply [1]. Despite the fact of its positive impact, green energy, has increased the complexity of procurement planning of Load Serving Entities (LSEs). Modern energy portfolios encompass conventional and renewable energy contracts as a mean to reduce costs and hedge against price volatility, while matching supply and demand unbalances through real-time adjustments in the spot market (SM).

The non-deterministic nature of future events, such as fossil-fuel prices and weather conditions, calls for strategic electricity portfolios to hedge against volatility. Therefore, an important concern for a LSE is to determine the proportions of conventional and/or renewable to total demand.

In this paper, we study, from the perspective of an LSE, the energy allocation strategies from two type of markets, bilateral long-term contracts (LT) and real-time trading. To account for the uncertainty prevailing in future energy prices and in the availability of wind we develop a Stochastic Procurement Model (SPM). A mean-reverting Lévy process is used to model the spiky behavior of electricity prices. Wind speed is modeled with a stochastic differential equation (SDE) with Brownian noise adapted to follow a given probability density function (pdf). The proposed SPM is discretized and solved numerically. Then, the different procurement strategies are assessed within the framework of Portfolio theory. We present a risk analysis based on a coherent measure and we propose a metric for a user defined risk threshold. The assessment is concluded with the portfolios' efficient frontier and the corresponding probability for the aforementioned threshold. We show an easily implementable methodology that can serve an LSE to define the optimal energy mix and to quantify the trade-off between risk and cost.

Previous work has considered the uncertainty, in wind and spot price, through a finite number of scenarios. Several studies have shown that wind speed can be approximated by a Weibull distribution or its particular case, the Rayleigh distribution (RD) [2]–[4]. On the other hand, as already highlighted in the work of [5], a sound energy price differential equation should incorporate not solely a Brownian-like motion but possible spikes along the trajectory. To account for price jumps, we model the SM dynamics with a mean-reverting Lévy process.

The remainder of the paper is organized as follows. In section II we present a brief literature review, comment on the related work and state our contributions. In sections III and IV we present our model and simulation method. The risk metrics are presented and numerical results analyzed in section V. Finally, in section VI we conclude the work done.

II. Related Work

The problem of optimizing the energy mix, among bilateral contracts, self-production and the SM, for a large consumer is studied by [6]. They developed a linear programming model to minimize the consumer's electricity bill. They considered conventional generation whereas we also address the problem of integrating an intermittent source or energy. More recently, [7] discussed the application of financial risk methods in electricity procurement. In the paper, they converted the cost and risk problem into a single optimization model.

The research on bilateral contracts has greatly considered the fossil-fuel type of generation. [8], under the assumption of perfect inelastic demand, simulated three cases of energy pricing and contracting. They concluded that the scenario with bilateral contracts is of mutual interest for generation and demand. Whereas [9], proposed an *on-the-fly* demand allocation adjusting scheme. A penalty was used to compensate the generation company for positive difference between energy contracted and consumed. In this context, the earlier work [10] developed a multi-stage algorithm to modify electricity delivery from a bilateral contract. A risk measure is used in the work of [11]. The paper asses forward contracts against spot market procurement on the basis of *Insufficiency of Load Supply*. Because of the volatility of the energy market and load demand, they adopted a Monte Carlo (MC) method to estimate the buyer's risk exposure. Thereafter they determined the next contracts negotiating conditions. In earlier studies, [12] presented a game theoretic approach to the portfolio creation for multi energy wholesalers and buyers. Whereas, [13], with a similar theoretic background, determined the equilibrium contracting electricity price.

The recent work [14] presented a method for coalitions of renewable producers. They used cooperative game theory and applied the Nucleolus allocation method. A main contribution of the method is to make computational tractable the problem of maximizing the worst-case quota of the aggregated generation. Nevertheless, the authors considered a fixed set of scenarios. In a similar setting, although different value function, [15] have previously analyzed the allocation strategies of aggregated bidding. The paper shows the existence of a payoff such that coalition stability is assured and hence an increase of expected profit.

These literature has approached the dynamics underlying the uncertainty mostly through fixed scenarios. The work presented here can serve as bridge between randomness modeling and electricity contracting.

The SPM is reliable in that it quantifies the long-term cost and risk of procuring energy from intermittent resources. The SPM can scale up to incorporate other type or energy sources. It can be easily tailored to the particularities faced by the LSE. The SPM formulation is also flexible to explore different portfolios. Our contribution to electricity contract management moves forward the state-of-the-art of the commonly adopted finite scenario analysis by proposing the SPM.

III. Stochastic Procurement Model

We consider the LSE can procure electricity from the SM and from LT with conventional and renewable energy wholesalers. The modeling of wind power variability and SM price uncertainty is done through a non-zero variance term in the differential equation.

Electricity markets are assumed frictionless. At a given moment t of the trading day, the market price is the result of marketeers' buy and sell bids, which the system operator uses to calculate the energy marginal price. PJM defines the locational marginal price as the "cost to serve the next MW of load at a specific location, using the lowest production cost of all available generation" [16].

A *geometric Brownian* SDE is limited in modeling, e.g., leptokurtic distributions and price clustering effects [17]. To obtain a realistic price dynamics we incorporate a Lévy process. Along with the Brownian motion, a compound Poisson process is considered to account for "rare" events. These unexpected events are beyond the day-to-day marketeers interactions, instead they are due to sudden regional or global changes. Hence, to account for both, the daily market "collisions" and exogenous market events we formulate a mean-reverting jump-drift-diffusion SDE electricity price model.

Literature reviews and site studies have shown the applicability of polynomial forms as estimates for the dependency of power upon wind speed [2], [18]. In our work, the energy procured from a WPP is obtained by numerically solving a transformed SDE.

A. Lévy Driven Price Dynamics

The spot price is represented by $p_{sm}(t)$. Let $(\Omega, \mathcal{F}, \mathbf{P})$ be a complete probability space on which the stochastic processes are defined. Where $\{\mathcal{F}_t\}_{t\in[0,T]}$ is the information available up to time t. Let $\mathbb{E}$ denote expectation under probability measure $\mathbf{P}$. To account for unexpected price increments we follow the convention that the underlying process is right continuous. This can be expressed as $p_{sm}(t) = \lim_{u\downarrow t} p_{sm}(u)$.

We use a Poisson counting measure $N(t)$ because of the memory-less property of the renewal process, reflected on the i.i.d. inter-arrival times. We exploit this feature to account for unexpected electricity price spikes. The probability of an event occurring during a finite time interval Δ can be described as

$$\text{Prob}\{\neg\text{event in } (t, t+\Delta)\} = 1 - \lambda\Delta + \mathcal{O}(\Delta),$$
$$\text{Prob}\{\text{one event in } (t, t+\Delta)\} = \lambda\Delta + \mathcal{O}(\Delta),$$
$$\text{Prob}\{\text{more than one event in } (t, t+\Delta)\} = \mathcal{O}(\Delta),$$

where λ is the intensity or jump rate. The probability of n jumps taking place in the interval $\Delta = t - s$, is given by

$$P(N(t) - N(s) = n) = \frac{e^{-\lambda\Delta}(\lambda\Delta)^n}{n!}, \tag{1}$$

where $0 \le s < t$. $N(t)$ represents the total number of events that have occurred up to time t and is constant between any two consecutive jumps. From (1) it can be seen that increments are exponentially distributed, same sized and with negligible probability of more than one jump in the same time interval.

The SM price of electricity just before a jump is denoted by $p_{sm}(t\text{-})$. Then $p_{sm}(t)$ is given as the limit from the left, i.e., $p_{sm}(t\text{-}) = \lim_{u\uparrow t} p_{sm}(u)$.

Spot price spikes are characterized by its martingale evolution. For a jump process to exhibit those properties a compensator for $N(t)$ must be included. The martingale version (or in this case a right continuous martingale) is a compensated Poisson process given by $J(t) = N(t) - \lambda t$, such that $\mathbb{E}[N(t) - \lambda t|\mathcal{F}_t] = 0$. The latter implies that jumps exhibit no trend, i.e., they are totally unpredictable, irrespective of the time interval size.

The power-market electricity price jump-drift-diffusion model, with initial condition $p_{sm}(0) = p_o$, drift and diffusion μ_{sm} and σ_{sm} respectively and $t \in [0, T]$ is given by

$$\frac{dp_{sm}(t)}{p_{sm}(t\text{-})} = \gamma[\mu_{sm} - \lambda \log p_{sm}(t)]dt + \sigma_{sm} dB(t) + dJ(t), \tag{2}$$

where γ is the process rate towards the long-range mean μ_{sm}, $dB(t)$ represents the Brownian motion to account for the energy traders interactions. Equation (2) represents a Lévy process with mean-reversion and additive noise.

Furthermore, for a realistic price model we consider a non-constant jump size. A Poisson process with variable increments is called a Compound Poisson process. Following the derivation presented by [19], let us define the size of the jump as $Y_j - 1$ where $Y_1, Y_2, \dots$ are i.i.d. random variables independent of $N(t)$ and $B(t)$. The change dp_{sm} of p_{sm} depends on its value before the jump. The increment at the time of a jump is $p_{sm}(t) - p_{sm}(t\text{-})$. This change is different from zero only if J jumps at $t = t_j$, then

$$\begin{aligned} p_{sm}(t_j) - p_{sm}(t_j\text{-}) &= p_{sm}(t_j\text{-})[J(t_j) - J(t_j\text{-})] \\ &= p_{sm}(t_j\text{-})(Y_j - 1). \end{aligned} \tag{3}$$

From (3) it is straightforward to show that $p_{sm}(t_j) = p_{sm}(t_j\text{-})Y_j$. To obtain a solution to the price SDE, we can try an ansatz of the form $X(t) = X(0)e^{\mu t}$ and use Itô Integral. To account for the non-zero first moment of p_{sm}, Itô calculus' random term $dB^2(t)$ is proportional, in a mean square sense, to dt [20]. Eq. (2), is justified as a symbolic representation of

$$\int_t^{t+\delta} \frac{dp_{sm}(s)}{p_{sm}(s\text{-})} = \gamma \int_t^{t+\delta} [\mu_{sm} - \lambda \log p_{sm}(s)] ds + \int_t^{t+\delta} \sigma_{sm} dB(s) + \int_t^{t+\delta} dJ(s),$$

because Brownian's motion unbounded variation is nowhere differentiable. The first term on the RHS is understood in the Riemann sense and δ is an infinitesimal time. To solve for $p_{sm}(t)$, we use Itô-Doeblin formula for one jump process [21]:

$$\begin{aligned} &f(X(t)) = f(X(0)) + \\ &+ \int_0^t f'(X(s)) dX^c(s) + \frac{1}{2}\int_0^t f''(X(s)) dX^c(s) dX^c(s) + \\ &+ \sum_{0<s\leq t} [f(X(s)) - f(X(s\text{-}))], \end{aligned} \tag{4}$$

$X^c(t)$ is the continuous part of a Lévy process $X(t)$. Using $\Phi(t) = \log P_{sm}(t)$, the solution to (2) can be obtained from

$$\begin{aligned} \Phi(t) &= e^{-\gamma t}\Phi(0) + \gamma\mu_{sm}\int_0^t e^{-\gamma(t-s)} ds + \\ &+ \sigma_{sm}\int_0^t e^{-\gamma(t-s)} dB(s) + \sum_{j=N(t)+1}^{N(t+1)} \log(Y_j). \end{aligned} \tag{5}$$

To derive (5) we used the ansatz, Itô Integral and the fact that $\log(p_{sm}(t_j)) = \log(p_{sm}(t_j\text{-})) + \log(Y_j)$ such that $f(X(t)) = \log(p_{sm}(t))$ in (4).

Fig. 1 shows typical realizations of spot market hourly price, $p_{sm}(t) = \exp[r(t)]$, of electricity dispatched. The effect of the mean-reverting term can be seen on the come-back-to-trend after a price spike.

B. Transformed Stochastic Wind Dynamics

The electricity generation of a wind farm depends on, e.g., blade design, gearbox, hub height. Nevertheless, the largest impact variable is wind speed [22]. In wind turbine design and technical literature, a widely used relation between wind speed v and power w is the cubic power law [2]:

$$w(v(t)) = \frac{1}{2}\rho A C_p \eta v^3(t). \tag{6}$$

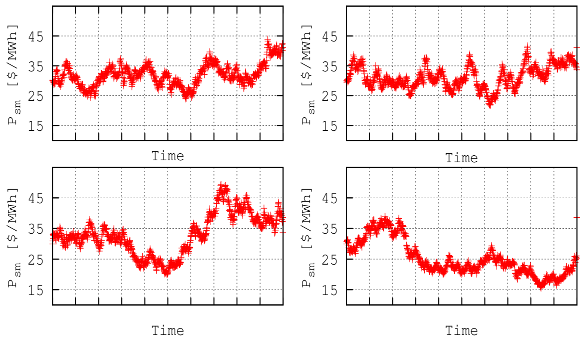


Fig. 1. Different electricity price paths according to Eq. (5).

where A is the swept area of the rotor in m^2, η is the efficiency of the wind turbine, $\rho = 1.225\ kg/m^3$ is the air density at mean sea level and C_p is the rotor efficiency [23].

We use Eq. (7) to map wind speed and power. This model can be easily parametrized to an specific WPP.

$$dv(t) = \mu_w(v(t), t)dt + \sigma_w(v(t), t)dB(t) \tag{7}$$

The functions $\mu_w(\cdot)$ and $\sigma_w(\cdot)$ are expressed in terms of a given pdf to resemble the distribution and autocorrelation of the wind speed statistics. Here we use the method presented in [24]. It relates the SDE coefficients and a probability density, $p(\cdot)$, through the Fokker-Planck differential equation,

$$\begin{aligned} \frac{\partial p(v(t),t)}{\partial t} &= -\frac{\partial}{\partial v(t)}[\mu_w(v(t),t)p(v(t),t)] + \\ &+ \frac{1}{2}\frac{\partial^2}{\partial v^2(t)}[\sigma_w^2(v(t),t)p(v(t),t)]. \end{aligned} \tag{8}$$

The randomness associated with the stochastic quantity is in a steady state phase hence we consider the case of stationary processes. In other words, random events are time invariant and second order measures depend only on time differences [25]. Thus, (8) can be written as

$$\frac{\partial}{\partial v(t)}[\mu_w(v(t))p(v(t))] = \frac{1}{2}\frac{\partial^2}{\partial v^2(t)}[\sigma_w^2(v(t))p(v(t))]. \tag{9}$$

To closely resemble any site specific wind speed behavior, the autocorrelation resulting from the SDE should follow that of a wind distribution. Zárate-Miñano and Milano's method is motivated by the Regression theorem applied to a Markovian process [20]. Firstly, the drift term is determined. This is done by using Itô's lemma and the stationary properties of the second order moments. Then, the autocovariance differential equation of the underlying stochastic process is solved. Lastly, the drift is *adapted* to the desired exponential decay. After integration of (9), the method solves for the diffusion term.

It has been compared how closely the Weibull and its particular case the RD fits speed data. For instance, [26] found a more accurate data fit from the Weibull pdf over RD. They estimated, for a particular month, the RMS deviation as 0.0031 and 0.0073, respectively. On the other hand, [2], [3] and [23] argued differently. Since wind speed is location dependent and to keep the exposition easy to follow, we use the RD.

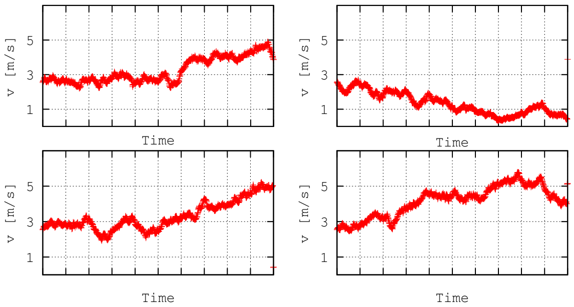


Fig. 2. Different wind speed paths according to Eq. (12).

For the one parameter, γ, RD with pdf given by $f(v) = \frac{2v}{\gamma^2}\exp[-(v/\gamma)^2]$ the drift and diffusion are expressed as

$$\mu_w(v(t)) = -\alpha\left(v(t) - \gamma\sqrt{\frac{\pi}{2}}\right) \tag{10}$$

and, where α is the autocorrelation decay rate,

$$\sigma_w(v(t)) = \sqrt{\frac{\alpha\gamma^2}{v(t)}}\times \times\sqrt{\left[2v(t) + \gamma\sqrt{2\pi}\left(e^{\frac{v^2(t)}{2\gamma^2}}\operatorname{erfc}\left(\frac{v(t)}{\gamma\sqrt{2}}\right) - 1\right)\right]}. \tag{11}$$

An algorithm to solve (7) can be derived from integrating both sides of the SDE, i.e.,

$$v(t) = v(0) + \int_0^t \mu_w(v(s))ds + \int_0^t \sigma_w(v(s))dB(s) \tag{12}$$

In section IV we present a 4th order Runge-Kutta time-discretization scheme to solve the SDE (12). Fig. 2 shows four different wind realizations according to (7) with drift and diffusion given by (10) and (11) respectively.

C. Energy Procurement Cost

In this section we present a methodology to determine the energy mix that minimizes procurement cost. We consider that the LSE is subject to penalty fees for under fulfillment of the committed demand.

Wind power is a competitive source for electricity generation. The variability and the inability to dispatch at command can counteract the benefits of its renewable nature. A major benefit of LT is price stability in an arbitrage-free framework [17]. In this context, a forward contract with bilateral options entitles the buyer the right to partially exercise the contracted electricity, albeit a fixed reservation cost.

Equation (13) is the total cost of procuring electricity, CEP. It is composed of 1) ξ the minimum, at delivery time t, of d_w and $w(v)$, i.e., electricity contracted and available, respectively, bought at p_w, the WPP selling price; 2) execution and reservation costs, g and s respectively and the share d_c of electricity allocated to a CG; 3) x, the energy bought from the spot market at price p_{sm}; lastly, 4) depending on the wind power generation ζ, a penalty $\mathcal{P}$ for under fulfillment of the LSE committed total demand D.

$$\begin{aligned}\text{CEP}(t) &= \xi p_w + d_c g + s(d_c) + x(t)p_{sm}(t) + \mathcal{P}\zeta p_{sm}(t)\\ D &= d_w + d_c + x(t) \\ \xi &= \min[d_w, w(v(t))]\end{aligned} \tag{13}$$

$$\zeta = \begin{cases} 0 & \text{if } w(v(t-1)) < d_w \\ \max[D - w(v(t)) - d_c, 0] & \text{if } w(v(t-1)) > d_w \end{cases}$$

$$x(t) = \begin{cases} 0 & \text{if } p_{sm}(t-1) > s(d_c) + g \\ D - d_w & \text{if } p_{sm}(t-1) < s(d_c) + g \\ d_w & \text{if } w(v(t-1)) < d_w. \end{cases}$$

We assume the LSE electricity adjustment process is bound to the period before the next delivery time. This means that the next period executed conventional energy and real-time procurement have to be notified prior to dispatch time. This is motivated by the martingale assumptions about wind speed and market price dynamics. The decision-making algorithm of our model (13) is shown in Fig. 3. The flowchart diagram is the LSE electricity allocation algorithm. At trading session the algorithm adapts the LSE short-term procurement strategy, such that, in the long-term the energy contracts and intraday adjustments minimize penalty fees and procurement costs.

IV. Simulation and Discretization Method

The dynamical portfolio of the LSE assumes an amount allocated in a riskless asset and the rest of its demand in a risky electricity generator. In this paper, we use a MC approach to estimate expected values for the LSE procurement costs. We divide the length of the period $[0, T]$ into m equal parts. The time step is $h = T/m$ such that $0 = t_o < h < \cdots < t_m = T$ and $\Delta T = t_{i+1} - t_i = h$.

To determine the price dynamics, we simulate (5) with a recursive scheme. The discretization routine is

$$\Phi(t_{i+1}) = e^{-\gamma t}\Phi(t_i) + \mu_{sm}(1 - e^{-\gamma t}) + + \sigma_{sm}\sqrt{\frac{1 - e^{-2\gamma\Delta t}}{2\gamma}}Z + M,$$

where $Z \sim \mathcal{N}(0,1)$ and M is the summation of the logarithm of N Poisson distributed jumps [19]. To solve the SDE for the speed of wind, (12) is numerically integrated with the stochastic Runge-Kutta scheme (14). The value of the coefficients φ_p, c_p and a_{pq} and the covariance among the z_q values are those derived in Kasdin's fourth order ($n = 4$) explicit Runge-Kutta method [27].

$$\begin{aligned}v(t_{i+1}) &= v(t_i) + \varphi_1 k_1 + \varphi_2 k_2 + \cdots + \varphi_n k_n \\ k_1 &= h\mu_w(t_i + c_1 h)v(t_i) + h\sigma_w(t_i + c_1 h)z_1 \\ k_q &= h\mu_w(t_i + c_q h)\left(v(t_i) + \sum_{p=1}^{q-1} a_{pq}k_p\right) + h\sigma_w(t_i + c_q h)z_q.\end{aligned} \tag{14}$$

A principal virtue of the method, compared to an Euler-Taylor approximation, is to avoid computing the derivatives of

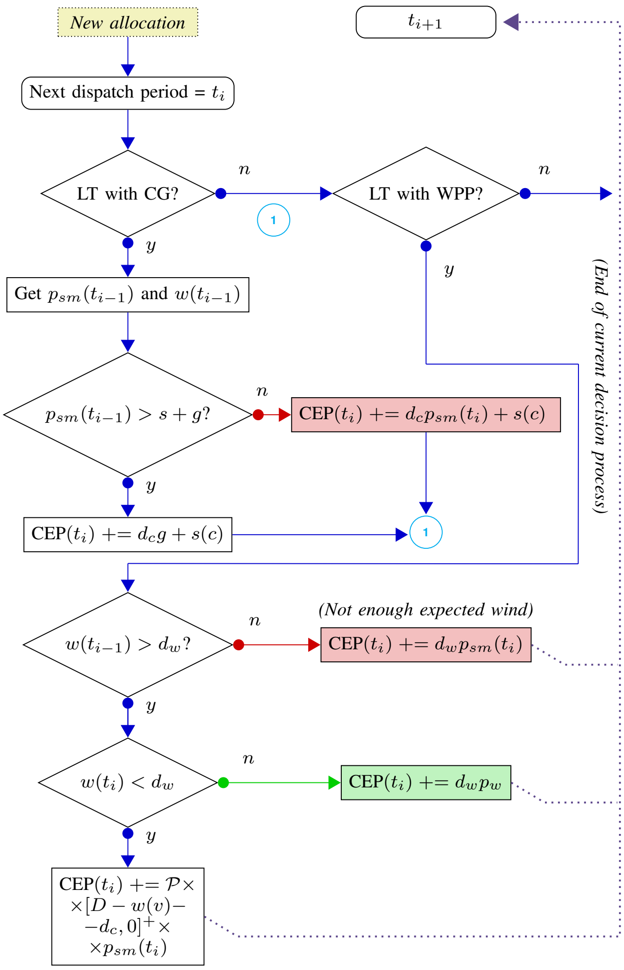


Fig. 3. Flowchart diagram of the LSE procurement decision support algorithm.

the drift and diffusion coefficients. This is achieved without sacrificing order of convergence. On the other hand, the drawback is the required multi-step calculations. Nevertheless, given (10) and (11) a derivative free method is preferred.

V. Results and Risk Analysis

The penetration of intermittent energy resources and distributed technologies is increasing the complexity of the risk diversification process. For a reliable estimation of future profits the extent of potential non-desirable extreme events has to be addressed. We use two risk measures. Firstly, we use Conditional Value-at-Risk (CVaR) to analyze the relation between risk and costs. Based upon the CVaR measure, we show the efficient frontier for various possible diversification schemes. Lastly, through the Excess Cost metric, we contrast the cost of electricity procurement, for different portfolios, with the probability of exceeding a given cost threshold.

A. Risk Metric: CVaR

When the risk in the decision process is not considered, the uncertainty prevailing in commodity markets might negatively

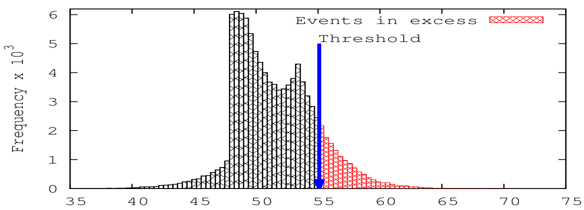


Fig. 4. A process dependent on a random variable can be evaluated by the probability that the random variable surpasses a threshold.

transfer the price volatility to the LSE procurement cost. We use CVaR to quantify the risk of the electricity portfolios.

Among other desired properties, CVaR is a coherent metric. Specifically it complies with the subadditivity property. This means that, for any portfolio composed of a linear combination of other portfolios, the risk is not overestimated [28].

Another useful characteristic is that the formerly popular, but not coherent, Value-at-Risk (VaR) measure is a byproduct of optimizing CVaR; as can be seen in (15) and (16).

$$\mathrm{VaR} = \min\{\nu : P(\mathrm{CEP}(t) \le \nu) \ge \beta)\} \tag{15}$$

$$\mathrm{CVaR} = \nu + \frac{1}{1-\beta}\mathbb{E}[(\mathrm{CEP}(t) - \nu)^+], \tag{16}$$

where ν represents the value-at-risk, β is a specified confidence level for the probability of CEP(t), typical values are 0.9, 0.95 and 0.99. The $(x)^+$ notation stands for the maximum among x and 0.

B. Risk Metric: Excess Cost

We propose a risk metric that is based on the cumulative probability exceeding a defined threshold. In this context, risk can be understood as the expected energy procurement cost in excess of a zero-risk portfolio. The histogram in Fig. 4 is an example of the idea behind our *Excess Cost* metric. Excess Cost is a quantitative evaluation of the probability of events occurring with a negative impact on the LSE profit.

An LSE riskless strategy, although expensive, would be to procure the total demand D from a LT with a dispatchable source. We can set the benchmark to be the LT electricity price with a CG as the threshold. For a given portfolio we estimate the probability that the cost surpasses the threshold.

C. Results

The applicability of our model is shown by simulating for $m\!=\!1000$ and $\gamma\!=\!3.4$. The time step $h = 0.001$, represents the time slots, during a trading day, for contract adjustments and hourly bids. The statistics are the outcome of 100000 paths. Table I, summarizes the wind turbine specifications of the WPP [2]. The LSE total demand is $D = 2$ MWh and contract prices are $p_w = 18\$$ and $g = 24\$$ per MWh. Fig. 5 shows the expected cost, $\mathbb{E}$[CEP], for different electricity portfolios and distinct decay rates, α. It can be seen the possible wind energy diversification strategies that will keep procurement cost below θ. Values above the solid line mean that, in the long run, the uncertainty in the wind power availability, either from low or

Table I. Wind turbine data used in the MC simulations.

Wind Turbine Specs	
Rated power	1.3 MW
Rated speed	15 m/s
Cut-in speed	4 m/s
Cut-out speed	25 m/s
Swept area	3019.5 m^2

extremely high wind speeds, counteracts the price advantage of the renewable source. For $\alpha = 0.7$, the minimum expected costs comprises 16% energy from the WPP.

The non-linear dependence of the minimum $\mathbb{E}[\text{CEP}(t)]$ on the wind correlation decay rate is shown in Fig. 6. The initial steep increase of the minimum expected cost reflects the strong dependence upon lower values of α. Nevertheless, there exist a diversification scheme such that the WPP can be profitably incorporated; in our testbed it spans from 15% to 18%. This means that for different α's, the LSE can allocate its electricity demand, among the WPP a CG and the SM, such that the minimum expected procurement cost is less than $d_c = 100\%$.

Fig. 7, is the procurement cost and risk map for the LSE. The graph shows that lower CVaR levels can be obtained by sacrificing (i.e., increasing) the portfolio's expected cost.

CVaR risk is the expected payable cost in the worst 10% and 5% cases ($\beta = .9, .95$). Fig. 7 shows that for a greater confidence level, higher cost are implied from within the profit adverse events. Thus, for a risk averse LSE, the minimum CVaR is achieved with a 8% share of wind electricity.

The Excess Cost assessment can be seen in Fig. 8. The threshold θ is defined as the total procurement cost under a pure CG portfolio. Under this measure, the portfolio with minimum probability of events above θ is comprised of 11% electricity from the WPP. This corresponds to the inflection point where increasing the share of renewable energy no longer benefits profit creation.

Fig. 9 shows histograms for the three aforementioned renewable allocation schemes. Besides the skewness and location of the peak, the kurtosis and spread of the procurement cost (Fig. 9d) are the factors determining the size of the renewable share that minimizes the risk measure. The backbone of the SPM is the martingale adapting scheme. In this respect, CVaR sheds light on the average tail events while Excess Cost provides an insight into the likelihood of a given procuring portfolio flooding into the undesired costs events. Moreover, Excess Cost is understood as a trade-off among the relaxed and conservative hedged strategies. This can be seen by contrasting the three portfolios: no risk assessment, Excess Cost and CVaR, i.e., $dw = 16\%, 11\%$ and 8%, respectively.

VI. Conclusions

This work studied the energy procurement problem with renewable energy sources. The methodology presented is easily implementable and customizable to serve an LSE in defining contracting strategies in deregulated markets.

With respect to the research in this field and the methods therein this work advances the state-of-the-art by introducing a differential model underlaid by stochastic processes rather than relying on past or given scenarios.

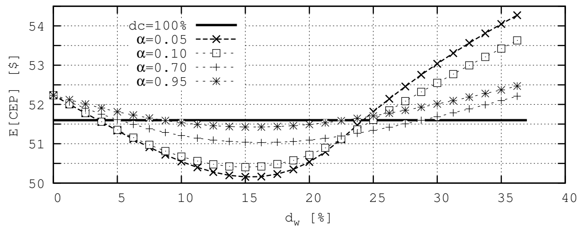


Fig. 5. Effect of α on the expected procurement cost for different d_w.

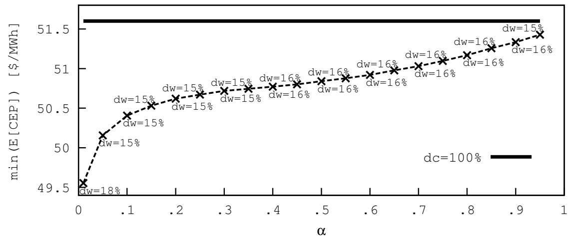


Fig. 6. Minimum $\mathbb{E}$[CEP] the $\%$ of d_w for different α.

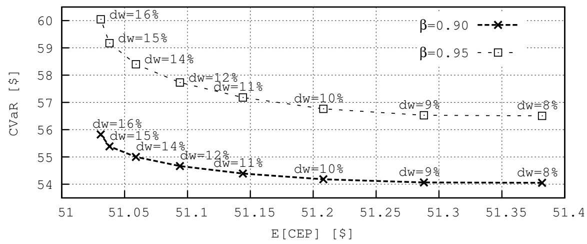


Fig. 7. Efficient frontier for different d_w. $\alpha = 0.7$ and two β levels.

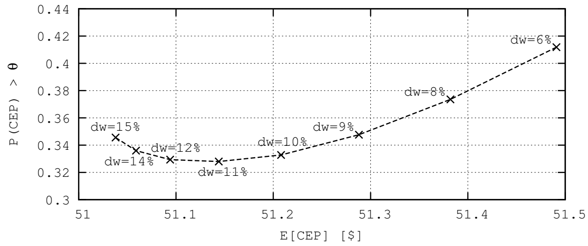


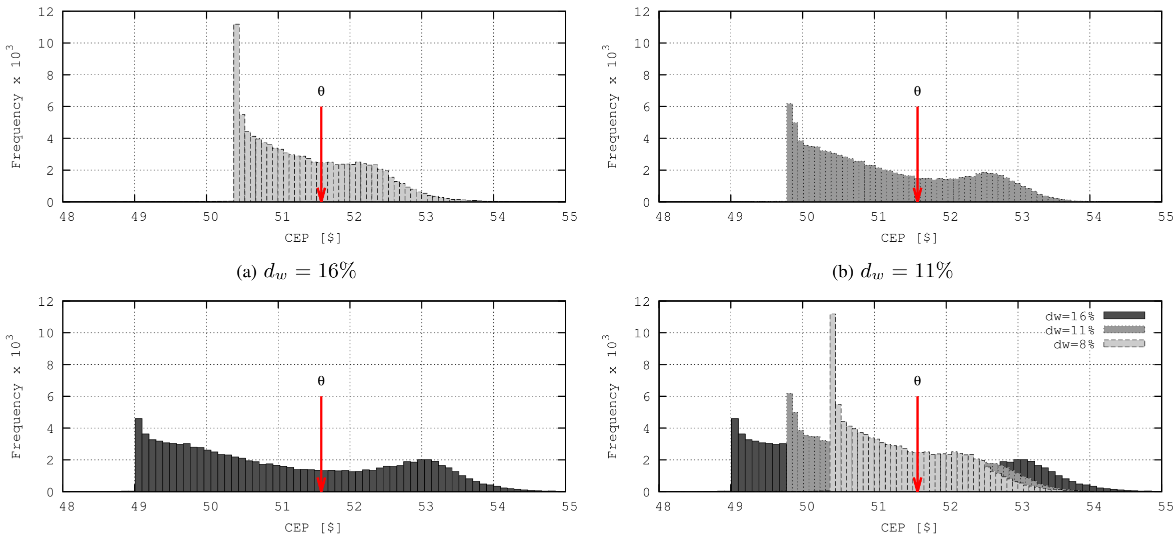
Fig. 8. Excess Cost metric for $\theta = 51.6\$$ and $\alpha = 0.7$ for different d_w.

The formulation addresses the merge of renewable and conventional sources with real-time trading. The SPM uses a mean-reverting Lévy process to model the spiky nature of electricity spot prices. We used a Brownian process with multiplicative noise to model the output of a WPP. The drift and diffusion were transformed to follow a RD. The SPM is easily scalable and can incorporate other energy sources.

The SPM was complemented with two risk metrics: CVaR and Excess Cost. We formulated the Excess Cost risk metric as a user defined risk threshold. We considered the threshold to be proportional to the dispatchable source.

We tested the SPM with a MC algorithm. We presented the feasible portfolios to hedge against market's volatility and weather uncertainty. The results are general in the sense that they provide an answer irrespective of the policy towards risk.

This work presented a theoretical approach to electricity procuring using a Ornstein–Uhlenbeck and Lévy process.



(a) $d_w = 16\%$ (b) $d_w = 11\%$ (c) $d_w = 8\%$ (d) Cost distributions for three different portfolios.

Fig. 9. Comparison of cost of electricity procurement for three different risk profiles: (a) non risk assessment, (b) Excess Cost and (c) CVaR with $\theta = 51.6\$$ per hour and $\alpha = 0.7$. Graph (d), shows the relative spread among the three risk profiles.

Future work is aimed at extending the SPM to incorporate the seller's decision process.

References

[1] F. Pazheri, M. Othman, and N. Malik, "A review on global renewable electricity scenario," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 835–845, Mar 2014.

[2] Z. O. Olaofe and K. A. Folly, "Wind energy analysis based on turbine and developed site power curves: A case-study of darling city," *Renewable Energy*, vol. 53, pp. 306–318, May 2013.

[3] S. Pishgar-Komleh, A. Keyhani, and P. Sefeedpari, "Wind speed and power density analysis based on weibull and rayleigh distributions (a case study: Firouzkooh county of iran)," *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 313 – 322, Feb 2015.

[4] J. Carta, P. Ramírez, and S. Velázquez, "A review of wind speed probability distributions used in wind energy analysis: Case studies in the canary islands," *Ren. and Sus. Energy Rev.*, vol. 13, no. 5, pp. 933 – 955, Jun 2009.

[5] R. Bjorgan, H. Song, C. C. Liu, and R. Dahlgren, "Pricing flexible electricity contracts," *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 477–482, May 2000.

[6] A. J. Conejo, J. J. Fernandez-Gonzalez, and N. Alguacil, "Energy procurement for large consumers in electricity markets," *IEE Proc. - Gen., Tran. and Distribution*, vol. 152, no. 3, pp. 357–364, May 2005.

[7] M. Chen and R. Xiaohong, "Research on strategy of purchasing electricity for large electricity consumers based on cvar," in *AIMSEC, 2011 2nd International Conference on*, Aug 2011, pp. 5760–5764.

[8] G. Kneževic, S. Nikolovski, and P. Marić, "Electricity spot market simulation involving bilateral contracts hedging," in *2011 8th EEM*, May 2011, pp. 122–127.

[9] M. B. J. Jimenez and A. C. Nerves, "Optimal allocation of spot market and bilateral contract transactions through quantity declaration adjustments," in *2013 IEEE PES APPEEC*, Dec 2013, pp. 1–6.

[10] S. Palamarchuk, "Bilateral contract correction and cancellation in the competitive electricity markets," in *PowerTech, 2009 IEEE Bucharest*. IEEE, Jun 2009, pp. 1–5.

[11] J. C. Mateus and P. Cuervo, "Bilateral negotiation of energy contracts from the buyer perspective," in *2009 IEEE Power Energy Society General Meeting*, Jul 2009, pp. 1–7.

[12] D. J. Wu, P. Kleindorfer, and J. E. Zhang, "Optimal bidding and contracting strategies in the deregulated electric power market: Part ii," in *34th Int. Conf. on System Sciences*. IEEE, Jan 2001, pp. 1–10.

[13] W. Peng, W. Yan-Hong, Y. Hua-Chun, and H. Ren-Mu, "Bayes equilibrium on negotiation means transaction of the power market long-term contract," in *PowerCon*, vol. 3, 2002, pp. 1814–1818.

[14] L. Freire, A. Street, D. A. Lima, and L. A. Barroso, "A hybrid milp and benders decomposition approach to find the nucleolus quota allocation for a renewable energy portfolio," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3265–3275, Nov 2015.

[15] E. Baeyens, E. Y. Bitar, P. P. Khargonekar, and K. Poolla, "Coalitional aggregation of wind power," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3774–3784, Nov 2013.

[16] S. Watts, "LMP Overview," https://pjm.adobeconnect.com/_a16103949/p3c7rb6whya/, 2013, [Online; accessed 19-July-2016].

[17] F. E. Benth, J. Š. Benth, and S. Koekebakker, *Stochastic Modelling of Electricity and Related Markets*. Singapore: World Scientific, 2008.

[18] M. Lydia, S. S. Kumar, A. I. Selvakumar, and G. E. P. Kumar, "A comprehensive review on wind turbine power curve modeling techniques," *Ren. and Sustainable Energy Reviews*, vol. 30, pp. 452 – 460, Feb 2014.

[19] P. Glasserman, *Monte Carlo Methods in Financial Engineering*. New York: Springer-Verlag, 2003.

[20] C. Gardiner, *Stochastic Methods: A Handbook for the Natural and Social Sciences*. Heidelberg: Springer-Verlag, 2009.

[21] S. E. Shreve, *Stochastic Calculus for Finance II Continuous-Time Models*. New York: Springer, 2004.

[22] Y. Zhang, J. Wang, and X. Wang, "Review on probabilistic forecasting of wind power generation," *Renewable and Sustainable Energy Reviews*, vol. 32, pp. 255–270, Apr 2014.

[23] E. Hau, *Wind Turbines Fundamentals, Technologies, Application, Economics*. Heidelberg: Springer-Verlag, 2013.

[24] R. Zárate-Miñano and F. Milano, "Construction of sde-based wind speed models with exponential autocorrelation," ERC UCD, 2015, https://arxiv.org/abs/1511.02345.

[25] A. Leon-Garcia, *Probability, Statistics, and Random Processes for Electrical Engineering*. Upper Saddle River, NJ: Pearson Edu., 2008.

[26] M. Gökçek, A. Bayülken, and Ş. Bekdemir, "Investigation of wind characteristics and wind energy potential in kirklareli, turkey," *Renewable Energy*, vol. 32, no. 10, pp. 1739 – 1752, Aug 2007.

[27] N. Kasdin, "Runge-kutta algorithm for the numerical integration of stochastic differential equations," *Journal of Guidance, Control, and Dynamics*, vol. 18, no. 1, pp. 114–120, Jan-Feb 1995.

[28] P. Artzner, F. Delbaen, J. Eber, and D. Heath, "Coherent measures of risk," *Mathematical Finance*, vol. 9, no. 3, pp. 203–208, Jul 1999.

Appendix E

Subsidies-Free Renewable Energy Trading: A Meta Agent Approach

Subsidies-Free Renewable Energy Trading: A Meta Agent Approach

Genaro Longoria, Alan Davy and Lei Shi *Member, IEEE*

***Abstract*—Can we automate the energy exchange of a power trader? To address this challenge, we present the Meta Agent Learner (MAL). The MAL is a tiered and multi-policy energy trader. It comprises data analytics (DA), a deep sequence-to-sequence recurrent neural network (DS2S) and reinforcement learning (RL). The DA phase draws knowledge out of the sheer flow of data. The DS2S phase creates wisdom and provides the intelligence for decision making. The RL phase senses and learns from the market to act strategically. We demonstrate the MAL in a scenario of a price-taker wind farm with a hydro plant. The testbed is real data from the NordPool and East Denmark (DK2). More specifically, electricity consumption, wholesale and balancing prices, cross border energy exchange, and weather conditions. The MAL optimizes the combined production of the wind farm and hydro pumped storage. Runs the hydro plant such that spillage of wind power is avoided or stores cheap market electricity. The performance is benchmarked with three traders.**

***Index Terms*—Electricity supply, energy trading, hybrid power generation, meta agent, recurrent neural network, sequence-to-sequence.**

I. Introduction

DISTRIBUTED energy resources (DER) are becoming ubiquitous in deregulated electricity markets. A significant proportion of the DER installed capacity are renewables sources [1]. Profit creation from renewable energy has been characterized for its inability to be self-sustained. Government support in the form of subsides and tax incentives had been the solution to socialize the risk and thus attract investment. However, in the short term the renewable/fossil-fuel ratio is required to expand significantly [2], making support schemes no longer bearable. Hence, countries had begun to update their energy legislation and market design. The new laws require renewable energy producers to be liable of balancing their positions [3]; whereby coming closer to market fairness. For example, in Ireland the Renewable Electricity Feed-in Tariff support scheme, a public service obligation levy charged to electricity consumers, will cease to exist. Instead, new energy markets will be introduced to balance close to real-time the traders' energy commitments [4].

This work tries to provide a sustainable solution for electricity retailers of hybrid wind power plants (HWPP). The work addresses the central question of the HWPP operation: How to dynamically allocate the HWPP generation and operate the pumped storage in order to reduce the trading costs? In fact, revenues from intermittent power trading depend on two main factors: 1) The reliability of the committed power and 2) Wholesale prices. The renewable energy producer is subject, as a consequence of weather variability, to up and down regulating prices. A better outlook of wholesale price would signify less exposure to the more volatile balancing market; thereby reducing costs and increasing profit.

Two mainstream approaches exist to balance supply and demand. On the one hand, accurate forecasting of high impact variables (e.g. weather and energy price). On the other hand, energy storage. The sought result is the smoothing of the total power output. There exist vast literature on price forecasting [5]–[7] and strategic decision-making [8]–[10]. Recent studies in simulated hybrid power scenarios have proposed agent modeling to minimize trading cost [11], [12]. However, most works have focused on consumption management in office or residential areas and no relevant study has been done on the energy management of the supply side.

This paper presents the MAL, an holistic agent-based methodology to power supply management. The MAL incorporates a tiered framework to manage a hybrid energy system on behalf of a power producer. The three fundamental instances of the MAL are 1) A clustering algorithm to draw knowledge out of the raw data; 2) A deep sequence-to-sequence recurrent neural network to forecast spot prices; and 3) A multi-policy Q-learning algorithm for decision-making. The agent was trained and validated with real market data from NordPool. The validation is done for a price-taker HWPP and benchmarked with three traders: 1) Perfect information; 2) Markovian agent; and 3) A vanilla artificial neural network.

This paper presents three new contributions. First, a robust machine intelligence framework for autonomous energy trading. A wait-and-see strategy and the foundational Q-learning (QL) algorithm performs better than a more sophisticated variation. Most importantly, this translates as a reliable operation of the hydro plant. Second, a sequence-to-sequence model to predict spot energy prices that advances previous ANN implementations. Third, a thorough analysis of energy consumption and prices of real-valued market data. Recent studies have focused on the scheduling and trading challenges while regarding the dynamics of the market price as periodic [11], [12] or simply as scenarios from a normal distribution [13], [14]. In the long-term the periodic assumption is not applicable. Whereas our method considers real-time adaptive decision-making. Unlike existing approaches it does not rely on a probability density of market data.

The remainder of the paper is organized as follows. Section II presents a brief literature review, we comment on the related work and state our contributions. Sections IV presents

G. Longoria and A. Davy are with the Telecommunication Software and Systems Group, Waterford Institute of Technology, Waterford, Ireland (e-mail: glongoria@tssg.org; adavy@tssg.org).

L. Shi is with Carlow Institute of Technology, Carlow, Ireland (e-mail: lei.shi@itcarlow.ie).

the Meta Agent Learner. Followed by the details of the testbed, results and discussion in section V. Lastly, section VI concludes the work presented.

II. Related Work

A multi-agent system is presented in [15]. The authors report a lack of robustness. We address this. First, entropy reduction of input data such that more reliable decision making can be done. Secondly, we use a price predictor model with short- and long-term memory. Lastly, we overcome the scalability drawback of the multi-agent approach with the MAL, a unique agent that reasons on different instances of itself.

Pinto *et al.* propose a solution to energy bidders in the wholesale market [5]. The paper analyses the problem of price forecasting in the Iberian markets. The price predictions are then passed to the Particle Swarm Optimization algorithm to determine the best allocation of resources in a federated portfolio. A feedforward neural network with one hidden layer and single node output layer is implemented as forecasting engine. The authors recommend the need to explore other topologies that could improve the prediction performance. Similarly, [16] relies on a vanilla ANN (VNN) to forecast market prices. Our work implements a neural network model that improves the temporal capabilities of the VNN. The DS2S has the advantage of retaining temporal features of different time scales. In addition, the energy market in this work is a more complex exchange, in that, dependencies reside beyond geopolitical boundaries.

In contrast to [11] and [12], our work relaxes the assumption of periodic electricity rates. The authors considered a 24 hrs period. Although this is highly accurate for load patterns it is not always the case for market prices.

[17]–[20] are among the few great solutions to scheduling distributed energy resources (DER) and virtual power plants (VPP) with agent modeling. These implementations contribute towards a target energy profile of the network while preserving privacy of the constituents. COHDA [17] is a distributed optimization algorithm of agent managed DERs. Each agent has a global and local target to meet. The contributions of each agent add to form the global profile. The architecture is network agnostic in the sense that any degree or topology is admissible. ISAAC [18] and DynaSCOPE [19] build on top of COHDA. The former aggregates small DER into marketable VPP. ISAAC improves the reliability of the system by centralizing the convergence observation and termination control that a self-organized network lacks. DynaSCOPE differs from ISAAC in the VPP configuration, rather than a static cluster of DERs it relaxes this constraint with a dynamic VPP. In these architectures our agent fits in the network of distributed agents. The MAL adapts to unforeseen market profiles; it learns to think beyond the current state and if necessary sacrifice immediate gains for long-term profitability.

In [21], Kong *et al.* have shown the applicability of the recurrent neural network (RNN) in the electricity domain. The authors use an LSTM-based RNN to predict a household's power consumption. They argue that meter-level consumption forecast, in contrast to aggregated demand, is more challenging since it exhibits a more volatile pattern. Similarly, the MAL exploits the long and short memory characteristics of the LSTM cell to anticipate spot prices in the DK2 market.

An RNN is implemented in [22] to forecast wind and solar power production of a micro grid. They assume a cooperative approach to maximize the social welfare of the producers and consumers. Parallel to their approach this study also considers a storage device to smooth the intermittency of the renewable source. Our work extends their contributions with a novel model to estimate the wholesale electricity price. Furthermore to strategically manage the hybrid power plant we use multi-policy reinforcement learning.

In [23] the authors use agents to study the demand response of a competitive system formed by commercial buildings, power generators, load serving entities and an independent system operator. The input data is based on past events whereas the neural-like network of the LSTM cells in the DS2S creates temporal dependencies of different timescales keeping track of short and long-term price drift trends.

The energy consumption of a residential building and aggregation of buildings is studied in [24]. An important challenge for smart buildings is to use energy efficiently. The authors present a hybrid agent that combines ML and AI. The agent can minimize the cost of consumption or shave the demand profile. In the former, a demand response scheme beckons costumers into delaying appliance use to off-peak time. Our work focuses, instead of demand, on the challenge of energy offering in a support-free market.

The authors in [25] contrast four autonomous agents to accomplish demand response of a fleet of 90 electric vehicles. They consider a residential setting with varying mileage scenarios. The work shows that RL, in particular a multi-policy multi-agent version of Q-learning, adapts well to environment and device changes. Our study capitalizes on this feature, the MAL uses RL to autonomously manage the combined power generation of a wind farm and a hydro plant.

Several studies [26]–[29] have analyzed the effect of government subsidies. In [26] the authors use a real options model to estimate the optimal subsidy for a photovoltaic project. [27] singles out another disadvantage of subsidies: conflict of interests between policy makers and renewable energy producers. And presents policy changes to improve the effectiveness of subsidies. In [28] and [29] the authors present an appropriate subsidies policy to balance the benefit to the private capital and the government's budget. The goal of our work is to change this paradigm by eliminating the need to any subsidy.

The use of ML and AI in trading markets is experiencing a surge. Nevertheless, in the power market field, the literature combining both techniques is as yet very sparse. The paper contributions are threefold. Firstly, it presents an integrated ML framework and contrast it to the art. We find that a wait-and-see strategy and QL provide the required reliability. Secondly, a deep sequence-to-sequence model for energy spot price prediction. Our approach is validated with Europe's leading power market and one of the most complex trading pools. Lastly, a semi-homeomorphic homotopic transformation applied to the DK2 electricity consumption and wholesale prices analysis.

III. Problem Statement

In modern electricity markets, power suppliers face the problem of auto regulating the offered power. Mismatches between offered and real output are settled in hefty balancing markets. The HWPP energy allocating problem for an arbitrary time frame Γ can be stated as the optimization problem (2), i.e., minimize $\mathcal{C}(\cdot)$, the trading cost, $\forall t \in \Gamma$. The optimization variables are κ the share of energy to procure from the wholesale market $\jmath_{sm}$. The power from the hydro plant $\jmath_{hm}$. And the wind power to store in the hydro plant $\jmath_{st}$.

The wind power allocated to the market $\jmath_{wm}$ is the difference between the farm's total generation $\jmath_{wf}$ and the fraction stored $\jmath_{st}$ in the hydro plant (2d).

The state of the hydro plant is $\jmath_{hp}$; it has three mutually exclusive modes of operation (1). In one mode the motors act as generators (discharge). In a second mode the motors work as pumps (charge). Thirdly, the sate remains unchanged (idle).

$$\jmath_{hp}^{t} = \begin{cases} \jmath_{hp}^{t-1} + \jmath_{st}^{t} & \leftarrow \text{charge} \\ \jmath_{hp}^{t-1} - \jmath_{hm}^{t} & \leftarrow \text{discharge} \\ \jmath_{hp}^{t-1} & \leftarrow \text{idle.} \end{cases} \tag{1}$$

The spot price is p_{sm} and balancing prices are p_{ur} and p_{dr} for up and down regulation respectively. The set of constrains include: 1) Balancing supply $S_t(\cdot)$ and demand $\mathcal{D}_t$ (2b); 2) Mismatch tolerance ϵ; 3) The maximum energy supply (2c); 4) Wind power offer (2d) subject to the forecast $\jmath_{wf}^{\mathfrak{F},t}$; 5) Power to procure from the spot market (2e) in terms of the demand forecast $\mathcal{D}_t^{\mathfrak{F}}$; and 6) The hydro plant reservoir levels r^{max} and r^{min} (2f) and (2g), respectively.

$$J = \min_{\jmath_{hp}^{t},\kappa} \mathcal{C}(S(\cdot), \mathcal{D}, p_{sm}, \kappa) = \tag{2a}$$

$$= \sum_{t=t_o}^{\Gamma} p_{sm}^{t}\jmath_{sm}^{t} + p_{dr}^{t}[S_t - \mathcal{D}_t]_{+} + p_{ur}^{t}[S_t - \mathcal{D}_t]_{-},$$

s.t.

$$|S_t(\cdot) - \mathcal{D}_t| \le \epsilon \tag{2b}$$

$$S_t(\jmath_{wf}^{\mathfrak{F},t}, \mathcal{D}_t^{\mathfrak{F}}, \jmath_{hp}^{t}, \kappa) \le \kappa \jmath_{sm}^{t} + \jmath_{hm}^{t}(\jmath_{hp}^{t}) + \jmath_{wm}^{t}, \tag{2c}$$

$$\jmath_{wm}^{t} = \jmath_{wf}^{\mathfrak{F},t} - \jmath_{st}^{t} \tag{2d}$$

$$\jmath_{sm}^{t} = \jmath_{wf}^{\mathfrak{F},t} - \mathcal{D}_t^{\mathfrak{F}} - \jmath_{st}^{t}. \tag{2e}$$

$$\jmath_{st}^{t} \le r^{max} \tag{2f}$$

$$r^{max} \ge \jmath_{hp}^{t} \ge r^{min} \tag{2g}$$

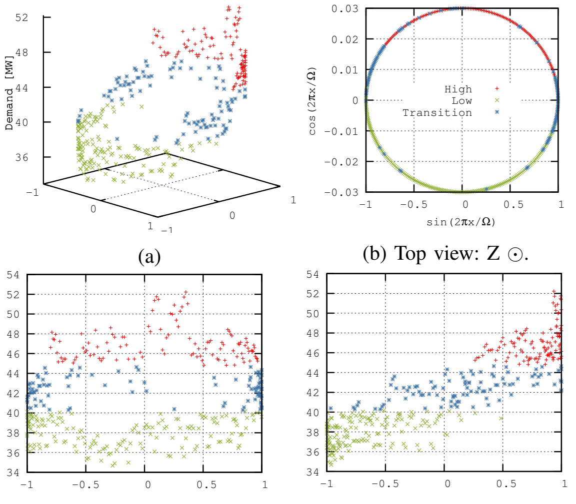
$$0 \le \kappa \le 1 \tag{2h}$$

where $[x]_{+} := \max(x, 0)$ and $[x]_{-} := \min(x, 0)$. In this work, $\mathcal{D}$ is a scalar and input to our model whereas S is a function of the own generation of the HWPP and the energy procured.

The following section presents a flexible alternative to (2) that self-adapts to market changes.

IV. The Meta Agent Learner

The agent is formed of several selves [30]. The energy management is an analytics-driven consensus of all selves of itself. Formally, the state of the HWPP, market and weather compose the environment of the MAL. The agent has a tiered structure that comprises analytics, an AI model and reinforcement learning. It is composed of different phases that are agents themselves. Thus the state and action of the decision-making agent is influenced by the beliefs of the other intra-agents; this is the metareasoning. Those beliefs are, e.g., the wholesale price predictions made by the DS2S self. These in turn are influenced by the Analytics instance of the self. This metareasoning is the backbone of the decision-making.



(a) (b) Top view: Z $\odot$.

(c) X $\odot$. (d) Y $\odot$.

Figure 1: Homotopic coordinate transformation. Plot 1b shows the XY-plane view of the resulting Jordan curve.

The boxing is by the Data layer. The Data layer represents the environment of the agent and links with the market and weather data to reason about the state of the system. The MAL decreases the overall trading cost in an incomplete information setting. It forecasts wholesale prices, efficiently trades wind power, smooths the supply curve with the pumped storage system and runs it within safety operational levels.

A. Analytics

The task of the analytics phase is to extract endogenous knowledge before attempting to forecast wholesale prices. Driven by renewable integration, smart metering and demand response, the information generated on energy markets consist of sheer volumes of data. In addition, the data transmission takes place in a short time frame just before real-time. The flows are wisdom rich. However in the raw state the added value is of poor relevance for decision-making. Before actions are performed the MAL reasons and adds value on the data.

The *a priori* assumption, on the input, are seasonal patterns of different time scales. An unsupervised classifier characterizes the seasonality in various clusters. In addition, speeds up the training of the DS2S phase.

We define a semi-homeomorphic homotopic coordinate transformation such that, for a given year, the clustering is confined to a Jordan curve. The homotopic map forms a topological space for the directionality of time and the cyclic nature of seasons such that $f(x) : \mathbb{R} \to \mathbb{R}^2$. Instead of using a sequential counter, each time stamp of the input data is transformed according to (3). January and December are morphologically at the ends of the time line, however (3)

(a) (b)

Figure 2: DK2 hourly electricity spot prices from 2015 to 2017. Fig. (a) shows the raw values. Fig (b) shows the histograms of the K-means clusters. 5 clusters are used: Low-low (LL), Low (LO), Mid (MI), High (HI) and High-high (HH).

reveals the periodicity hindered by time's unidirectionality.

$$y_1{=}sin\left(\frac{2\pi x}{\Omega}\right), y_2{=}cos\left(\frac{2\pi x}{\Omega}\right), \Omega{=}\sum_{i=0}^{\tau}\mathbb{1}_{\{x_i\in X\}}. \quad (3)$$

Where $X = \{x_1, x_2, \cdots, x_\tau\}$ is the set of input values to the Analytics phase. The time interval, τ, is typically one year.

The MAL utilizes the K-means algorithm to cluster the seasonality. (4) minimizes the $\|\cdot\|_{\mathcal{L}_2}$ of n data points to an element M_k of a finite set $\mathcal{M}$ of centroids.

$$\underset{\mathcal{M}}{\text{argmin}} \sum_{k=1}^{K} \sum_{x_n\in M_k} \|x_n - \mu_k\|^2. \quad (4)$$

Voronoid algorithm iteratively finds a solution to (4). The average complexity is $\mathcal{O}(KnI)$, where K is the number of clusters and I the number of iterations. This implementations guarantees a fast convergence. The algorithm initializes the centroids and iterates two operations: a) update the clusters with the data points closest to the centroids (5) and b) recalculate the centroids given the new set of clusters (6).

$$M_k = \{x_n : \|x_n - \mu_k\| \leq \|x_n - \mu_l\| \,\forall\, l \neq k\} \quad (5)$$

$$\mu_k = \frac{1}{C_k} \sum_{x_n\in M_k} x_n. \quad (6)$$

The DA phase outputs the demand and spot price clusters. Given space constraint we present only the resulting spot price at the year scale in Fig. 2. The bars represent five price bands: Low-Low, Middle, High and High-High. Further discussion and the benefit of decreasing the entropy and skewness of the raw data is presented in the following sections.

B. Deep Sequence-to-Sequence Recurrent Neural Network

This section details the DS2S phase of the MAL and its implementation for spot energy price forecasting. The architecture of this model accounts for temporal learning of different scales such that predicting is done with an holistic perspective. Hence in challenging large sequential datasets the DS2S can performs better than neural network models [31].

Table I: Input Parameters.

Subset	Value	Unit
Date	Hour Weekday	Hr. Mo → Su
Energy exchange	SWE GER DK1	MW MW MW
Energy price	Day-ahead System Up\Down regulation Balancing Consumption Price prediction	€ € € € €
Power	Primary production Local production Wind production Solar production Up\Down regulation Demand	MW MW MW MW MW MW
Forecast	Wind power Demand	MW MW

Revenues from intermittent power trading depend on two main factors: 1) The reliability of the committed power and 2) The accuracy of future wholesale prices.

The topology of the DS2S consists of vertically stacked sequence-to-sequence recurrent neural networks. The Hidden layer in Fig. 4 represents the LSTM stacked units. Energy prices exhibit mean reversion of different timescales [32]. We use the gated architecture of the LSTM to keep long-term trends in memory in the short-term when decision-making is done [33]. The Encoder receives the vector $[d_0, d_1, \cdots, d_n]^t$ where n is the number of parameters. Table I summarizes the elements of d. The output of the Decoder is the vector of spot price predictions, $[p^t, p^{t+1}, \cdots, p^{t+T}]$; $T = 8$. The case study contrasts the prediction accuracy of the DS2S and thus the

Table II: Components of the State of the System.

Class	State definition
Energy Price	- p_{sm}(t-1) - $\overline{p}_{sm} \rightarrow$ monthly average up to p_{sm}(t-1)
Net Forecast	- $\Delta_E \rightarrow$ forecasts difference $\jmath^{\mathfrak{F}}_{wf}$(t) and $\mathcal{D}^{\mathfrak{F}}$(t)
Hydro Plant	- Difference between r_{up} and r^{max}_{up} - Difference between r_{up} and safety threshold r^{th}_{up}
DS2S Energy Price Prediction	- $\varrho \rightarrow p_{sm}$(t) prediction - $\theta \rightarrow$ swing prediction of p_{sm}(t) w.r.t p_{sm}(t-1)

impact on trading cost of using the clusters or the raw values.

The input data is pre-processed in the Embedding layer. A mask is applied to the input at this final stage. The DS2S terminates the input and output sequences with <GO> and <EOS> respectively. The purpose of the end-of-sentence symbol is to unequivocally communicate the beginning of the prediction phase and the end of the output sequence. The decoder reverses the process. Before delivering the results the decoder *translates* the output to meaningful values.

The decoder has two modes of operation. In training the output of the RNN units is fed sequentially to the next neighboring unit: $\mathbf{h}_t \rightarrow \mathbf{X}_{t+1}$. This is represented as the vector **p** in the dashed boxes. Whereas, in predicting the feedback becomes optional. Based on our empirical tests we chose not to avail of this connection for forecasting.

C. *Q-learning*

The control phase of the agent solves problem (2) with a multi-policy Q-learning algorithm. The set of actions of the MAL are the share κ of the energy to procure from the wholesale market $\jmath_{sm}$, the power to discharge from the hydro plant $\jmath_{hm}$ and the power to store from the wind farm $\jmath_{st}$. The decisions to be made upon these three variables have a twofold aim. To achieve the first objective, the MAL seeks to balance supply S (2c) and demand $\mathcal{D}$ at each trading slot t. Minimizing the absolute value of the difference (2a) means less exposure to the more volatile balancing markets. On the other hand, the MAL grubs to guarantee secure operational levels of the hydro plant, i.e., prevent overfilling the dam reservoirs beyond their capacities and avoid dry running the hydro pumps.

To represent the state-action space of this problem we utilize a boolean model similar to the Universal Smart Grid Agent [34]. This guarantees scalability with respect to diversity of HWPP configurations. The state space subsumes wind power and consumption forecasts, $\jmath^{\mathfrak{F}}_{wf}$ and $\mathcal{D}^{\mathfrak{F}}$ respectively, to gauge the spot energy to procure (2e).

The state of the system s is a tuple that comprises four classes: energy price, net energy forecast, pumped storage and the DS2S energy price predictions. Table II shows the definitions of each class.

The reward (7) is expressed as a wait-and-see conjunctive function of the multiple policies controlled by the agent. The domains (8)-(9) of the indicators in (7) are containers of the agent's objectives.

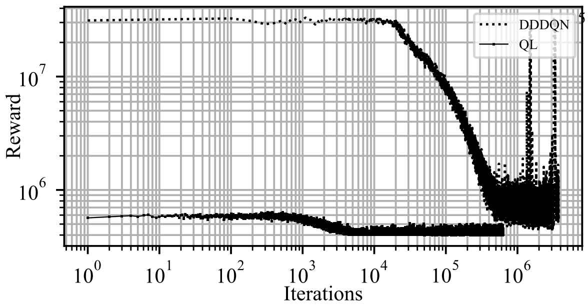


Figure 3: Training of the QL and DDDQN.

$$
\begin{aligned}
\Delta^t_E &= \jmath^{\mathfrak{F},t}_{wf} - \mathcal{D}^{\mathfrak{F}}_t \\
\Delta^t_F &= \Delta^t_E - \jmath^t_{st} + \jmath^t_{hm} \\
\mathcal{R}_t(s,a) &= p^t_{ur}[S_t - \mathcal{D}_t]_- - p^t_{dr}[S_t - \mathcal{D}_t]_+ - w_1 \varrho \Delta^t_F \varkappa \\
&\quad - w_2 r^{t-1}_{up} - w_3 \mathbb{1}_{\{r^{t-1}_{up} - r^{max} > 0\}} \\
&\quad - [w_4 \mathbb{1}_{\{\jmath^t_{hm} > 0\}} + w_5 \jmath^t_{st}] \mathbb{1}_\xi \\
&\quad - w_6 \mathbb{1}_{\{\jmath^t_{hm} > 0\}} \mathbb{1}_\chi
\end{aligned} \tag{7}
$$

where

$$\xi = \{\varrho < \overline{p}_{sm}(0:t-1) \wedge \Delta_E < 0 \wedge \overline{\Delta}_E(t:t+8) < 0\} \tag{8}$$

$$
\begin{aligned}
\chi = \{&\neg[p_{sm}(t-1) < \varrho \wedge \theta \wedge \varrho > \overline{p}_{sm}(0:t-1)] \mid \\
&[\Delta_E(t) > \overline{\Delta}_E(t:t+8) \wedge r(t-1) < r^{th}_{up}] \wedge \\
&\overline{\Delta}_E(t:t+8) < 0\}
\end{aligned} \tag{9}
$$

$$\theta = \begin{cases} 1 \text{ if } p_{sm}(t) > p_{sm}(t-1) \\ 0 \text{ otherwise.} \end{cases} \tag{10}$$

The domain ξ compares ϱ against the average of the market and the surplus or lack of forecast energy Δ_E. χ checks 3 clauses: 1) Price prediction against current and averages and θ a boolean prediction of sign change of the difference between the current spot price and the next; 2) Compares the forecast energy difference with the average energy mismatch $\overline{\Delta}_E$ and the state of the pumped storage r and; 3) The expected energy imbalance. w_i are positive constants.

Innovative algorithms that build on top of Q-learning have been found promising. We implemented the art and contrasted the performance with respect to the foundational reinforcement learning algorithm (11). A recent innovation, that has outperformed several benchmark video games, is the Dueling Double Network for Deep Q Learning with Prioritized Experience Replay (DDDQN) [35]. The two novelties of this architecture are, firstly, a double network to estimate the value of the state and the advantage of the action, respectively. Secondly, the sampling process of the agent's memory weighs more SARSA memories that have more value to the agent and thus are replayed more often during training.

$$Q(s_t,a_t) \leftarrow (1-\alpha)Q(s_t,a_t) + \alpha[\mathcal{R}_t + \gamma \min_a Q(s_{t+1},a)] \tag{11}$$

For our problem, the DDDQN did not provide better performance of the agent. Despite the overhead and resource intensive computations the learning speed and test results perform worse than (11). In particular we find that the monthly trading cost of the HWPP is at best comparable to the results of

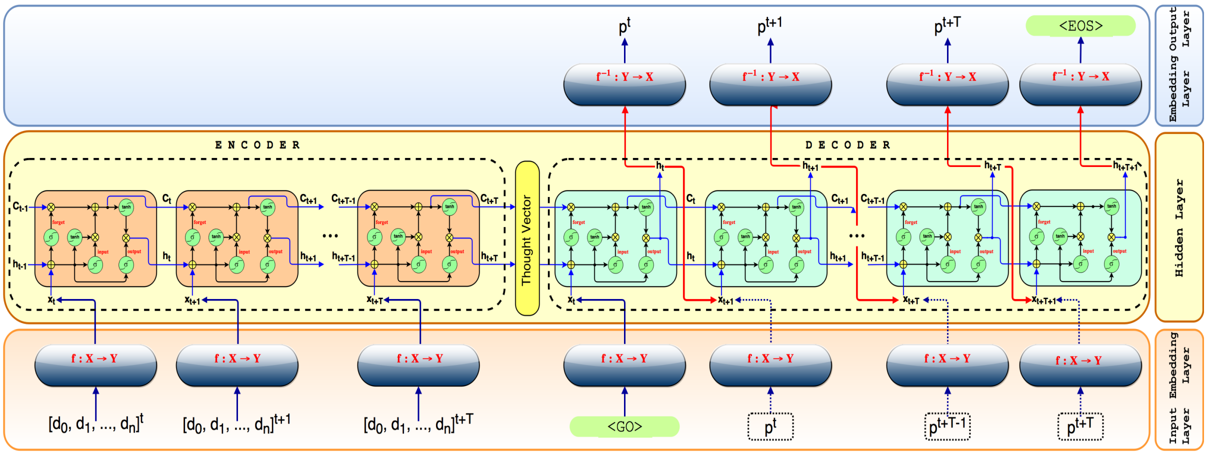


Figure 4: The architecture of the DS2S prediction instance are three main layers: Input, Hidden and Output. And the ancillary Embedding layers. The Hidden layer consists of stacked LSTM cells.

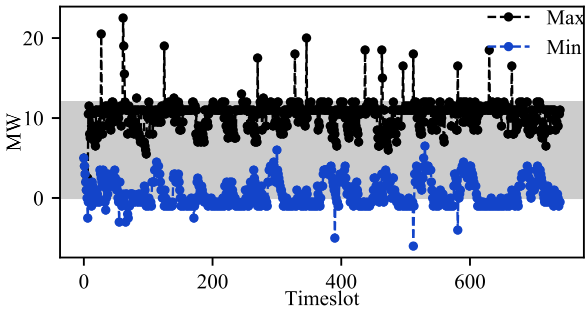


Figure 5: Maximum charge and minimum discharge of the pumped storage by the DDDQN. The shaded area is the safe operational region.

the (11). However, and more importantly, the operation of the pumped storage is not completely reliable. DDDQN runs dry or overflows 3% and 1% respectively (Fig. 5). The novelties that have proven successful in other domain are not necessarily applicable to a more volatile, state and action rich problem, like the one at hand. Figure 3 contrast both realizations of Q-learning. It can be seen that (11) converges faster to a better results than DDDQN. The initial spread is attributable to the anti-correlation memory sampling of DDDQN. In contrast to problems where there exist states of low significance action-wise (e.g. racing cars video game), in real-time control of energy flows this is seldom true. Hence the splitting of the network represents an overhead rather than a deeper insight to the agent. The simple yet robust reinforcement learning algorithm is better in managing the high frequency trading.

V. Experimental Validation

The data for case study was obtained from NordPool. The HWPP comprises a wind farm and hydro plant with installed capacity of 100 MW and 12 MW respectively. The wind power generation corresponds to a percentage of DK2.

The validation setup is from the procurement point of view, i.e., cost (negative values) instead of revenue is considered. The aim of the MAL is to reduce the cost incurred in operating the HWPP, consequently reducing the exposure of the renewable energy producer to the volatile markets. The performance of the proposed agent is compared with three traders and analyzed.

A. Market Data Processing

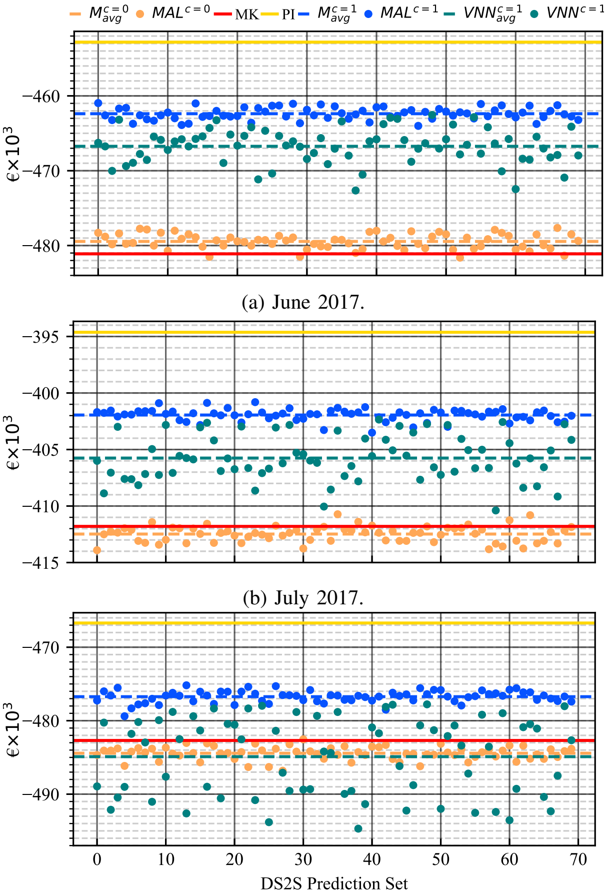
NordPool is integrated by the Scandinavian, Northern and Baltic European countries and the United Kingdom. Generation and demand from East Denmark are considered in this work. It can trade power via three intra-connectors: Great Belt is the exchange of electricity between West and East Denmark (DK1 and DK2), Continent exchanges power with Germany, and Nordic sends and receives power from Norway and Sweden.

The training set covers the time period from 1st January 2015 to 31st May 2017. The test dataset corresponds to the months of June to August 2017.

The Data layer is summarized in Table I. The *Energy price* category considers the different energy markets. For instance, the wholesale price reflects the cleared bids and asks submitted by retailers and producers. The System price reflects the cost of energy without taking into account congestions. Therefore it serves as a reference price for the NordPool areas. The *Energy exchange* category is the bidirectional flow of electricity between areas.

We have two levels of aggregation. The upper level comprises three patterns: yearly, weekly and daily. The lower level breaks the upper level in 4, 2, 3 clusters respectively.

The results are in agreement with the expected regularity. A gradual shifting from low, during the early hours, to high demand starting shortly before midday and back again to the low regime by the end of the day. The energy demand starts to ramp up at 7 am and eases back at 9 pm. During the low temperature months there is a higher demand than the rest of the year. May to mid August are clustered as low demand months. The transition months are from the latter half of March to the end of April and from the last half of August to the end of October. From January to mid March, November and December as high demand months. The same day serves as mid point on both March and August to prevent over-fitting.



(a) June 2017.

(b) July 2017.

(c) August 2017.

Figure 6[a]: Comparison of the TET cost of the HWPP. Each plot shows the total cost for Perfect Information (PI), a Markovian trader (MK), the MAL and average ($M_{avg}^{c=x}$), and the VNN and average ($VNN_{avg}^{c=1}$). We also contrast the Analytics phase by switching it off and on, i.e., $x \in \{0,1\}$ respectively.

This is not the case of the spot price (see Fig. 2a). To quantify the degree of order between years we use Shannon's entropy, $H = -\sum_{i=1}^{n} p_i \ln(p_i)$. The entropy of the energy consumption for the years 2015 to 2017 is 1.1. A 30% less than the spot price in the DK2 wholesale energy market. The spot electricity prices in DK2, for the years 2015 to 2017, are shown in Fig. 2a. In contrast to electricity demand, there is no apparent pattern. However the Analytics with the coordinate transformation (3) reveals a high-level clustering. Fig 2b shows the relative frequency of 5 clusters, i.e., Low-low, Low, Mid, High and High-high. It manifests the market and the actions of the System Operator to maintain the wholesale price within the low range. It is also noteworthy that the corrections to revert back price escalations are now evident. In the three years span, 78.5% of the values are in the mid to low range clusters, almost half of the spot prices, i.e. 46.2% are found in the low and low-low ranges; whereas only 5.9% of the analyzed sample is on the highest price band.

The added value of the DA instance can be seen in the lowering of entropy and skewness. The raw electricity prices present 8.19 and 1.9 respectively, whereas the entropy and skewness of the clustered data is 1.5 and 0.3 respectively.

Table III: Set of Actions Used on the Testbed.

Action	Definition	Unit	Bit
Energy to Store	$\jmath_{st}$={0,.5,4,6}	MW	0
Hydro Plant Usage	$\jmath_{hm}$={0,.5,1,6,10.5}	MW	1
Wholesale Market	$\varkappa \in \{0,1\}$	-	2

B. Results and Analysis

We generated multiple prediction sets to collect the total energy trading (TET) cost per month. To train the DS2S we tried a varying number of epochs. The predictions with 350 epochs had the best trade-off between accuracy and statistics. The results and statistics correspond to 70 prediction sets of the DS2S.

Figure 6 shows the comparison of the MAL with three traders. First, the yellow line represents the perfect information case, i.e. assuming complete knowledge of future conditions. Second, the red line is the result of markovian trading; it regards the current price to be independent of the past given the last event. Thirdly, the DS2S is replaced with a VNN. Lastly, we also contrast the clustering instance, represented by $MAL^{c=1}$, from the non-clustered data, $MAL^{c=0}$.

The MAL vanquishes the markovian scheme in all prediction sets in the three test months. It can be seen the effect of the Analytics phase. The MAL achieves lower costs with clustered data. Moreover, when the Analytics was off the trading cost were higher than those of the markovian scheme of the latter two months, see Fig. 3b and 3c. With respect to the prediction phase, the DS2S estimates substantially better the energy prices than a standard implementation of an ANN.

Figure 7 shows the statistical contrast of the TET cost with $MAL^{c=1}$, $MAL^{c=0}$ and VNN. The first and third quartiles and the minimum and maximum values of $MAL^{c=1}$ result in better performance than its counterparts with $MAL^{c=0}$ and the VNN instead of the DS2S. With clustering, the average TET cost for the month of July is 3% lower than without clustering and 2.4% than the markovian trader. The variance of the DS2S is on average 28% lower than with the VNN.

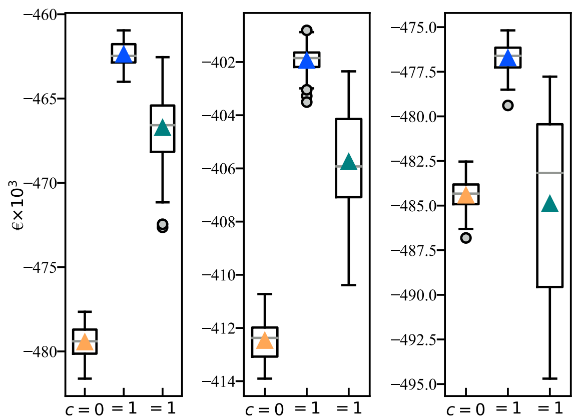
C. Discussion

The discrete values allowed for wind storage and hydro power withdraw are chosen such that the agent can avail from a sparse yet sufficient range. Table III summarizes the possible actions. The allowed actions are in relation to the capacity of the hydro plant. These are easily customizable for other configurations of the HWPP. *Bit* is a string-encoding-structure that distinguishes all possible action combinations. For instance, the string 030 (see *Action* in Fig. 8) represents no storage of wind energy, discharge 6 MW from the hydro plant and no procurement from the wholesale market.

Figure 8 shows the hourly costs and control of the HWPP, the wholesale price, demand, wind power, and hydro usage. The MAL learns a cost-effective charge/discharges of the hydro plant. It discharges the hydro plant when there is lack of wind power. The effect of the wait-and-see strategy can be

[a]The two topmost graphs share the x axis scale of the lowest graph.

seen in holding the hydro capacity and discharging when the spot price is disadvantageous. For example, the shaded areas highlight a discharge of the hydro plant to cover the lack of wind power. However, based on the predictions, waits until a peak price. Also, prevents wind spillage and curtailment by pumping water to the reservoir when the spot price is low or with surplus wind power (left most shaded area).



(a) June 2017. (b) July 2017. (c) August 2017.

Figure 7: Comparison of the DS2S and a vanilla ANN. Quartiles and mean of the TET cost with and without the Analytics phase, $c \in \{1,0\}$ respectively for the DS2S.

In the MAL, the analytics on spot energy prices reduced the entropy 82% and skewness 84%. In contrast to a vanilla ANN the DS2S the better predictions served to lower the trading costs. The kurtosis of the hourly costs is 2.2 characteristic of a platykurtic distribution: fewer extreme outliers. In contrast to other algorithms the MAL is better in terms of both prediction accuracy and dispatch learning.

The robustness of MAL is tested with random outages of the hydro plant and/or the wind farm. As a consequence of lack of internal energy capacity, the results show an increase in the overall TPC as expected. However of more significance is the control of the hydro plant. In Fig. 9 we observe that the outages does not impact the management of the flows by either dry running or overflowing the reservoirs. The shaded areas of the figure υ stands for wind power outage, ζ for a failure of the hydro plant and in λ both plants are out of service. In the first outage event, both plants are out for a period of 5 hrs. Followed by the hydro plant for 24 hrs. Lastly, in the third event the wind plant is out of service for 24 hrs.

VI. Conclusion

In this work we presented a solution to automate the management of a hybrid power producer. Our contributions are threefold. The MAL, a meta agent to orchestrate the energy trading of the HWPP. Second, a short- and long-term memory sequential network to estimate electricity prices. Third, a through analysis of energy consumption and prices of real-valued market data. The MAL consists of a metareasoning structure of Data Analytics, a sequential price prediction model and Machine Learning.

The Data Analytics gathers and clusters the streams of

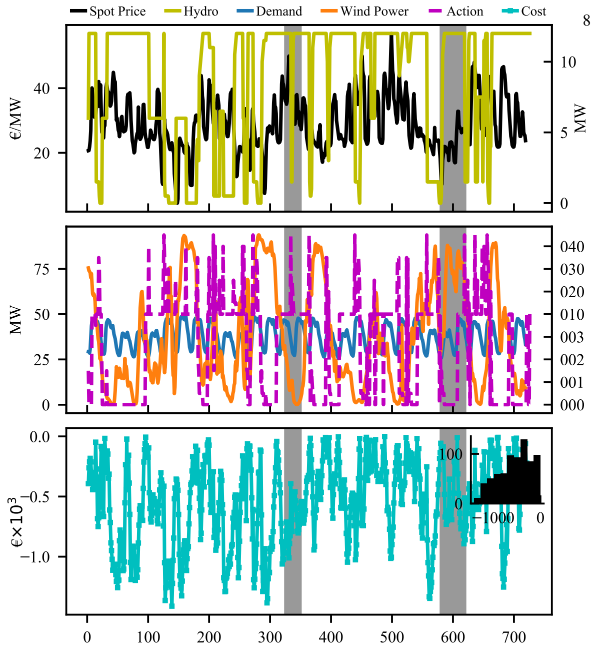


Figure 8[a]: Management of the HWPP for July 2017.

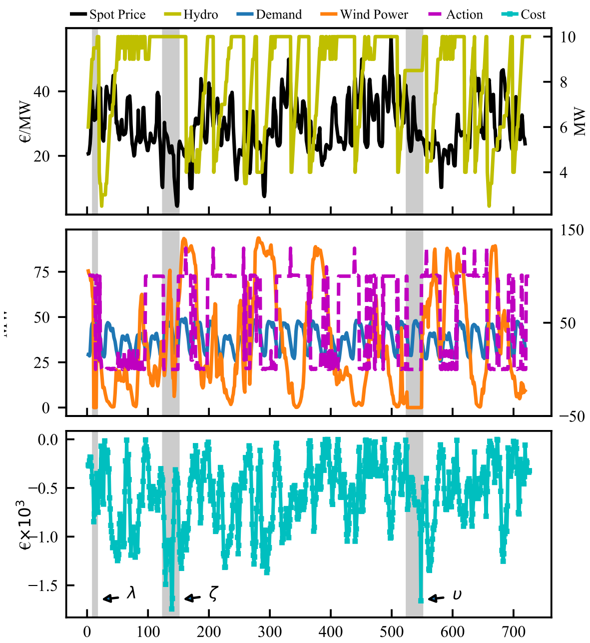


Figure 9[a]: Management of the HWPP with power outages for July 2017. υ and ζ are the time periods with wind or hydro outage respectively. In λ both plants are out of service.

market data. The AI phase is a deep sequence-to-sequence model that predict future wholesale energy prices. The RL consists of a multi-policy Q-Learning algorithm to allocate the HWPP generation and operate the hydro pumped plant.

The MAL was trained with data from NoordPool and tested in the eastern Danish market setting. The results show the foundational Q-learning algorithm is more robust than recent innovations. In particular, a reliable operation of the pumped storage was accomplished in all validation runs. The performance of the MAL was contrasted with three agents. A trader with perfect information, i.e., access to future energy prices, a markovian agent and replacing the DS2S instance of the MAL with a vanilla artificial neural network.

The MAL brings together energy and the stat-of-the-art in machine intelligence. The work facilitates the integration of renewables reducing the gap of self-sustainment and support-free markets. A direct impact of this could be seeing in lower energy tariffs to electricity customers and seamless increase of the renewable quota. Suggestion for future studies include incorporation of decentralized contracts and edge energy trading to explore a P2P energy market.

REFERENCES

[1] REN21, "Renewables 2016 Global Status Report," Renewable Energy Policy Network for the 21st Century, Tech. Rep., 2016.

[2] International Renewable Energy Agency, "Renewable power generation costs in 2017," 2018.

[3] "Renewable electricity support scheme: Transitioning to i-sem," Department of Communications, Climate Action and Environment, 29-31 Adelaide Road, Dublin, Tech. Rep., May 2017.

[4] "Integrated Single Electricity Market (I-SEM) SEM Committee Decision on High Level Design," DCENR-DETI, Ireland, Tech. Rep., 2014.

[5] T. Pinto, H. Morais, T. M. Sousa, T. Sousa, Z. Vale, I. Praa, R. Faia, and E. J. S. Pires, "Adaptive portfolio optimization for multiple electricity markets participation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 8, pp. 1720–1733, Aug. 2016.

[6] S. Borovkova and M. D. Schmeck, "Electricity price modeling with stochastic time change," *Energy Economics*, vol. 63, pp. 51–65, 2017.

[7] L. I. Hagfors, H. H. Kamperud, F. Paraschiv, M. Prokopczuk, A. Sator, and S. Westgaard, "Prediction of extreme price occurrences in the german day-ahead electricity market," *Quantitative Finance*, vol. 16, no. 12, pp. 1929–1948, 2016.

[8] T. Huang and D. Liu, "A self-learning scheme for residential energy system control and management," *Neural Computing and Applications*, vol. 22, no. 2, pp. 259–269, Feb. 2013.

[9] M. Boaro, D. Fuselli, F. D. Angelis, D. Liu, Q. Wei, and F. Piazza, "Adaptive dynamic programming algorithm for renewable energy scheduling and battery management," *Cognitive Computation*, vol. 5, no. 2, pp. 264–277, Jun. 2013.

[10] G. K. Venayagamoorthy, R. K. Sharma, P. K. Gautam, and A. Ahmadi, "Dynamic energy management system for a smart microgrid," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 8, pp. 1643–1656, Aug. 2016.

[11] G. Shi, D. Liu, and Q. Wei, "Echo state network-based q-learning method for optimal battery control of offices combined with renewable energy," *IET Control Theory Apps.*, vol. 11, no. 7, pp. 915–922, 2017.

[12] Q. Wei, G. Shi, R. Song, and Y. Liu, "Adaptive dynamic programming-based optimal control scheme for energy storage systems with solar renewable energy," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 7, pp. 5468–5478, Jul. 2017.

[13] A. A. S. de la Nieta, J. Contreras, and J. P. S. Catalo, "Optimal single wind hydro-pump storage bidding in day-ahead markets including bilateral contracts," *IEEE Trans. on Sus. Energy*, vol. 7, no. 3, Jul. 2016.

[14] A. A. S. de la Nieta, J. Contreras, and J. I. Muoz, "Optimal coordinated wind-hydro bidding strategies in day-ahead markets," *IEEE Trans. on Power Sys.*, vol. 28, no. 2, pp. 798–809, May 2013.

[15] B. M. Radhakrishnan and D. Srinivasan, "A multi-agent based distributed energy management scheme for smart grid applications," *Energy*, vol. 103, pp. 192–204, 2016.

[16] M. Liu, F. L. Quilumba, and W. Lee, "Dispatch scheduling for a wind farm with hybrid energy storage based on wind and lmp forecasting," *IEEE Trans. on Ind. Apps.*, vol. 51, no. 3, pp. 1970–1977, May 2015.

[17] C. Hinrichs, S. Lehnhoff, and M. Sonnenschein, "COHDA: A combinatorial optimization heuristic for distributed agents," in *Agents and Artificial Intelligence*, J. Filipe and A. Fred, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 23–39.

[18] A. Nieße and M. Tröschel, "Controlled self-organization in smart grids," in *2016 IEEE Intl. Sym. on Sys. Engineering (ISSE)*, Oct 2016, pp. 1–6.

[19] A. Nieße and M. Sonnenschein, "A fully distributed continuous planning approach for decentralized energy units," in *GI-Jahrestagung*, 2015.

[20] S. Lehnhoff, *Dezentrales Netzmanagement*. Wiesbaden: Vieweg+Teubner, 2010, pp. 87–127.

[21] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, and Y. Xu, "Short-term residential load forecasting based on resident behaviour learning," *IEEE Trans. on Power Systems*, vol. 33, no. 1, pp. 1087–1088, Jan. 2018.

[22] C. Napoli, G. Pappalardo, G. M. Tina, and E. Tramontana, "Cooperative strategy for optimal management of smart grids by wavelet rnns and cloud computing," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 8, pp. 1672–1685, Aug. 2016.

[23] Z. Zhou, F. Zhao, and J. Wang, "Agent-based electricity market simulation with demand response from commercial buildings," *IEEE Transactions on Smart Grid*, vol. 2, no. 4, pp. 580–588, Dec. 2011.

[24] E. Mocanu, D. C. Mocanu, P. H. Nguyen, A. Liotta, M. E. Webber, M. Gibescu, and J. G. Slootweg, "On-line building energy optimization using deep reinforcement learning," *IEEE Trans. on Smart Grid*, 2018.

[25] I. Dusparic, A. Taylor, A. Marinescu, F. Golpayegani, and S. Clarke, "Residential demand response: Experimental evaluation and comparison of self-organizing techniques," *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 1528 – 1536, Jul. 2017.

[26] M. Zhang, D. Zhou, P. Zhou, and H. Chen, "Optimal design of subsidy to stimulate renewable energy investments: The case of china," *Renewable and Sustainable Energy Reviews*, vol. 71, pp. 873 – 883, 2017.

[27] H. Zhang, L. Li, D. Zhou, and P. Zhou, "Political connections, government subsidies and firm financial performance: Evidence from renewable energy manufacturing in China," *Renewable Energy*, vol. 63, pp. 330–336, 2014.

[28] S. Chou, N. T. A. Tuyet, T. Yu, and P. N. Phuc, "Financial assessment of government subsidy policy on photovoltaic systems for industrial users: A case study in Taiwan," *Energy Policy*, vol. 87, pp. 505 – 516, 2015.

[29] N. T. A. Tuyet and S. Chou, "Impact of government subsidies on economic feasibility of offshore wind system: Implications for Taiwan energy policies," *Applied Energy*, vol. 217, pp. 336 – 345, 2018.

[30] J. Dix, V. Subrahmanian, and G. Pick, "Meta-agent programs," *The Journal of Logic Programming*, vol. 46, no. 1, pp. 1–60, 2000.

[31] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in *Advances in Neural Information Processing Systems 27*, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 3104–3112.

[32] D. W. Bunn, Ed., *Modelling prices in competitive electricity markets*. West Sussex, England: John Wiley & Sons, 2004.

[33] K. Greff, R. K. Srivastava, J. Koutnk, B. R. Steunebrink, and J. Schmidhuber, "LSTM: A search space odyssey," *IEEE Trans. on Neural Nets. and Learning Sys.*, vol. 28, no. 10, pp. 2222–2232, Oct. 2017.

[34] E. M. S. P. Veith and B. Steinbach, "Agent-based power equilibrium in a smart grid with XBOOLE," in *2017 International Conference on Information and Digital Technologies (IDT)*, Jul. 2017, pp. 406–416.

[35] Z. Wang, N. de Freitas, and M. Lanctot, "Dueling network architectures for deep reinforcement learning," *CoRR*, vol. abs/1511.06581, 2015.

Genaro Longoria received his M.S. degree in Computational Physics from Umeå University, Sweden in 2009. He has lectured in Nanjing University of Information Science and Technology. He is currently doing research on energy trading automation. His areas of expertise are probabilistic path prediction, molecular dynamics with MCMC and evolutionary optimization. His research interests include energy policy, edge energy trading and RDER integration.

Alan Davy received the B.S. degree in applied computing and Ph.D. degree from the Waterford Institute of Technology, Waterford, Ireland, in 2002 and 2008, respectively. He is currently a Senior Research Fellow and Manager of the Emerging Networks Laboratory with the Telecomunications Software and Systems Group Research Center, Waterford, Ireland. His research interests include software defined infrastructure, wireless network management, extreme edge computing, bio-inspired systems, and nano/molecular network communications.

Lei Shi (M'09) received his M.S. degree in Computer science from Uppsala University, Sweden in 2006 and the Ph.D. degree from the University of Göttingen, Germany, in 2010. He was a visiting professor in Technion, Israel and a visiting researcher at the University of Massachusetts, USA. He is a lecturer at Carlow Institute of Technology, Carlow, Ireland. His research interests include network resource and service management, mobile cloud computing and renewable energy economics.

Appendix F

Details of Techniques used in the Thesis

This appendix presents the technical details of the algorithms used in the thesis. The first part includes the description of the objective function minimized by the RGAn and the hyperparameters used for both implementations of the genetic algorithm. The second part describes the reinforcement learning, neural networks and the hyperparameters used in the energy trader agent.

RGAn

To find an approximate solution to the Nash equilibrium I designed the RGAn; a solver based on the Genetic Algorithm. The population pool size is fix and consists of $100,000$ chromosomes. Each chromosome represent a potential equilibrium portfolio for each LSE, more specifically the share of energy to procure from the CG and the share to procure from the WPP.

The RGAn uses crossover and mutation to evolve the members of the population pool. The selection of the mutation rate parameter was done empirically. To accomplish this I ran the solver for different rates to quantify the effect upon the final result. This derived in a mutation rate equal to 0.35. With respect to the crossover, I used random single point. This means that the offspring gets its first genes from parent A and the genes after the crossover point from parent B. At each iteration the location of the crossover point is selected randomly from a uniform distribution.

Based on the objective function evaluation if the resulting offspring is rejected this triggers a routine in the solver for controlled acceptance. The motivation behind not implementing the *Elitism Selection* strategy of the SGA is to provide a mechanism for fast escape from local minimum. The routine first measures the Euclidean distance of this offspring with respect to the worst member in the population. Then the control is regulated by a fixed temperature parameter $T = 0.5$. In the long run, the algorithm seeks that the probability of keeping these offspring in the pool is 50%.

To contrast the performance of both algorithms I used the same hyperparameters: number of iterations, initial population, population size, crossover and mutation rates.

The equilibrium point is a distribution over the pure strategy set that in expectation has the same level of risk as a portfolio comprising of only the low risk strategy. The RGAn minimizes the risk deviation from the diversified portfolio with respect to low risk but costlier portfolio. Thus the objective function of the RGAn solver is to minimize the absolute value of the difference, for each load serving entity, between 1) the expected utility for choosing the low risk pure strategy and 2) the expected utility of choosing the high risk pure strategy; given all other players chosen strategies in both scenarios. For a player $i \in \mathcal{N}$ the expected utility of choosing the strategy `LR` is 1) the cost of procuring energy from the CG source multiplied by the weight it has in the portfolio taking into account other players also selecting this strategy plus 2) the cost of procuring energy also from the CG but multiplied by the corresponding weight in the portfolio taking into consideration the number of other players with HR as the played strategy. Then the expected utility of selecting the other pure strategy (i.e., `HR`) is calculated similarly as in the previous case however in this scenario the cost incurred by the LSE corresponds to procuring energy from the WPP; like before the proportions that constitute the portfolio are influenced by the decisions of the other players in $\mathcal{N}$. When this two expectation coincide the resulting mix is then the equilibrium diversified energy portfolio.

BinaryTable is a way of retrieving in a fast way the total number of players choosing the same pure strategy and the LT contract price. It does this by indexing the combination of players willing to sign a contract with the LR or with the HR power source. So instead of counting every time which players are active in a given strategy I indexed the paths of the binary tree thus when doing the depth first search I get the total number of players in either sigma or beta via the BinaryTable through the index.

Agent Trading

The DA instance of the agent uses K-means clustering algorithm. The algorithm is also known as Lloyd's algorithm or Voronoi Iteration [44]. There are two main steps that iterate sequentially [59]. In the first step the data points are assigned to the cluster with the closest mean in an Euclidean sense. The second step recalculates the means of the clusters. The nearest mean clustering operation results in a Voronoi partition.

In Appendix E I used Q-learning, a model free reinforcement learning algorithm, to dispatch the HWPP. The algorithm determines a policy that maps from states to actions. The state of the system s is a 4-tuple: energy price, net energy forecast, pumped storage and the DS2S energy price predictions. Table F.1 shows the definitions of each element. There are two objectives that need to be met concurrently. The first is to balance supply and demand. And the safe operation of the HWPP, i.e., avoid overflowing or dry running the pumped storage. I use a boolean model for the latter. From the perspective of the control this approach provides scalability and robustness, the Reward function is agnostic to any specifics

Table F.1 Components of the State of the System.

Class	**State definition**
Energy Price	- p_{sm}(t-1) - $\overline{p}_{sm} \rightarrow$ monthly average up to p_{sm}(t-1)
Net Forecast	- $\Delta_E \rightarrow$ forecasts difference $\jmath^{\mathfrak{F}}_{wf}$(t) and $\mathcal{D}^{\mathfrak{F}}$(t)
Hydro Plant	- Difference between r_{up} and r^{max}_{up} - Difference between r_{up} and safety threshold r^{th}_{up}
DS2S Energy Price Prediction	- $\varrho \rightarrow p_{sm}$(t) prediction - $\theta \rightarrow$ sing prediction of p_{sm}(t) - p_{sm}(t-1)

of the HWPP system. The robustness is tested with random outages of the pumped storage and the wind farm. The boolean model is composed of conjuncted clauses that include several predicates. The predicates are the mechanism to model the state of the HWPP. The boolean model forms the backbone of the reward function in the Q-learning algorithm. In addition, at each trading time, the energy unbalance is penalize. In the case study I used Nordpool's regulating market data. In this market positive and negative unbalances are priced as up and down regulation (see Section IV-C in Appendix E). To train both algorithms: QL and DDDQN, I use ϵ-greedy. The hyperparameters can be seen in table F.2. At the core DDDQN utilizes the same updating scheme as Q-learning however it decouples the state-action space in two networks: 1) value of the state and 2) benefit obtained from the action. The stacked states passes through 3 convolution networks, the output is flatten and split in the two networks. The stack size corresponds to the number of previous states to keep with the current state. Table F.3 show the particular details of the DDDQN implementation. The coding was done in Python with the Tensorflow API. The hardware consisted of two Tesla K20m GPUs managed with CUDA version 10.1.

Table F.2 Training hyperparameters for QL and DDDQN.

Hyperparameter		**Value**
Exploration probability	ϵ_t	$\epsilon_{max} = 1.0$, $\epsilon_{min} = 0.01$, $\delta = 0.00005$ $\epsilon_t = \epsilon_{min} + (\epsilon_{max} - \epsilon_{min})e^{-\delta t}$
Learning rate	α	0.00025
Discount factor	γ	0.95

Table F.3 DDDQN network details and hyperparameters.

Hyperparameter	**Value**
Convolutional networks	3
Fully connected layers	2
Stack size	4
State size	[100,140,4]
Episodes	5000
Steps per episode	744
Batch size	64
Q network update step	1000
Initial stored events	100
Memory size	100000

The performance of the agent was contrasted with the DS2S replaced with a vanilla neural network (VNN). The VNN is a simple feed-forward neural network (FFNN) consisting of weights and biases yet it contains all the basic elements of a neural network. The motivation for using the VNN was to show that the architecture lacks a mechanism to distinguish among trends of different timescales In particular with energy, given the lack of storability of scale, the dynamics are significantly different from other commodities. Electricity wholesale prices exhibit sudden escalations of short duration and a mean reversion process. A solution that accounts theses specific characteristics is the long-short-term-memory topology (the gates) of the LSTM.

For both implementations, the optimizer, number of epochs and learning rate are the same: Root-mean-square-propagation, 350 and 0.0001, respectively. The inputs to both forecast engines are the same however the internal structure differs. The architecture of the former can be seen in Appendix E, it consists of the encoder layer (the equivalent of the input layer in the FFNN), 4 vertically stacked layers of 64 LSTM neurons and the decoder layer (the equivalent of the output layer in the FFNN). The VNN uses a Sigmoid activation function and consists of the input layer, 2 fully connected hidden layers with 24 neurons per layer and the output layer. The distinctive feature of the LSTM are the activation functions inside each cell. This captures nonlinearities better than the traditional nodes in the FFNN. Internally each LSTM contains 3 Sigmoid and 2 Hyperbolic Tangent activation functions. These activation functions in conjunction with pointwise operations build the Gated structure of the cell. The gates and the recurrent coupling of the cells provide the mechanism for the whole network to discard non essential data (the left-most sigmoid function), update stored data (center sigmoid and tanh functions) and output the results based on the state of the cell (right-most sigmoid and tanh functions).