Peer to Peer Smart Energy Distribution Networks

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The purpose of this document is to define a consistent set of working procedures, processes and best practice guidelines in order to ensure highest quality standards of the project outcomes.

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EXECUTIVE SUMMARY

Existing electrical energy systems were designed and operated to accommodate large-scale generating plants, with demand traditionally viewed as uncontrollable and inflexible, and with centrally controlled operation and management. At a regional level, currently looked after by Distribution System Operators (DSOs), electricity is delivered from transmission to the distribution networks and then to end consumers in a unidirectional fashion with very little active control and management. Tight real-time control is almost entirely rest at the transmission level for maintaining the balance between demand and supply at all times, facilitated through balancing services from central generation and very limited demand responses. Power is bought and sold in the national wholesale markets, through the interaction of large-scale generators and energy suppliers. Network controls are hierarchical in nature, becoming increasingly absent as the end-users are approached. There are only very limited information and communication infrastructure built at the distribution level.

Peer-to-peer (P2P) energy trading concepts provides local and regional energy producers with options to trade energy fairly within the neighbourhood, within the community and within the vicinity of the distribution system. This will fundamentally change the current P2G (peer-to-grid) paradigm where any surplus of local produce can only be sold to transmission grids, and transform consumers' position from energy/price takers to energy/price makers.

This deliverable report aims to identify the infrastructure context in which P2P energy exchange can offer significant benefits in terms of value creation and capture over the centralized approach. More important, based on the innovative models developed in previous deliverables of this work package, this report quantify the benefits from introducing such P2P trading mechanism and business models of P2P platform, Microgrid trader and DSO from the perspective of various stakeholders.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

EU	European Union
P2P	Peer-to-Peer
ICT	Information and Communication Technology
IoT	Internet of Things
DER	Distributed Energy Resource
DSO	Distribution System Operator
WP	Work Package
DG	Distributed Generation
FIT	Feed in Tariff
DSM	Demand Side Management
FIT	Feed-In-Tariff
PV	Photovoltaic
GB	Great Britain
RES	Renewable Energy Source
SG	Smart Grid
SGAM	Smart Grid Architecture Model
LV	Low Voltage
SNA	Shared Network Access
EV	Electric Vehicle
HP	Heat Pump
LGR	Load Growth Rate
SPE	Special Purpose Entity
NPV	Net Present Value
FMV	Fair Market Value

1 INTRODUCTION

To ensure Europe produces world-class science, removes barriers to innovation and makes it easier for the public and private sectors to work together in delivering innovation, Horizon 2020 (The EU Framework Programme for Research and Innovation) is implemented and backed by Europe's leaders and the Member of the European Parliament. By coupling research and innovation, Horizon 2020 is helping to achieve the goal with its emphasis on excellent science, industrial leadership and tackling societal challenges. P2P-SmartTest project is one of the Horizon 2020 projects.

P2P-SmartTest project investigates and demonstrates a smarter electricity distribution system based on the regional markets and innovative business models enabled by advanced ICT. It will employ Peer-to-Peer (P2P) approaches to ensure the integration of demand side flexibility and the optimum operation of DER and other resources within the network while maintaining the energy balance, second-by-second power balance and the quality and security of the supply.

The objectives of this project is:

(1) To investigate and develop alternative business models for DSOs, ESCOs, Suppliers and Consumers for P2P energy trading to capture the whole supply chain value while maintaining second-by-second power balance, maximizing Demand Response (DR) and DER utilization and ensuring supply security. The magnitude of benefits from introducing P2P energy trading is quantified and the required changes in technical, commercial and regulatory arrangements will be identified. (This corresponds to WP2.)

(2) To evaluate existing ICT technologies and new ones for P2P energy trading. The focus is on investigating the last-mile technologies, which support inter- and intra-MicroGrids operation, also the backbone telecom infrastructure is considered, which is critical for intra CELLs operation and data exchange with transmission network operators. (This corresponds to WP3.)

(3) To develop P2P advanced optimization techniques to provide efficient P2P energy market trading, while considering the new business models and ICT technologies. In order to fulfil a real integration of the flexibility of demand and DER management using P2P, the whole market domain will be explored including products/services to be traded and certification mechanisms to be implemented. (This corresponds to WP4.)

(4) To develop alternative P2P based control paradigm of distribution networks, integrate probabilistic and predictive control functions to enable and facilitate the P2P based energy trading and better network operation under extremely dynamic and uncertain conditions, and model of dynamic demand for operational functions of P2P smart distribution networks. (This corresponds to WP5.)

This deliverable is part of WP2.

2 INFRASTRUCTURE UPGRADING

2.1 Smart Grid

Traditional electrical power systems were designed and built to accommodate large-scale generation plants, with demand traditionally viewed as uncontrollable and inflexible, and with centrally controlled operation and management. At a regional level, currently looked after by Distribution System Operators (DSOs), electricity is delivered from transmission to distribution networks and then to end consumers in a unidirectional fashion with very little active control and management. Tight real-time control is almost entirely applied at the transmission level for maintaining the balance between demand and supply at all times, facilitated through balancing services from central generation and very limited demand responses. Power is bought and sold in the national wholesale markets, through the interaction of large-scale generators and energy suppliers.

Recently, there has been a rapid growth in DERs, such as distributed generation (DG) and energy storage connecting to the distribution network, and micro-generation and flexible loads at the premises of end users. Estimates reveal [1] that renewable energy sources based on solar, wind, geothermal, tides, etc., suffice to meet a large portion of the energy demand. These resources are not actively utilized at the distribution level at present, but aggregated to support the transmission system. It is well known that renewables suffer from the problem of uncertain availability due to varying weather conditions, and responsive demand is not currently taped for balancing local intermittent generation. Another problem is the dispersive energy profile of renewables which can vary between a large-scale energy farm and massively distributed sources from individual entities. This has also brought difficulties in harvesting these energy resources and responding the flexible demand in order to balance the demand and supply in local areas.

With the increasing penetration of DERs, on the one hand DSOs are under significant pressure on enormous infrastructure investment, on the other hand the decreasing energy exchange between demand and energy suppliers (due to DERs) will reduce their revenue. This is a vital challenge to revive the traditional DSO responsibilities – providing secure network to meet peak demand, moving to or creating more active DSO roles with new business models, which will increase the efficiency, flexibility and responsiveness of local resources. However, these business models cannot be effectively implemented within the existing power and ICT technical schemes, and the commercial and regulatory frameworks. They may even result in a compromise of system security, and a potential degradation of economic and environmental performance.

The key solution to overcoming the challenges of integrating DERs at the distribution level is the design of new control systems that ensure reliable, secure and economical operation of the distribution networks.

It is a challenge to develop a new reliable, secure and smart system operation paradigm capable of offering increased flexibility to support P2P based energy trading cost-effectively under scenarios characterized by distributed generation and active demand with stochastic nature. The new system operation paradigm should be able to enable P2P based energy trading, reduce energy losses at the distribution level, increase the use of renewable energy sources, reduce and shift peak loads, and increase energy distribution system resilience.

At present, penetration of DER is mainly promoted by governments' various incentives. For example, Feed in Tariff (FIT) is a government program, used in many countries over the world, to promote widespread uptake of a range of small-scale renewable and low-carbon electricity generation technologies. The goal of FIT is to offer cost-based compensation to renewable energy producers, providing price certainty and long-term contracts that help finance renewable energy investments.

With the falling installation costs and continuous increasing number of installations of distributed generation, such as solar PV, wind, hydro, etc., the governments are facing difficulties to subsidize for new applications.

For instance, in GB the FIT scheme starting tariff (FIT was introduced in GB on April 1, 2010) for solar PV with a total installed capacity of less than 4 kWp was 48.84 p·(kW·h)-1. This figure fell to 22.59 p·(kW·h)-1 in March 2012 and is currently 13.39 p·(kW·h)-1 (as of April 1, 2015) [2]. The government is now consulting reducing the incentives for renewable, because the FIT scheme has exceeded all renewable energy deployment expectations in terms of both the number of installations and the total installed capacity. As a results, the government has proposed a further cut of the generation tariff for new applicants starting in January 2016, while keeping the export tariff as a route to market for renewable electricity [3]. In this proposal, the tariff for generation from solar PV with an installed capacity of less than 10 kWp will be further decreased to 1.63 p·(kW·h)-1.

A business as usual trading market has to be found, so that the DER can be integrated and compete fairly with the large-scale electricity generators. However, the intermittence nature makes the DER cannot operate as the large-scale generation plants that provide power when needed. Also, the DER has a distributed characteristics which brings difficulties to be managed. Meanwhile, the demand for electricity, with the potential electrification of transport and heating, will become more variable.

Therefore, it is expected to drive the transition from the today's centralized electricity trading market to a more open and flexible one. The rationale behind this follows from the fact that energy will be also generated at the customer side which requires a fair trading arrangement in place at a local level. As an example, a customer (and/or group customers) might be able to trade energy with other customers, and that transaction might depend on the energy generation and transportation costs. Therefore, this on-going revolution of the distribution network will entail peer-to-peer energy transactions akin to the popular P2P sharing file software.

The power system will need to become smarter at balancing demand and supply in local levels. If a regional energy trading mechanism can be provided, the following benefits can be achieved:
The stress of network congestion in high voltage levels, particularly the transmission networks, can be reduced and the necessary network reinforcement can be delayed or avoided.

A fair platform for energy trading in distribution network level can be created, and this will considerably stimulate customers for responding their demand to the available energy resources in local areas. Therefore, technical issues resulting from the DERs might be mitigated, which would increase significantly the penetration level of DERs. Energy bills for electricity customers can be significantly reduced. The share of resources with demand will reduce the overall demand from the conventional energy suppliers.

The change to the proposed scenario affects deeply the operation of the distribution networks as they evolve from passive to active networks. It brings a higher complexity on the management of distribution networks, but it also opens great opportunities for DSO to enhance the reliability and security of the network.

2.2 Information and Communications Technologies (ICT)

The energy industry is undergoing massive shift towards addressing climate change and improve the efficiency of energy system operations [4]. An efficient, reliable and secure energy system is indispensable in a modern power grid infrastructure. Energy utilities are especially under pressure to reduce costs, streamline operations and meet more regulatory, security and environmental goals. By strengthening the information and communications technologies (ICT) in the grid, the power of a smart grid shapes the future capabilities of utility infrastructure and services [5].

The ICT infrastructure of the electricity utilities needs to be able to deliver accurate, reliable, and secure data to and from the grids, the location of the large and small consumers and the control center to optimize operational systems and support electricity market functions, in this case, the P2P marketplace. Both mission critical and typical applications also have to be supported. Furthermore, the ICT infrastructure that runs data analytics, cloud technology and mobile applications could and needs to be scalable and resilient for data transfer and storage within the smart grid.

ICT also plays a vital role in improving efficiency of energy industry operations. For example, sensor-embedded transformers with Internet of Things (IoT) technology can be utilized to monitor electricity consumption real-time, informing and alerting control centers when unusual pattern of energy usage occurs [4].

Thus, these “smart” applications of ICT technologies to the energy sector are necessary and critical to improve the productivity of the energy industry value chain, optimizing energy systems, enhancing energy security, minimize losses, and optimize energy resources [6].

3 P2P PLATFORM MODEL BENEFIT QUANTIFICATION

In this section the effect of platform model is studied. In the first stage, platform optimizes the energy use of its members' boilers heating the domestic hot water such that electricity costs get minimized. The effect of the platform operation is quantified on two levels. On the household level, platform creates value by reducing the platform members' electricity bills. On the system level, the effect is lower electricity price volatility and higher value of wind power. In the second stage, small scale wind power production is included in the platform. This enables the platform operator to allocate part of the wind power production as peer-to-peer energy used to heat the boilers. The effect of platform operation on the household level is again quantified. Finnish power market data is used in the electricity price simulations. The optimal platform operation in different wind power and platform size environments are illustrated by simulating four different wind share scenarios (2.5%, 5%, 10% and 15% of electricity demand produced by wind power) and three different platform size scenarios (10 000, 50 000 and 100 000 platform members).

3.1 Model

The modelling approach combines econometric analysis of day-ahead prices and dynamic optimization of platform operation based on the price regression model. Electricity price is determined endogenously in the platform optimization model by using the estimated effects of load and wind on price formation.

3.1.1 Price Estimation

Finland is part of the Nordic power market Nord pool1. The day-ahead market receives production and consumption bids and calculates an hourly system price which balances the quantity traded. Because of the transmission capacity limitations, the power market is divided into separate bidding areas. The area prices may differ in case of congestion. Finland forms a single bidding area in the Nordic power market.

[1] For Nordic power market, see: http://www.nordpoolspot.com/

In order to estimate the hourly day-ahead electricity market prices hourly data over the year 2015 is used for the Finnish power market area. Regression model is based on the variables listed in Table 3.1. The average load in 2015 was 9220.91 MWh. This was fulfilled by a diverse production technology portfolio combining wind, nuclear, combined heat and power (CHP) and hydro and thermal power2. Additionally, inter-connections to neighbor market areas Estonia (EST), Sweden (SE1 and SE3 areas) and Russia (RUS) affect the price formation.

Table 3.1. Descriptive statistics of the price model variables

Variable	Min	Max	Mean	Std
Price (€/MWh)	0.32	150.06	29.66	14.46
Load (MWh)	6049.00	13 628.00	9220.91	1334.83
Wind (MWh)	16.87	832.00	238.29	166.45
Nuclear (MWh)	1641.69	2775.97	2548.63	329.73
CHP (MWh)	59.93	3196.95	1383.49	762.06
Other (MWh)	0.00	5073.49	2246.98	685.05
Interconnector EST (MWh)	-738.00	1000.00	583.60	263.57
Interconnector SE1 (MWh)	-1560.00	61.70	-1171.27	432.85
Interconnector SE3 (MWh)	-1200.00	1163.40	-935.55	357.69
Interconnector RUS (MWh)	-1300.00	320.00	-378.27	467.00

In addition to variables presented in Table 3.1, binary indicators for moths, day-of-week and hour–of-the-day are included in the model. The regression model is the following:

$$p_t = \beta_0 + \beta_1 Load_t + \beta_2 Wind_t + \beta_3 Nuc_t + \beta_4 CHP_t + \beta_5 Other_t + \beta_6 EST_t + \beta_7 SE1_t + \beta_8 SE3_t + \beta_9 RUS_t + \sum_{i=1}^{11} \alpha_i Month_{it} + \sum_{j=1}^{6} \delta_i Day_{jt} + \sum_{k=1}^{23} \varphi_k Hour_{kt} + \varepsilon_t \qquad (3\text{-}1)$$

[2] Hydropower and separate condensing thermal power are included in the joint variable *Other*.

where term ε_t refers to normally distributed error term.

Model estimation results are shown in Table 3.2. The first model is an OLS model. However, the estimated residuals of this model are autocorrelated. Autocorrelation is corrected in the second model by assuming that the residuals follow a stationary AR(1) process: $\varepsilon_t = \rho\varepsilon_{t-1} + v_t, |\rho| < 1$, v_t is white noise. The second price model is used in the platform operation simulations.

Estimates for load and wind power are statistically significant and the signs for the coefficients β_1 and β_2 seem intuitively correct. Higher load increases the day-ahead prices by 0.00877 €/MWh, ceteris paribus. Higher wind power production reduces the day-ahead prices by 0.00946 €/MWh, ceteris paribus.

Table 3.2. Descriptive statistics of the price model variables

Dependent variable	p_t	p_t
	(1)	**(2)**
Constant	-61.39615***	-61.12806***
	(0.00642)	(11.270553)
Load	0.00642***	0.00877***
	(0.000303)	(0.000563)
Wind	-0.00971***	-0.00946***
	(0.000653)	(0.001726)
Nuclear	-0.00330***	-0.00542***
	(0.000542)	(0.001302)
CHP	-0.00124	0.00186
	(0.000483)	(0.001111)
Other	0.00528***	0.00671***
	(0.000287)	(0.000491)
Interconnector EST	-0.01232***	-0.00783***
	(0.000518)	(0.000733)
Interconnector SE1	0.00285***	0.00741***

	(0.000388)	(0.000601)
Interconnector SE3	-0.00146***	0.00448***
	(0.000403)	(0.000590)
Interconnector RUS	-0.00169***	0.00694***
	(0.000439)	(0.000627)
AR(1) Parameter	---	0.8086541
Month-of.year indicators	Yes	Yes
Day-of-week indicators	Yes	Yes
Hour-of-day indicators	Yes	Yes
Observations	8760	8760
AIC	61682.12	53631.36
BIC	62050.17	54006.49
Log Likelihood	-30789.06	-26762.68
Note: *** p<0,01		

The statistics of price simulations for wind share scenarios of 2.5%, 5%, 10% and 15% are shown in Table 3.3. As the wind share in the sample year was roughly 2.5%, the model results can be validated by comparing the simulated prices for the 2.5% wind share scenario and the 2015 prices listed in Table 3.1. Simulated prices match the mean and standard deviation of the 2015 prices rather well. Standard deviation is a bit lower in the simulated prices, implying the model is unable to explain all of the variation in day-ahead prices. Adding more wind power into the electricity market decreases mean of the simulated prices and increases the standard deviation of the simulated prices. When the wind share increases from 2.5% to 15%, mean price decreases by 10.83 €/MWh and the standard deviation increases by 3.27 €/MWh

Table 3.3. Simulated price statistics for wind power scenarios [€/MWh]

Wind share	Mean	Std
2.5 %	29.67	13.08
5.0%	27.59	13.44
10.0%	23.20	14.66
15.0%	18.84	16.35

3.1.2 Platform Optimization Model

Platform operator optimizes the boiler electricity use for its members in the first stage. In the second stage combined boiler heating and small scale wind power allocation optimization is simulated. Three different platform sizes are studied: $\mathrm{N} = 10\,000$, $\mathrm{N} = 50\,000$ and $\mathrm{N} = 100\,000$ households. Each household is assumed to have a boiler for domestic hot water, which consumes 24 kWh energy during 24 hour period. The hourly boiler electricity consumption profile estimate is based on the average daily load profile in the 2015 Finnish power market data[3]. Hourly consumption related to the daily average is used as weight for the boiler electricity use. The estimated boiler consumption profile for 24 hours is shown in Figure 1. Water boiler consumption per household c_t (in kW) for hour t over the annual period (t =1,2,…,8760) is drawn from the estimated daily profile in Figure 3.1 assuming that boiler consumption profile is constant over the year. All of the households in the platform are assumed to be homogeneous with respect to the boiler electricity use.

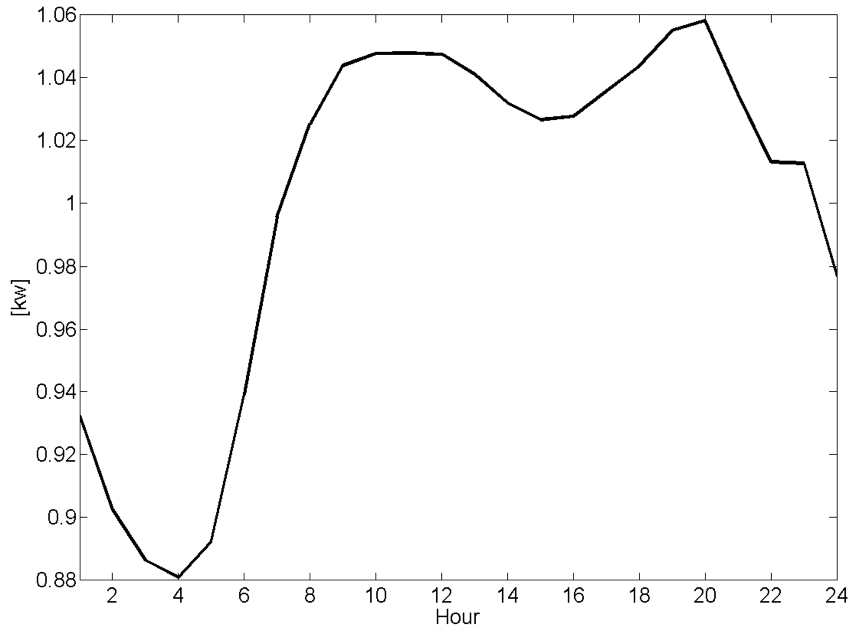


Figure 3.1. Daily boiler electricity consumption profile used in the simulations.

[3] In the absence of actual data, this was chosen as an estimate.

Night-time heating is used as the benchmark for the boiler operation. It is assumed that households outside the platform use passively only the night-time hours for boiler heating. Thus, the benchmark electricity water heating profile $\hat{h}_t$ consist of 3 kW electricity use in the hours 1-8 and 0 kW electricity use in the remaining hours 9-24.

The estimated price model (2) in Table 3.2 is used in the simulations. Importantly, using the price model makes electricity prices endogenous. When the operator optimizes the platform members' heat boiler consumption it has an effect on the total hourly load and thus on the hourly prices through coefficient β_1 in equation (3-2).

(1) Boiler heating optimization

The problem is formulated as a discrete-time model, with hourly time steps t and time-frame of one year $T = 8760$. Platform operator minimizes the total boiler heating costs in the platform by optimizing the hourly boiler electricity use h_t (in kWh/h) of its members. As all of the N households are assumed to be identical, the aggregated boiler heating profile is $h_t N$. During the optimization, operator has to keep track of the boiler energy content S_t (in kWh). The optimization problem is the following:

$$\min_{h_t} \sum_{t=1}^{T} f(h_t) \tag{3-2}$$

where target function is the platform members' total boiler heating cost

$$f(h_t) = p_t(h_t|N) * (h_t N) \tag{3-3}$$

and transition function is the energy content of platform members' water boilers (N homogeneous units)

$$S_{t+1} = S_t + (h_t - c_t) \tag{3-4}$$

The endogenous price function is the following:

$$p_t(h_t|N) = \hat{p}_t + \beta_1[(h_t - \hat{h}_t)N] \tag{3-5}$$

where $\hat{p}_t$ is the original hourly price, β_1 is the coefficient for load in equation (3-2), $\hat{h}_t$ is the benchmark night-time heating, h_t is the optimized boiler heating and N is the number of households in the platform.

The optimization problem is transformed into the recursive form[4]. The value function is the following:

$$V_t(S_t) = \min_{h_t}\{f(h_t) + \beta V_{t+1}(S_{t+1})\}, \forall t = 1, \dots, \mathrm{T} \tag{3-6}$$

where boiler heat content is the state variable S_t and boiler heating is the control variable h_t. State variable dynamics follows the transition function (3-4). With the assumption that individual water heater power is 3 kW and heater can store maximum of 24 kWh of energy, the limits for control and state variables are:

$$0 \leq h_t \leq 3.0 \tag{3-7}$$

$$0 \leq S_t \leq 24.0 \tag{3-8}$$

(2) Boiler heating and small scale wind power optimization

The operator chooses the boiler heating profile and the use of small scale wind production owned by the platform members such that the wind power revenue less the boiler heating costs are maximized. It is assumed that part of the total wind power production is produced by the platform members. Thus, the small scale wind power profile $\hat{w}_t$ follows the total wind power produced, but at a smaller scale. The scale of wind power capacity owned by platform member is chosen such

[4] For dynamic optimization, see e.g., Lars Ljungqvist and Thomas Sargent (2004) Recursive Macroeconomic Theory, 2nd edition. The MIT Press.

that is the maximum wind power produced matches the maximum boiler heating capacity, .i.e. wind power capacity per platform member is assumed to be 3 kW.

Now, the value function is the following:

$$V_t(S_t) = \max_{h_t, w_t}\{f(h_t, w_t) + \beta V_{t+1}(S_{t+1})\}, \forall t = 1, \dots, \mathrm{T} \tag{3-9}$$

where water boiler heat content is the state variable S_t, water heater energy is the first control variable h_t and wind power used in the platform as peer-to-peer energy is the second control variable w_t. Small scale wind not used as peer-to-peer $(\widehat{w}_t - w_t)$ is sold to the market at hourly market price. Target function is the platform members' wind power revenue from the market less boiler heating cost

$$f(h_t, w_t) = p_t(h_t, w_t|N)(\widehat{w}_t - w_t)N - p_t(h_t, w_t|N)h_t N \tag{3-10}$$

The endogenous price function is the following:

$$p_t(h_t, w_t|N) = \hat{p}_t + \beta_1[(h_t - \hat{h}_t)N] + \beta_2(-w_t)N \tag{3-11}$$

where $\hat{p}_t$ is the original hourly price, β_1 is the coefficient for load in equation (3-2), β_2 is the coefficient for wind in equation (3-2), $\hat{h}_t$ is the benchmark night-time boiler heating, h_t is the optimized boiler heating, w_t is wind power production used as peer-to-peer and N is the number of households in the platform.

Transition function is the energy content of platform members' water boilers (N homogeneous units)

$$S_{t+1} = S_t + (h_t + w_t - c_t) \tag{3-12}$$

The limits for control and state variables are:

$$0 \leq h_t \leq 3.0 \tag{3-13}$$

$$0 \leq w_t \leq \widehat{w}_t \tag{3-14}$$

$$0 \leq S_t \leq 24.0 \tag{3-15}$$

3.2 Results: Boiler Heating Optimization

The effect of boiler heating optimization is calculated on a household level (saved heating energy costs) and on system level (reduced price volatility and wind power revenue). Three different platform sizes are simulated ($N = 10\ 000$, $N = 50\ 000$ and $N = 100\ 000$ households) over four different wind power share scenarios (2.5%, 5.0%, 10.0% and 15.0% wind share).
As an illustration of optimized boiler heating, Figure 2.2 shows the simulated electricity prices $p_t(h_t, w_t|N)$ with optimized boiler profile and prices $\hat{p}_t$ without optimization (upper), optimized h_t and night-time $\hat{h}_t$ water heater profiles aggregated (middle) and boiler energy content S_t aggregated (lower) for the case with N=100 000 households in the platform and wind share 2.5%. Low priced hours are used to heat up the water boilers and during expensive hours the boilers are switched off. Optimization is restricted by the water heater energy content, which has to remain between 0 and 2400MWh.

With the 2.5% wind share and N=100 000 households scenario presented in Figure 2, the optimized heating profile h_t follows the night-time heating profile $\hat{h}_t$ closely. However, over the annual period the profiles are not identical ($corr(h_t, \hat{h}_t) = 0.76$). Table 4 shows that the greatest correlation between optimized and night-time heating occurs in the low wind share and high network size scenario. When wind share increases, the correlation between optimized and night-time heating decreases. This is because wind power disturbs the daily price pattern where prices are low at night time and high at day time. Consequently, the optimal heating strategy moves further from the night-time heating strategy with larger wind share.

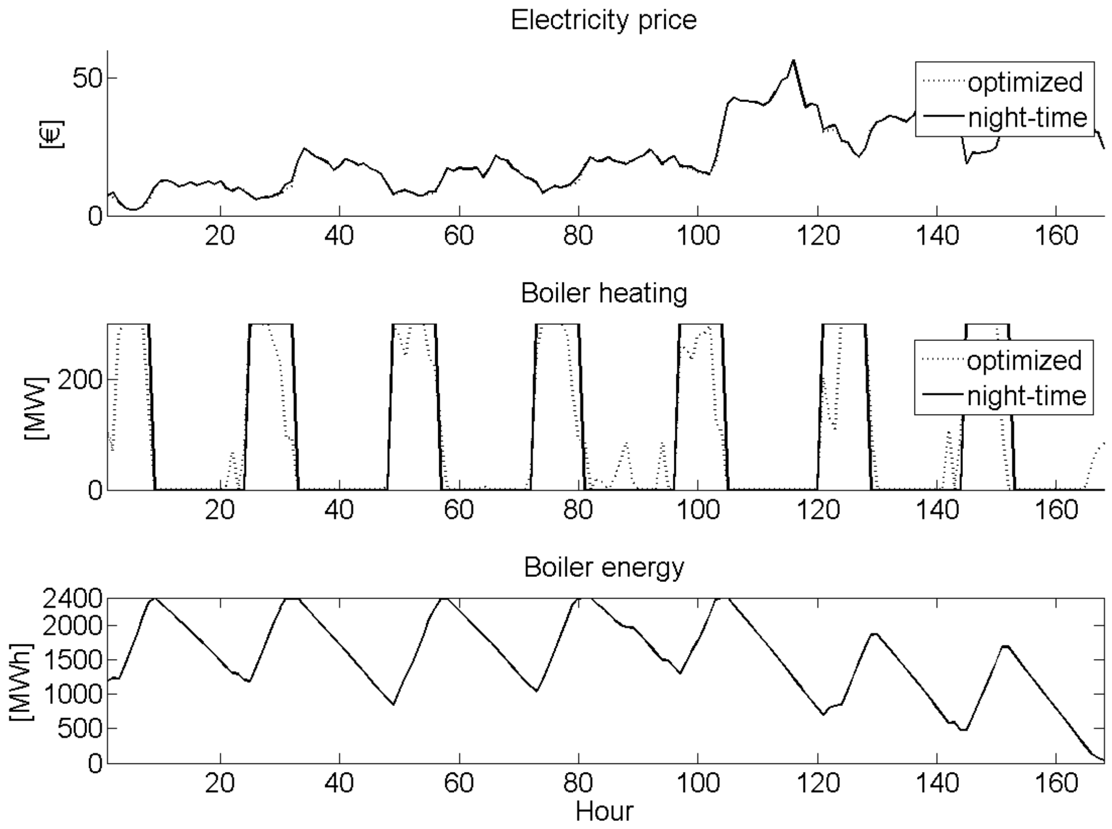


Figure 2.2. Week 1: electricity prices (upper), optimized boiler heating (middle) and boiler energy content (lower).

Table 3.4. Correlation between electricity use in night-time and optimal water heating strategies.

Wind share	**2.5%**	**5%**	**10%**	**15%**
N = 10 000	0.67	0.66	0.63	0.59
N = 50 000	0.72	0.71	0.67	0.64
N = 100 000	0.76	0.75	0.72	0.68

3.2.1 System Effect

The effect of boiler heating optimization on the annual electricity price profile is shown in Tables 3.5 and 3.6. Table 3.5 shows that on average, the difference between the highest and lowest prices during the day narrows with larger platform participation rate. Similarly, Table 3.6 illustrates how the standard deviation of prices becomes smaller with larger network size. Larger wind power share makes the daily price difference and standard deviation of prices larger. It follows that, platform dampens part of the price volatility induced by wind power increase. However, the wind power effect clearly dominates the platform effect.

Table 3.5. Average difference of daily maximum and minimum prices [€].

Wind share \ Network size	2.5%	5%	10%	15%
N = 0	25.89	26.54	28.29	30.58
N = 10 000	25.87	26.50	28.24	30.51
N = 50 000	25.79	26.39	28.06	30.26
N = 100 000	25.75	26.32	27.92	30.01

Table 3.6. Standard deviation of simulated electricity prices in different wind share scenarios [€].

Wind share \ Network size	2.5%	5%	10%	15%
---	13.08	13.45	14.66	16.35
10 000	13.06	13.43	14.64	16.33
50 000	12.99	13.36	14.56	16.25
100 000	12.92	13.28	14.48	16.16

Table 3.7 shows the wind power revenue over different wind share and platform size scenarios. Over the constant platform network size, the revenue wind power producers collect per energy unit on average decreases with larger wind share. Platform operation reduces this effect of decreasing wind revenues with higher wind share slightly. Compared to the original price scenario, the aggregator optimizing the use of 100 000 boilers increases wind revenue per MWh produced by 0.04€ in the 2.5% wind scenario and by 0.14€ in the 15% wind share scenario.

Table 3.7. Wind power revenue per energy unit in different wind share scenarios [€/MWh].

Wind share \ Network size	2.5%	5%	10%	15%
---	27.87	24.73	18.24	11.75
10 000	27.87	24.74	18.25	11.77
50 000	27.89	24.77	18.30	11.82
100 000	27.91	24.80	18.35	11.89

3.2.2 Household Effect

Individual household benefits from the platform membership in the form of reduced boiler heating costs. Figure 3 shows the annual boiler cost savings per platform member with different wind share and network size scenarios. Reduced costs range from 17.77€ to 36.38€ annually per household.

Two trends can be highlighted from the results. Firstly, higher wind share increases the potential cost savings of boiler heating optimization. Secondly, the higher the network size, the lower is the savings potential per individual household.

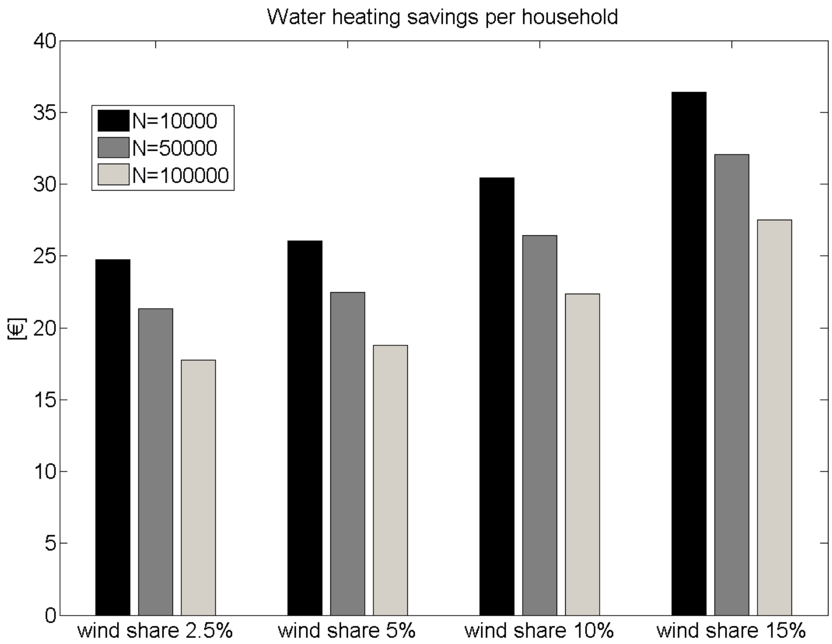


Figure 3.3. Annual savings of water heating costs per household.

The first trend is related to the higher price volatility of larger wind share system. Variable prices provide a greater potential for the platform operator to optimize boiler heating profiles. Thus, higher wind share increases the attractiveness of platform membership. On the other hand, the second trend shows that with larger network size, the savings potential per member of the platform decreases. This is because of the endogenous price effect of load optimization. Utilizing the price variability gets harder for the platform with larger network size, as the price level reacts more strongly to operator's boiler heating optimization. Moreover, non-members benefit slightly from the aggregated heating profile optimization. This reduces the monetary benefit of joining the platform for the non-members. These trends can be seen from Table 8 which shows the annual water heating costs for platform members and non-members in different wind share and platform size scenarios.

3.3 Results: Water Heating and Wind Power Optimization

In this section, small scale wind power produced by the platform members is included in the operation. The platform operator has two decision variables: the electricity use profile of boilers and the share of small scale wind power used in the platform as peer-to-peer energy (rest of small scale wind power sold to the market). Scenarios with platform size of 50 000 members are simulated.

Table 3.8. Annual water heating costs per platform member and non-member [€].

Wind share	2.5%		5%		10%		15%	
	member	non-member	member	non-member	member	non-member	member	non-member
N = 0	189.77	189.77	170.63	170.63	131.01	131.01	91.38	91.38
N = 10 000	164.47	189.22	144.02	170.06	99.95	130.38	54.33	90.90
N = 50 000	165.93	187.24	145.55	168.00	101.66	128.09	56.14	88.20
N = 100 000	167.23	185.00	146.91	165.70	103.19	125.55	57.92	85.40

We assume that part of the hourly wind energy is produced as small-scale wind by the platform members' power plants. Small scale wind power capacity owned by the platform members is set such that the maximum hourly wind power capacity does not exceed the maximum heating capacity of the platform members' water boilers. With 50 000 members, the maximum hourly wind power production in the platform is thus 150MW. This implies that 18.03% of the hourly wind energy produced in the 2.5% wind share scenario is assumed to be produced by the platform members' wind plants and the total annual wind energy produced by the platform members is 376.34GWh. Platform operator allocates this hourly wind power production $\hat{w}_t$ between peer-to-peer energy used to platform members' boiler heating w_t and energy sold to the market ($\hat{w}_t$-w_t) at hourly market price set according to equation (3-11).

As an example of the platform operation, optimized profiles for week 1 of boiler heating h_t, wind allocated as peer-to-peer inside platform w_t and the boiler heating consumption c_t for total wind share scenarios 2.5% and 15% are shown in Figure 3.4. As the upper part of Figure 4 illustrates, in the 2.5% wind share scenario peer-to-peer wind (gray area) is used to platform members' boiler heating mostly during the night-time. However, as the lower part of figure 4 illustrates, when the total wind share of the system increases to 15%, the night-time trend of peer-to-peer wind together with the boiler electricity use breaks. Additionally, larger share of wind produced by platform members is used as peer-to-peer (gray area in the bottom figure increases).

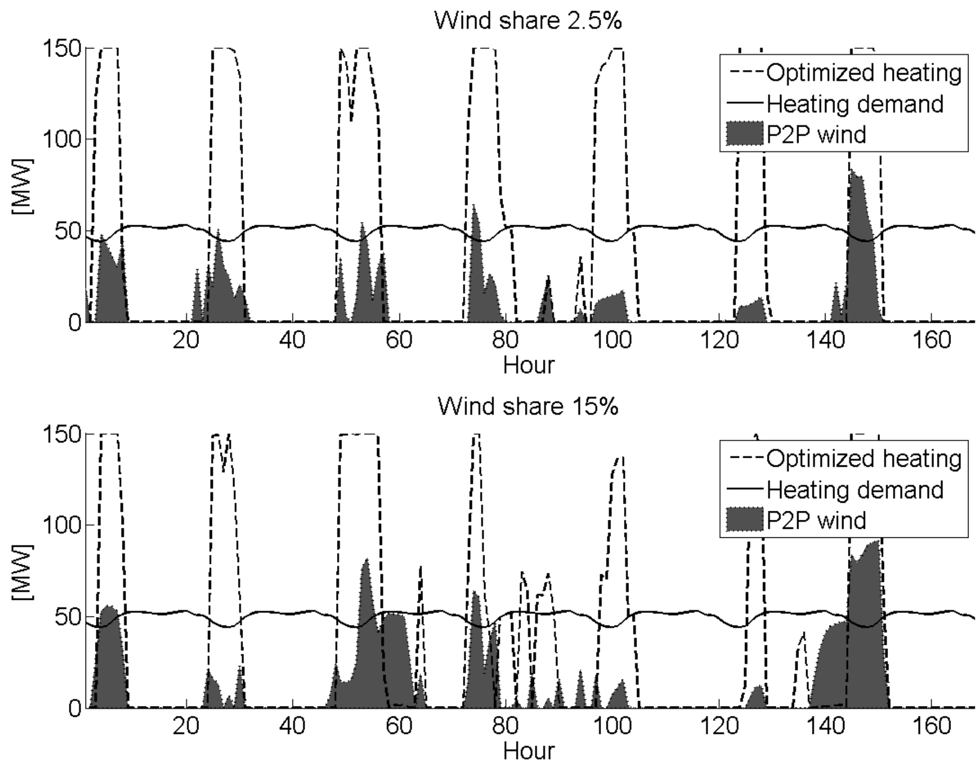


Figure 3.4. Week 1: P2P wind and boiler optimization.

Table 3.9 confirms the trend towards higher amount of peer-to-peer wind used inside the platform with larger wind share in the system. In the 2.5% wind share scenario, platform allocates 86.76 GWh (23.0% of the total 376.34GWh wind energy produced by the platform members) as peer-to-peer. In the 15% wind share scenario, platform allocates 100.77 GWh (26.8% of the total 376.34GWh wind energy produced by the platform members) as peer-to-peer.

Table 3.9. P2P wind used and platform savings per member over simulated wind share scenarios (N=50000).

Wind share	2.5%	5%	10%	15%
P2P wind [GWh]	86.76	89.38	95.39	100.77
Savings per member [euro]	29.42	30.91	35.54	41.83

Finally, Table 3.9 also shows that annual savings per platform member. The joint optimization of the members’ boiler electricity use and small-scale wind power production allocation gives a monetary benefit of 29.42€ in the 2.5% wind share scenario and 41.83€ in the 15% wind share scenario. Although the annual cost savings are still rather modest, the private benefit is clearly higher in the combined boiler heating and wind production optimization case than when only boiler heating is optimized.

3.4 Conclusions

In this section the operation of P2P platform is simulated and the results on the system and private level are quantified. The study is restricted to the operation of boilers which heat the domestic hot water and to the allocation of small scale wind power production in the platform between peer-to-peer energy and energy sold to market. The effect of load and wind power on the Finnish hourly electricity price is estimated and used in the price formation of platform operation simulations. Thus, prices are endogenous in the model and the effect of platform operation on the system level can be quantified.

Results indicate that the annual savings potential with only the boiler heating optimization is in the range of 20-30€ annually per platform member. The savings potential per household increases with larger wind share but decreases with larger platform size. The system effect of boiler heating optimization is lower electricity price variability and higher revenue for wind power producers. However, the results show that the effect on the system level is modest if only the use of boilers are optimized.

In the second stage of the study part of the total wind power production is assumed to be small scale production produced by the platform members. In this case, the platform operator optimizes jointly the boiler heating and wind power allocation. The savings potential per platform member is in the range of 30-40€ annually. Thus, compared to the pure demand optimization, the incentive to join the platform is higher when the members are producers as well as consumers. The results also show that the share of small scale wind used inside the P2P platform increases as the total amount of wind power in the system increases.

4 MICROGRID TRADER BENEFIT QUANTIFICATION

4.1 Introduction

With the increasing integration of distributed energy resources (DERs), traditional energy consumers are becoming prosumers, who both generate and consume energy [7]. Generation of DERs is unpredictable and intermittent, and prosumers who have surplus energy can either store it with energy storage devices, or supply others who are in energy deficit. This energy trading among prosumers is called Peer-to-Peer (P2P) energy trading. It not only contributes to the balance of energy [8], but also reduces congestions on transmission and distribution lines [8] [9].

Although energy trading is mainly based on large-scale transactions at present, trials of small-scale or medium-scale P2P energy trading have already been investigated across the globe, for example, Vandebron in Netherlands [10], Piclo in the UK [11], sonnenCommunity in Germany [12], and "Energy Internet" in China [13].

4.1.1 P2P Platform Model

Peer-to-Peer energy trading is a novel paradigm of power system operation, where people can generate their own energy from Renewable Energy Sources (RESs) in dwellings, offices and factories, and share it with each other locally.

4.1.2 Microgrid Trader Model

This section presents a P2P energy trading in a grid connected microgrid. An architecture model was proposed to present the design and interoperability aspects of components for P2P energy trading in a microgrid. A specific Customer-to-Customer business model was introduced in a benchmark grid-connected microgrid based on the architecture model. The core component of a bidding system, called Elecbay, was also proposed and simulated using game theory. Test results show that P2P energy trading is able to balance local generation and demand, therefore, has a potential to enable a large penetration of RESs in the power grid.

In Section 4.2, a four-layer architecture for P2P energy trading in a microgrid is proposed. Section 4.3 discusses a business model and the design of online trading platform 'Elecbay'. In Section 4.4, the objectives and game theory method for the simulation of P2P energy trading within a microgrid are presented. A case study in Section 4.5 is presented and the benefits of using the P2P energy trading are analyzed.

4.2 Four-Layer Architecture for P2P Trading in a Microgrid

A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it (generators, consumers and those that do both) in order to efficiently deliver sustainable, economic and secure electricity supplies. It employs innovative products and services together with intelligent monitoring, control, communication and self-healing technologies [8]. P2P energy trading cannot be implemented without the SG technologies including Information and Communication Technologies (ICT), monitoring, and control functions.

It is critical and quite challenging to define a standardized architecture of P2P energy trading which consolidates complicated technologies and infrastructures. A Smart Grid Architecture Model (SGAM) Framework [14] was proposed by CEN, CENELEC, and ETSI to enable European Standardization Organizations to perform continuous standard enhancement and development in the field of Smart Grids. Based on the SGAM, a four-layer architecture model for P2P energy trading in a microgrid is designed, as shown in Fig. 4.1.

There are three dimensions in the model. The first dimension is the time-scale of P2P energy trading. Bidding is the first process of trading when energy users (generators, consumers and prosumers) signing contracts with each other prior to real-time energy exchange. Exchanging is the second process, during which energy is generated, transmitted and consumed by users. Settlement is the final process when bills and transactions are finally settled via various payment methods. The second dimension shows the size of the P2P energy trading users, i.e. single premises, microgrids, CELLs, and regions. In the third dimension, the hierarchical process of P2P energy trading is categorized into four interoperability layers for management. The components in each layer are summarized in Table 4.1.

This work focuses on the interconnections between the business layer and the power grid layer during the bidding process within a grid-connected microgrid.

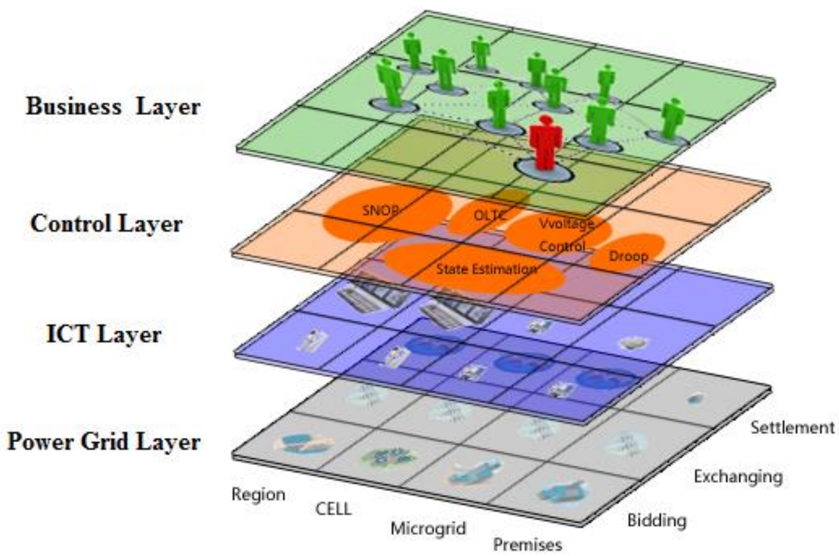


Fig. 4.1 Four-layer architecture model of peer-to-peer energy trading

Table 4.1 Components of Each of the four layers for P2P energy trading in a Microgrid

Layers	Components
Power Grid Layer	Existing power grid with DGs, flexible loads, storage, EVs, etc
ICT Layer	Communication network and devices, data storage, information flow, etc
Control Layer	Monitoring and control system owned by SO and DNOs, control functions, etc
Business Layer	Participants in local markets, market authorities, trading platforms, etc

4.3 Microgrid Trader Model

For P2P energy trading in a microgrid, a business model for local markets is required. In recent years, different business models for local supply have been proposed and tested [15], e.g. local white label model, local aggregator model, local pool model, etc. These business models were designed based on existing business models in large-scale electricity wholesale markets. Therefore, a new business model for local P2P energy trading was proposed based on the eBay-style C2C e-commerce business model and the GB electricity wholesale market [16] [17]. The platform, called "Elecbay", allows energy users to sign contracts and to make payment with each other. The operational structure of Elecbay is illustrated by Fig. 4.2. The processing of each order in Elecbay is demonstrated in Fig. 4.3 [16].

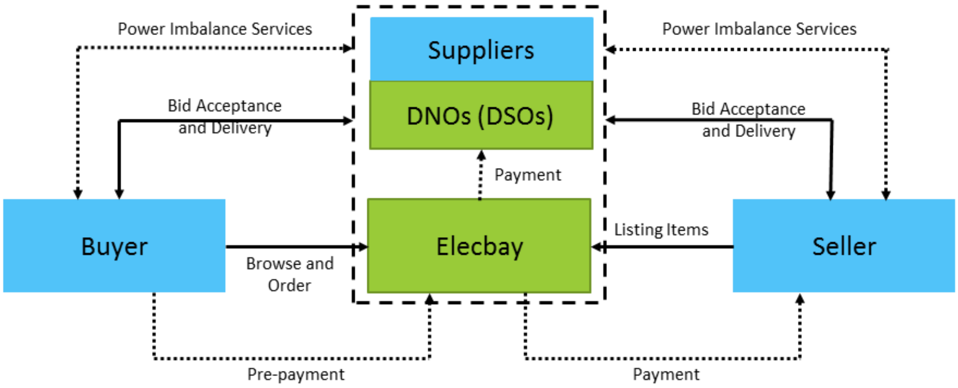


Fig. 4.2 Operational Structure of Elecbay

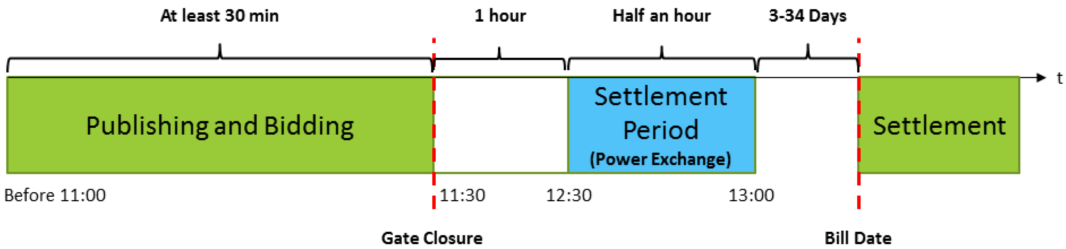


Fig. 4.3 Processing of Each Order in Elecbay

4.4 Simulation of Bidding Process in Elecbay

The objectives of simulating the bidding process amongst users in Elecbay are:

1. To clarify how users in a local market carry out P2P energy trading with each other;
2. To obtain new load profiles of users after the P2P energy trading;
3. To provide a platform for power system analysis of microgrid under P2P energy trading scenarios.

The Elecbay simulation model mimicked the bidding process before gate closure. All the input data is based on historical and forecast information. Beside, following assumptions were made when developing the model:

1. Uncertainties of generators or demand were not considered;
2. The P2P market is highly competitive, so that the unit price labelled by each user should be very close to each other's. Transaction fee which should be collected by Elecbay is also ignored;
3. Traditional energy suppliers act as passive users in the P2P market, and provide energy with less attractive unit prices. Therefore, they will mainly contribute to maintaining the energy balance.

Since the generation of RESs is uncontrollable, P2P energy trading among prosumers relies on the schedule and control of flexible demand and energy storage. In this paper, only the flexible demand is considered as a first trial.

(1) Simulation of a single time period using Game Theory

Game theory methodology has been widely used in the study of electricity market. It is a functional tool for modeling the competitions in electricity markets [18] [19] and assessing the performance of network constrained electricity markets [20].

There are two basic types of games in game theory: cooperative game and non-cooperative game. A non-cooperative game is a game in which players make decisions independently [21] and is therefore formulated for the simulation of bidding in Elecbay based on the rules of the market.

To find the most possible biding result of all energy users within the local P2P-based energy market, the Nash equilibrium is a used to solve the non-cooperative game involving two or more players, in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only their own strategy If each player has chosen a strategy and no player can benefit by changing strategies while the other players keep theirs unchanged, then the current set of strategy and the corresponding payoffs constitutes a Nash equilibrium[21]. A mathematical method for finding Nash equilibrium of a non-cooperative game in MATLAB [22] was used as illustrated below.

Players of the game: Energy users in the market with flexible demand, denoted by 1, 2*, …, i, …, n*. Strategies of the players: the ON/OFF status of the flexible demand owned by each user, denoted by $s_1^i, s_2^i, \ldots, s_j^i, \ldots, s_{mi}^i$.

Strategy combinations: $(s_1^1, s_1^2, \ldots, s_1^n), \ldots, (s_{m1}^1, s_{m2}^2, \ldots, s_{mn}^n)$. The total number of strategy combinations is,

$$\mathrm{M} = \prod_{i=1}^{n} m_i \tag{4-1}$$

The payoff function is presented by,

$$u_k^i = \frac{E_{out-i}}{|E_{mgout-k}| \times C_k^i} \tag{4-2}$$

where $k \in [1, \mathrm{M}]$; E_{out-i} is the energy output of user i in strategy combination k; $E_{mgout-k}$ is the energy output of the whole microgrid in strategy combination k; C_k^i is the cost index of user i in strategy combination k.

For users who own generators that burn fuels, the cost index is in proportion to the cost of fuel that has been burnt. However, for users who trade energy by scheduling the flexible demand, the cost index is related to the user's comfort level. The probability of the flexible demand ON ($p_{Flex-ON}$) is used to represent the value as shown in Fig 2.4(d) [23]. Then the cost index is defined as:

$$C_k^i = \begin{cases} \frac{1}{1 - 2p_{Flex-ON}}, & when\ flexible\ demand\ OFF \\ 1, & when\ flexible\ demand\ ON \end{cases} \tag{4-3}$$

Therefore, the payoff of a single user in a certain strategy combination is determined by the unit price of electricity supply and the comfort level of the user with flexible demand. The unit price of electricity supply is inversely proportional to the overall energy output of the microgrid. The comfort level of the user depends on the probability of using the flexible demand during the energy exchanging time period.

After calculating the Nash equilibrium in MATLAB, a strategy combination is chosen to be the most possible bidding result of users in the market for a certain energy exchanging time period.

(2) Simulation of multiple time periods considering the flexibility of demand

When multiple energy exchanging time periods are considered, the strategy chosen by a user for one period has significant influence on the strategies to be chosen for the following periods. That is because the input $p_{Flex\text{-}ON}$ changes in each exchanging time period. Two more parameters are used to indicate the different input $p_{Flex\text{-}ON}$ for different time periods:

$\Delta p_{Flex\text{-}ON\text{-}i}$: the change of $p_{Flex\text{-}ON}$ after flexible demand of user i was determined to be ON.

$\Delta p_{Flex\text{-}OFF\text{-}i}$: the change of $p_{Flex\text{-}OFF}$ after flexible demand of user i was determined to be OFF

Those two parameters vary based on the type of the flexible demand [17]. For example, electric water heaters depend on the temperature of water while air conditioners depend on the room temperature.

4.5 Case Study

To test the proposed simulation model in Section 4.4, the European Union Benchmark LV Microgrid Network [8][24] was used, as presented in Fig. 4.4.

There are totally 10 energy users with electric water heaters. Others are not considered as players in the game. Each home owns PV generators only. The PV generation profiles, load profiles of non-flexible demand, and the probability of turning ON electric water heaters are given in Fig. 4.4. Other information of energy users' is shown in Table 4.2.

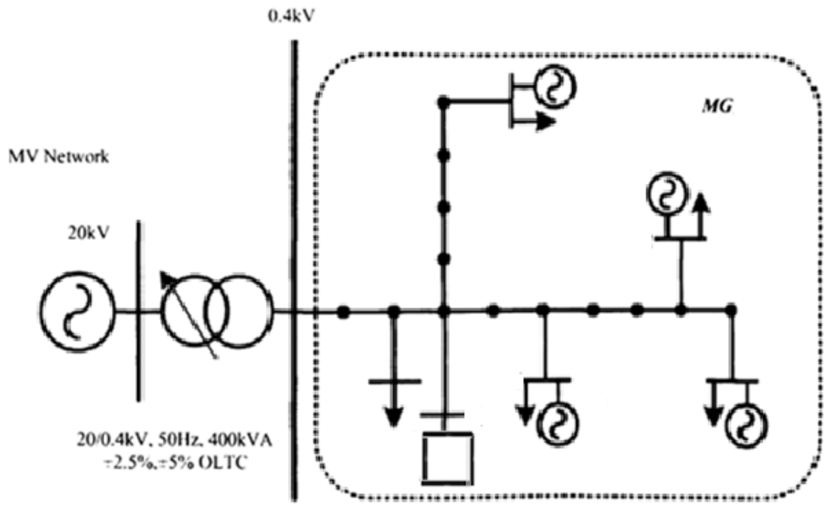
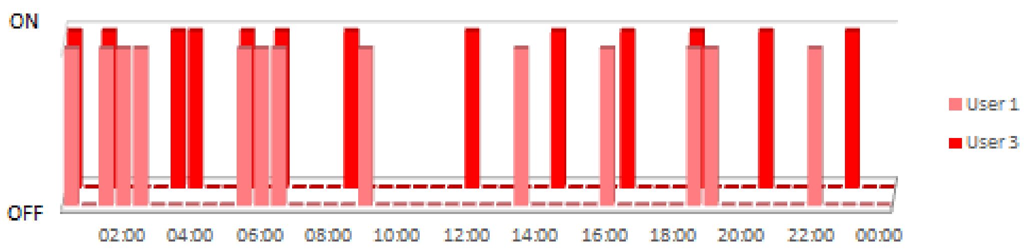


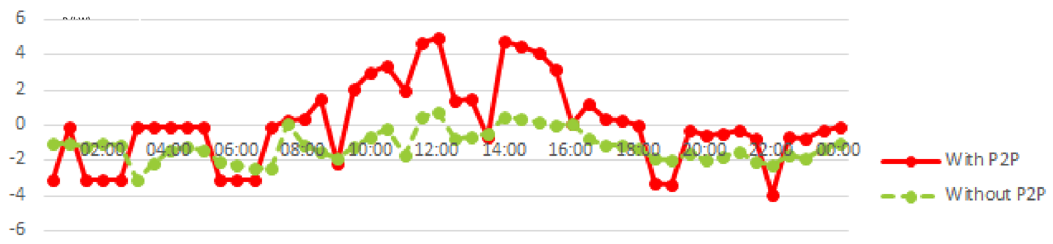
Fig. 4.4 European Union Benchmark LV Microgrid

Table 4.2 Parameters of Users 1, 2 and 3

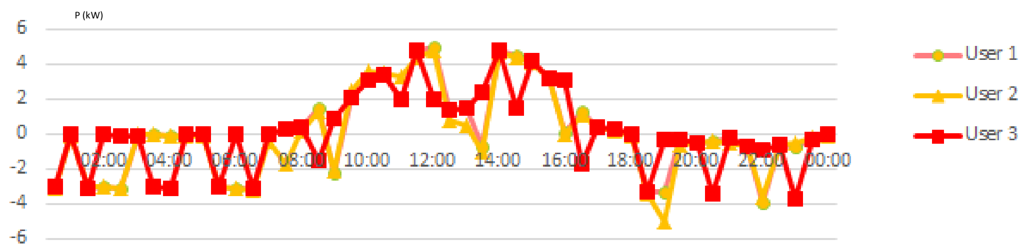
Parameters	User 1	User 2	User 3
P of maximum PV generation	5kW	5kW	5kW
P of maximum flexible demand	3kW	3kW	3kW
P of maximum non-flexible demand	4kW	4kW	4kW



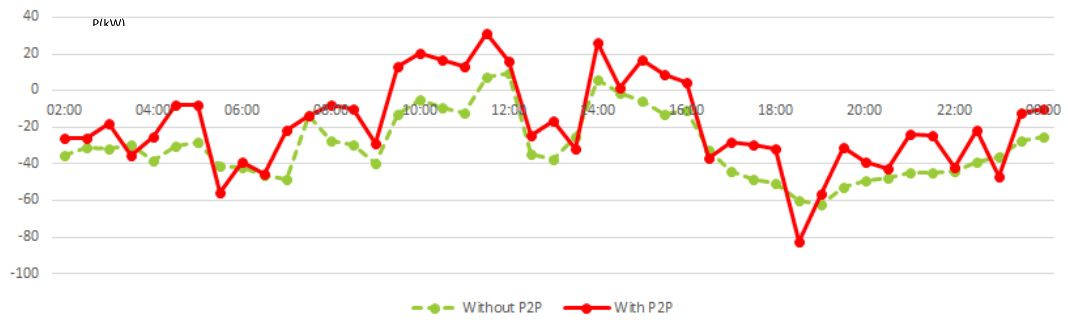
(a)



(b)



(c)



(d)

Fig.4.5 (a) ON/OFF status of flexible demand owned by users; (b) Power output comparison of user 1; (c) Power output of users with P2P trading; (d) Overall power output of Microgrid with/without P2P trading

Simulation results are presented in Fig. 4.5. Fig. 4.5(a) and Fig. 4.5(c) show that with P2P energy trading in the microgrid, the flexible demand of energy users with different load profiles, or probability of using the flexibility demand, are scheduled to be ON during different time periods of the day. The flexible demand are less likely to be turned ON or OFF simultaneously.

In Fig 4.5(b) and Fig 4.5(d), it can be seen that users try to inject more energy to the microgrid when PVs are generating power. As a result, the overall energy consumption of most users and of the whole microgrid decrease if implementing the P2P energy trading within the microgrid, although there are still the time periods that the peak energy consumption is higher than that without P2P energy trading. This is caused by some energy prosumers that choose the same strategy because of their own benefits. The overall reduction of energy consumption of the whole microgrid illustrates that the P2P energy trading is able to balance the local generation and demands.

4.6 Conclusions

P2P energy trading is one of the promising paradigms of smart grid in the near future. A four-layer architecture model was proposed to standardise the interactions amongst different technologies for P2P energy trading. An online platform "Elecbay" was designed based on the business model of a local P2P energy trading market within a grid-connected microgrid. To investigate the behaviour of energy prosumers in the new market, and to achieve new load profiles considering P2P energy trading scenarios, a simulation model of the bidding in Elecbay was developed in MATLAB based on the game theory method. Case study shows that P2P energy trading is able to balance local generation and demand, and therefore, has a potential to facilitate a large penetration of RESs in the power grid.

In the future research, power system analysis will be carried out using the load profiles of prosumers obtained in the P2P energy trading market in order to investigate the possible control methods. Sensitivity studies that consider demand and generation in multi-time scale, multi-locations are also considered as future works to be undertaken.

5 DSO Business Model Benefit Quantification

5.1 DSO Shared Network Access Model

Earning a fixed rate of return on invested capital, distributed system operator's (DSO) income has been largely determined by the amount of money spent on network investment each year. Under this business model, DSOs would extravagantly invest in the network to meet the load growth, assuming all load requires the same level of high reliability. As a consequence, a substantial amount of capacities is designed to support the temporary system peak while maintaining underutilised over the majority time of a year. More critically, this current DSO business model does not conform with flexible resources increasingly connected to the edge of the system.

This section quantifies the benefits from introducing shared network access (SNA) DSO business model as shown in Fig. 5.1, which has been introduced in D2.3. Compared with today's DSO business models, this SNA model developed in here aims to integrate flexible demand in a cost-effective manner, thus facilitating the transition to a P2P energy trading environment.

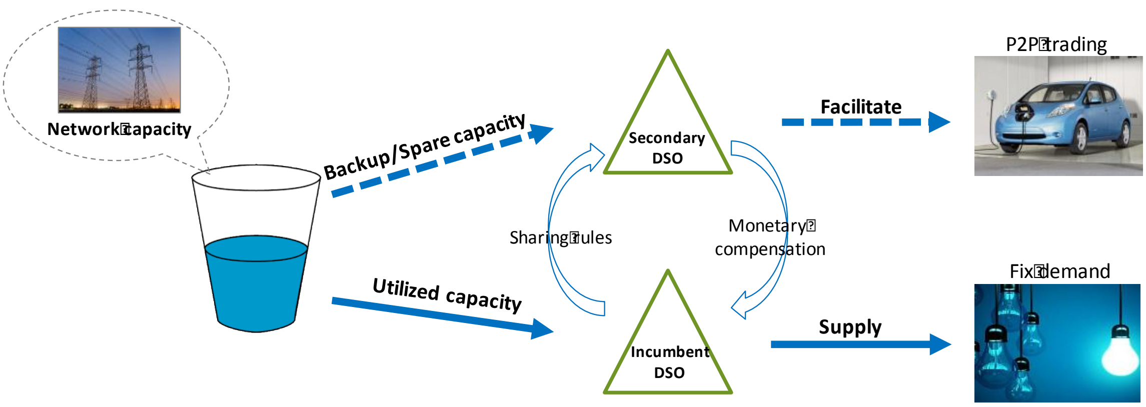


Fig. 5.1. Concept behind SNA DSO business model

The major benefits of SNA over conventional business models could be derived by examining the commercial and cash flow relationships among stakeholders shown in Fig. 5.2. More important, the SNA scheme incentivises the incumbent DSOs to give up its exclusive access to the network, leasing the spare capacity or back up capacity to licensed independent parties. The ownership of assets will be retained by the incumbent DSO while competition will be introduced in the operation of the spare capacity. The independent parties who have license for SNA will act as secondary DSOs to provided flexible network services using the spare capacity in the network, thus substantially reducing the network access cost for flexible demand.

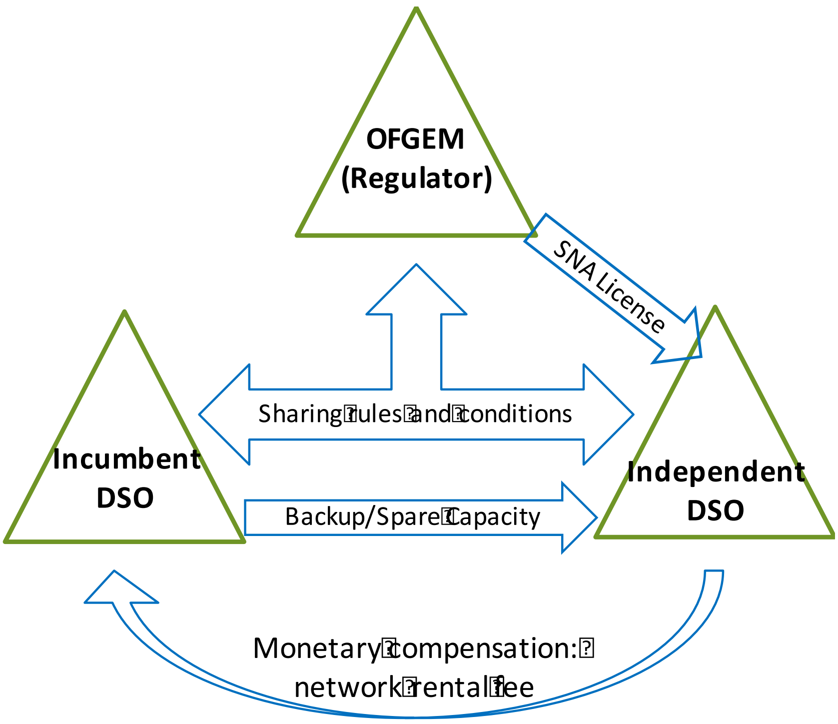


Fig. 5.2. Commercial/Cash flow connections among stakeholders

5.2 Benefit for Incumbent DSO

As increasing number of DG and flexible demand (such as EV and HP) are being connected in the distribution networks in a P2P energy trading environment, the prospective demand increase and bi-directional power flow will bring severe network pressures in terms of thermal and voltage violations. Under the conventional DSO business model, the incumbent DSO would need to carry out network reinforcement either by renewing old lines or by adding new line, assuming all additional loads require the same level of high reliability.

Traditionally, the unutilized capacity or headroom in an electrical component or circuit has been used to determine the length of time before network reinforcement is required. For a specific rate of load growth, the period until reinforcement will be needed is the time taken for the loading of the network component to reach its maximum rated capacity. And according to time value of money, the more reinforcement investment can be deferred, the lower the present value of the eventual cost, which is illustrated in Fig. 5.3.

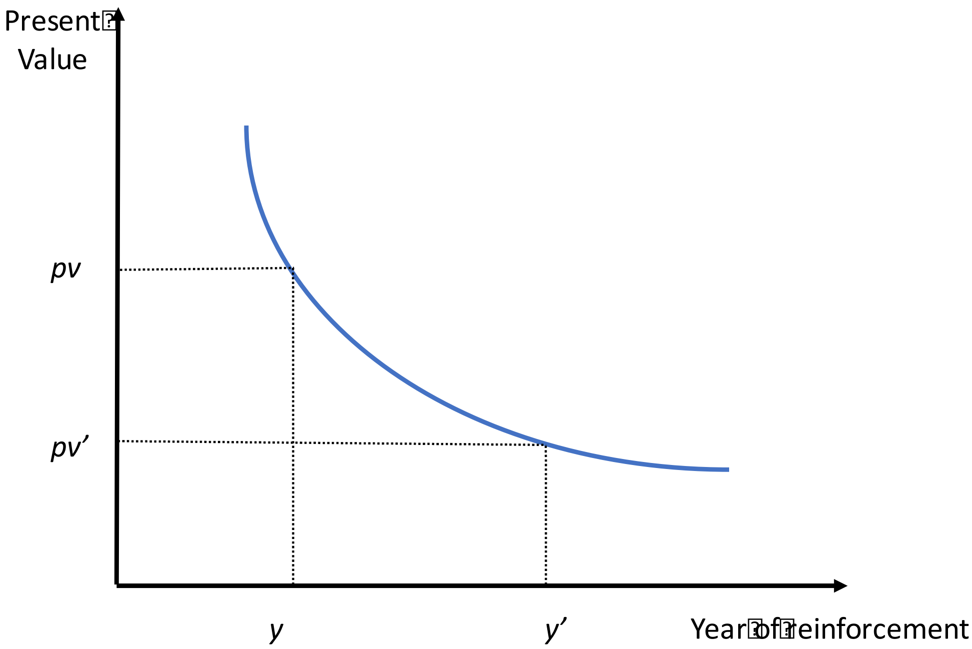


Fig. 5.3. The effect of network reinforcement deferral

Since, the present value of network investment cost is determined by the time horizon to which the loading of network component reaches its maximum rated capacity, under the SNA mechanism, such future investment is delayed by 1) incentivizing independent parties to provide customized reliabilities for flexible demands and 2) taking advantage of back up and spare network capacities. This contributes to a lower present value of eventual cost. The financial benefit received by incumbent DSOs, i.e. network infrastructure owners, can be quantified by the following steps.

1) Deriving the Time Horizon to Reach Network Capacity under Conventional Business Model

If a network component l has a normal capacity of C_l, a back capacity of B_l, and supports a power flow of D_l, then the number of years it takes to grow from D_l to $(C_l + B_l)$ for a given load growth rate (LGR) r can be determined with

$$(C_l + B_l) = D_l \times (1+r)^{n_l} \tag{5-1}$$

where n_l is the number of years taking D_l to reach $(C_l + B_l)$.

Rearranging (5-1) and taking the logarithm of it gives

$$n_l = \frac{\log(C_l + B_l) - \log D_l}{\log(1+r)} \tag{5-2}$$

2) Deriving the Time Horizon to Reach Network Capacity under SNA Business Model

Assume that within the aggregate power flow of D_l the flexible demand accounts for F%, thus the proportion of fix demand being (1- F%). As the fix demand must be supplied reliably all the time, assuming the same LGR the time to future reinforcement will change

$$(C_l + B_l) = (1 - F\%) \times D_l \times (1+r)^{n'_{l1}} \tag{5-3}$$

Equation (5-3) gives the investment horizon to meet the fix demand reliability under SNA

$$n'_{l1} = \frac{\log(C_l + B_l) - \log(1 - F\%) - \log D_l}{\log(1+r)} \tag{5-4}$$

If the flexible demand is supplied by an independent party with a promised reliability of R, the number of years it takes until such supply reliability cannot be met is defined as

$$(1 - R) \times F\% \times D_l \times (1+r)^{n'_{l2}} = D_l \times (1+r)^{n'_{l2}} - (C_l + B_l) \tag{5-5}$$

where the reliability for simplicity is defined as the ratio of satisfied amount over total flexible demand.

Equation (5-5) gives the investment horizon to meet the supply reliability of flexible demand under SNA

$$n'_{l2} = \frac{\log(C_l + B_l) - \log(1 - F\% + R \times F\%) - \log D_l}{\log(1+r)} \tag{\5-6}$$

The smaller of (5-4) and (5-6) is taken as the new time horizon to future reinforcement n'_l under SNA

$$n'_l = min\{n'_{l1}, n'_{l2}\} \tag{5-7}$$

3) Difference in Present Value as a Result of SNA

For a given discount rate of d is chosen, the present values of the future investment in year (5-2) and (5-7) respectively will be

$$PV_l = \frac{Asset_l}{(1+d)^{n_l}}, \quad \text{and} \quad PV_l' = \frac{Asset_l}{(1+d)^{n_l'}} \tag{5-8}$$

where $Asset_l$ is the modern equivalent asset cost.

Hence, the change in present value as a result of SNA is

$$DPV_l = PV_l - PV_l' = Asset_l \cdot \left(\frac{1}{(1+d)^{n_l}} - \frac{1}{(1+d)^{n_l'}}\right) \tag{5-9}$$

4) Calculating the Financial Benefit for Incumbent DNO

The financial benefit for incumbent DNO under SNA mechanism is the summation of incremental benefits over all network components:

$$Benefit = \sum_l DPV_l \tag{5-10}$$

To demonstrate the benefit of SNA business model for incumbent DSO, a simple two-busbar network firstly has been selected as the test network, which is shown in Fig. 5.4. The normal and back up capacity of circuit l are rated at 25 MW and 20 MW respectively, and both cost £3193400 at modern equivalent asset value. The initial Dl is 20 MW. Assuming a discount rate of 6.9% and a LGR of 1.6% per annum, Fig. 5.5 gives the financial benefits received by the incumbent DNO under different flexible demand penetrations and reliabilities.

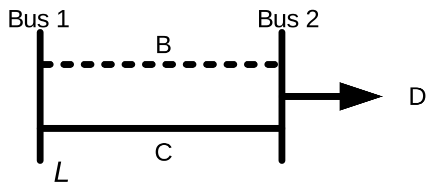


Fig. 5.4. Demonstration network 1

It shows by SNA mechanism the incumbent DSO financial benefit becomes significant when the flexible demand penetration increases. At the same time, a lower reliability requirement of flexible demand presents a positive effect on the result. An extreme scenario where the flexible demand requires uncompromising supply reliability is also shown in the demonstration. Conceivably, under this condition the SNA mechanism brings no additional financial benefit to the incumbent DSO.

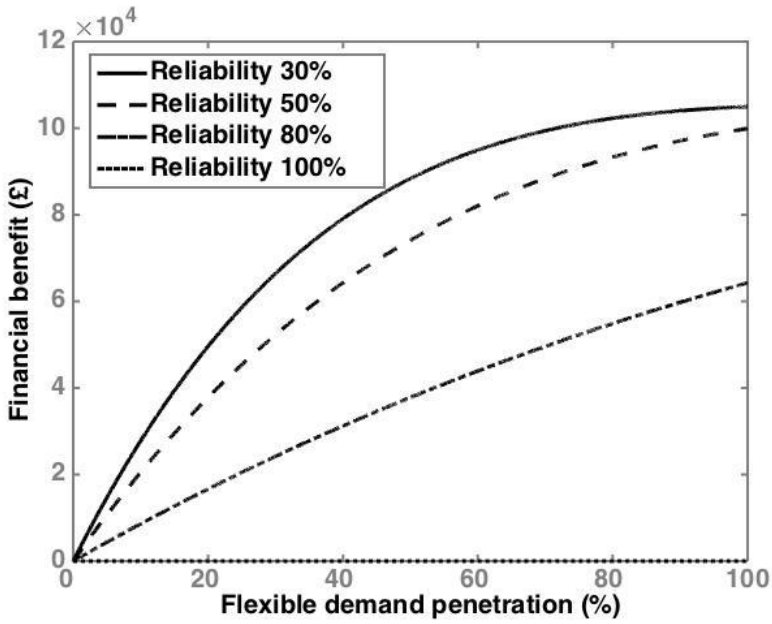


Fig. 5.5. Results of demonstration 1

To distinguish the difference between radial and meshed network situations, the developed SNA business model has been also applied to the network shown in Fig. 5.6. As could be seen, both the radial and meshed networks are supplied by normal as well as back-up capacities, and the parameters for this demonstration are given in Table 5.1. The results are given in Fig. 5.7.

Table 5.1. Parameters for the demonstration network

Normal capacity (MW)	Back-up capacity (MW)	Circuit cost (£)	Initial loading level (MW)	Discount rate	Load growth rate
25	20	3,193,400	20	6.9%	1.6%

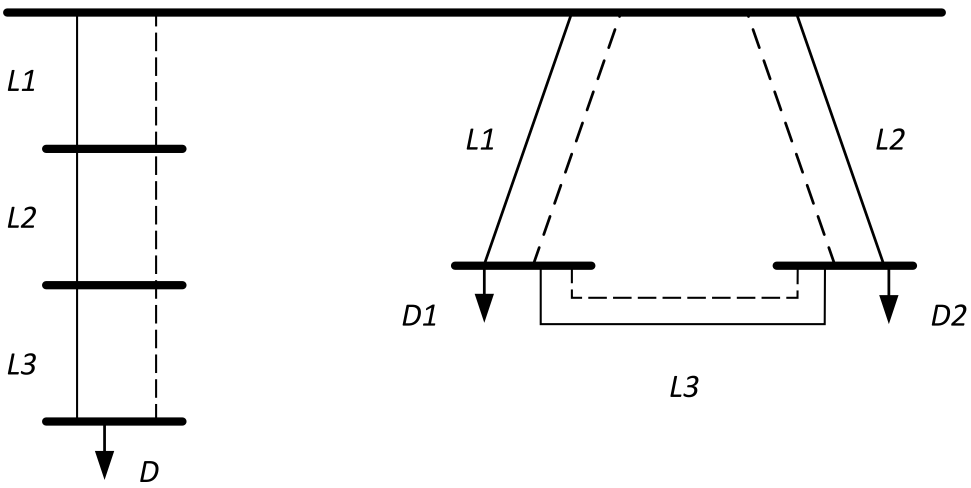


Fig. 5.6. Demonstration network 2

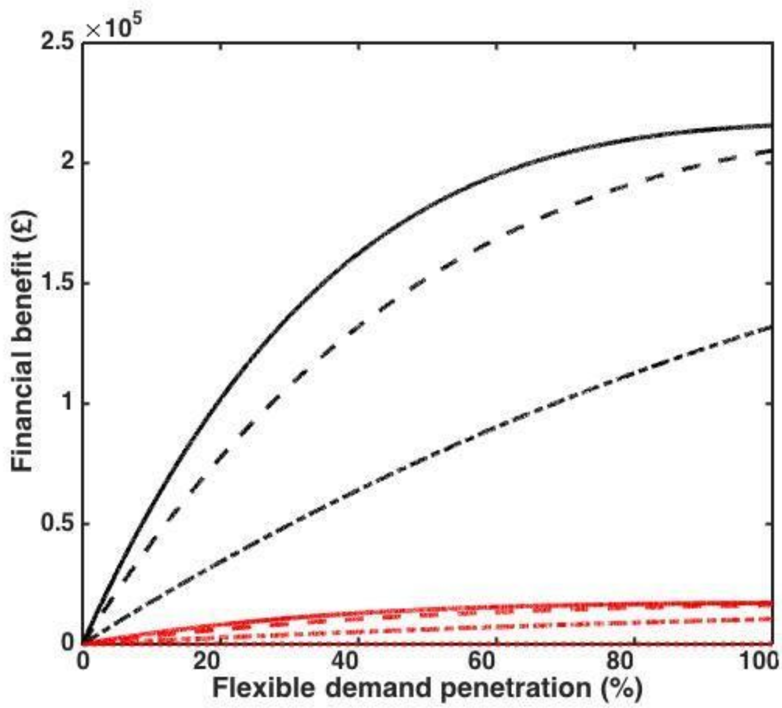


Fig. 5.7. Results of demonstration 2

In the chart, meshed network results are shown in black, while radial results are given in red. It is apparent that although with the same number of branches, i.e. cable costs, the financial benefit which could be contributed to incumbent DSO in a meshed context is substantially higher than radial's condition. This could be explained as the higher security of supply of meshed configuration than radial configurations. In the event of contingency, due to its unique interconnection in between busbars, meshed networks still have to some extent certain capabilities to supply fix and intermittent demands at the problematic busbar. As a result, this contributes to much more deferred network reinforcement caused by loading level annual growth. Eventually, this significantly deferred reinforcement turns into much lower present values, thus higher financial benefits for incumbent DSOs.

5.3 Benefit for Independent DSO

As shown in Fig. 5.2, independent DSOs lease back-up/spare network capacities from the incumbent DSO, aiming to supply flexible demands with differing supply qualities. One of the benefits brought by this SNA business model to these independent DSOs are that for the first time, the element of competition is introduced into the business of network operation, thus various entities are granted the opportunity to apply their expertise in this field and compete with the incumbent.

On the other hands, unlike traditional distribution network operators who have to acquire the necessary property, plant, and equipment before they can conduct their business, independent DSOs are able to lease them, thus saving a significant amount of initial investment cost and lowering the long-existing barriers to entry. The commercial connection in between the incumbent and independent DSO as shown in Fig. 5.2 is established by a lease contract. The lessee, which is the independent DSO in this case, is liable for periodic payments in exchange for the right to use the network assets; while the lessor, which is the incumbent DSO, is the owner of the asset, who is entitled to the lease payments in exchange for lending the assets.

Similar to most financial leases, the lease contract between the incumbent and independent DSO might involve little or no upfront payment. Instead, the independent commits to make regular lease payments for the term of the contract. At the end of the contract term, the lease might specify who will retain ownership of the assets and at what terms. The network lease contract for the independents would also specifies cancellation provisions, the options for renewal and purchase, and the obligations for maintenance and related servicing costs. More important, since according the proposed SNA business model, in the case of network contingency, the incumbent will be able to get back the leased-out back-up capacity to secure the supply to fix demands, the leasing contract would need to cover such areas.

Given the fact that leases are privately negotiated contracts and can contain many more provisions than typical financial lease contracts. They might include early cancellation options that allow the lessee to end the lease early (perhaps for a fee). They may also contain buyout options that allow the lessee to purchase the asset before the end of the lease term. Clauses may allow the lessee to trade in and upgrade the equipment to an improved one at certain points in the lease. Each lease agreement can be tailored to fit the precise nature of the asset and the needs of the parties involved.

<u>Leasing strategy types</u>

- Sales-type lease

Many types of lease transactions are possible based on the relationship between the lessee and the lessor. In a sales-type lease, the lessor is the manufacturer (or a primary dealer) of the asset. For example, IBM both manufactures and leases computers. Similarly, Xerox leases its copy machines. In the case of an incumbent DSO being the manufacturer of its network assets, it can generally set the terms of these leases as part of a broader sales and pricing strategy, and it may also bundle other services or goods (such as monitoring, maintenance, or capacity upgrades) as part of the lease.

- Direct lease

In a direct lease, the lessor is not the manufacturer, but is often an independent company that specializes in purchasing assets and leasing them to customers. For example, Ryder Systems, Inc., owns more than 135,000 commercial trucks, tractors, and trailers, which it leases to small businesses and large enterprises throughout the United States, Canada, and the United Kingdom.

In many instances of direct leases, the lessee identifies the equipment it needs first and then finds a leasing company to purchase the asset.

- Sale and leaseback

In the case of an independent DSO already owns the network asset it would prefer to lease, it can arrange a sale and leaseback transaction. In this type of lease, the lessee receives cash from the sale of the asset and then makes lease payments to retain the use of the asset. In 2002, San Francisco Municipal Railway (Muni) used the $35 million in proceeds from the sale and leaseback of 118 of its light-rail vehicles to offset a large operating budget deficit. The purchaser, CIBC World Markets of Canada, received a tax benefit from depreciating the rail cars, something Muni could not do as a public transit agency.

- Leveraged lease

With many leases, the lessor provides the initial capital necessary to purchase the asset, and then receives and retains the lease payments. In a leveraged lease, however, the lessor borrows from a bank or other lender to obtain the initial capital for the purchase, using the lease payments to pay interest and principal on the loan. Also, in some circumstances, the lessor is not an independent company but rather a separate business partnership, called a special-purpose entity (SPE), which is created by the lessee for the sole purpose of obtaining the lease.

Lease payments and SNA benefit calculation

These features of leases will be priced as part of the lease payment. Terms that give valuable options to the lessee raise the amount of the lease payments, whereas terms that restrict these options will lower them. Although in the business mode of SNA, the lease price is determined by the incumbent DSO, one of the most important influencing components deciding the cost of lease is the asset's residual value, which is its market value at the end of the lease. In a perfect capital market, the lease payment should be set so that the net present value (NPV) of the transaction is zero and the lessor breaks even:

$$PV(\text{Lease Payments}) = \text{Purchase Price} - PV(\text{Residual Value}). \tag{5-11}$$

In other words, in a perfect market, the cost of leasing is equivalent to the cost of purchasing and reselling the asset.

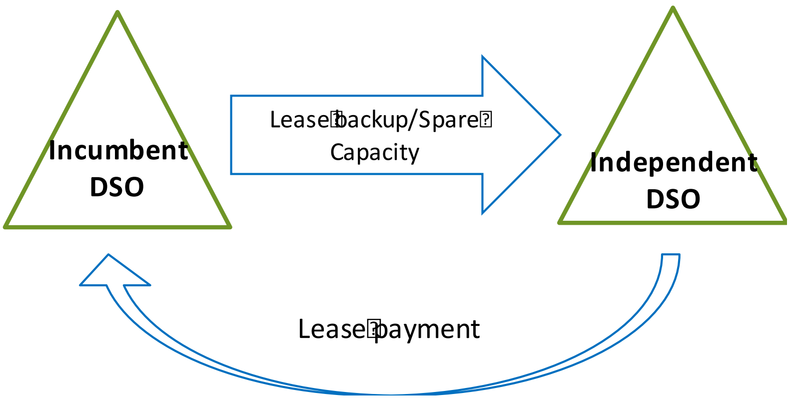


Fig. 5.8. SNA lease payment calculation

To demonstrate the calculation of lease payment, an incumbent-independent DSO SNA lease case study is provided below, and the inputs are presented in Table 5.2.

Table 5.2. SNA lease payment calculation inputs

Purchase price (£k)	Residual value (£k)	Lease contract length (months)	Lease payment frequency	Discount rate	Electricity bill (£k)
20,000	6,000	48	Per month	6%	500

Converting the annual discount rate into per month risk-free interest rate:

$$\frac{6\%}{12} = 0.5\%\ per\ month$$

From Eq. 5-11,

$$PV(\text{Lease Payments}) = £20{,}000 - \frac{£6{,}000}{1.005^{48}} = £15{,}277\text{k}$$

Considering the lease payment L as an annuity, we can find this monthly lease payment which has the present value above, which is shown in Fig. 5.9. Because the first lease payment starts today, we can view the lease as an initial payment of L plus a 47-month annuity of L. Thus, using the annuity formula, we need to find L so that

$$£15{,}277\mathrm{k} = L + L \times \frac{1}{0.005}\left(1 - \frac{1}{1.005^{47}}\right) = L \times \left[1 + \frac{1}{0.005}(1 - \frac{1}{1.005^{47}})\right]$$

Solving the equation above, we get the month lease payment

$$L = \frac{£15{,}277k}{1 + \frac{1}{0.005}\left(1 - \frac{1}{1.005^{47}}\right)} = £357\mathrm{k}\, per\ month$$

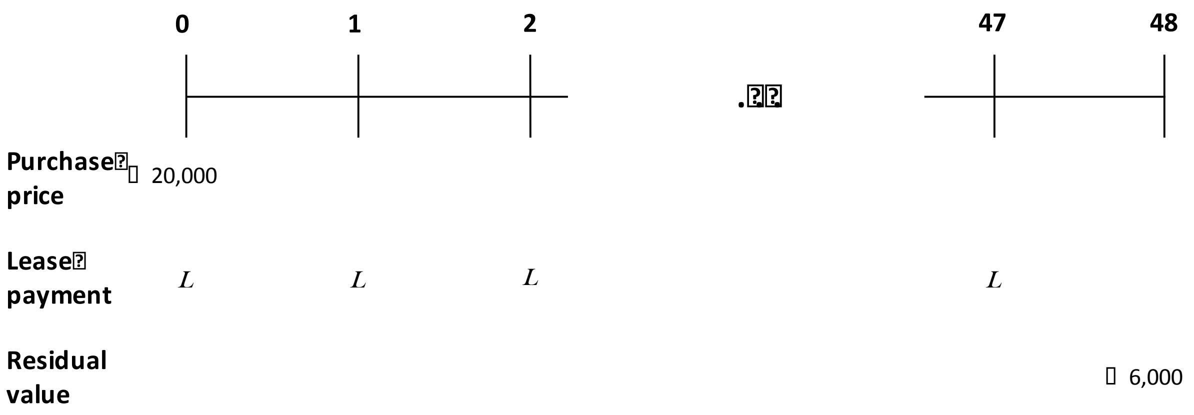


Fig. 5.9. Lease monthly payment by independent DSO

Taking a look at the cash flows for the role of independent DSO in Fig. 5.10, we can see the main inward cash flow is the electricity bill paid by its supplied flexible customer demand while the main cash outflow upstream is the lease payment to the incumbent DSO. Hence, the financial benefit can be approximately calculated as the difference of cash inflow and outflow present values:

$$Benefit_{independent\ DSO} = PV(\text{Electricity Bill}) - PV(\text{Lease Payment}) \tag{5-12}$$

Assuming the monthly electricity bill collected by the independent DSO during the lease contract period being E, the present value of these electricity bill streams can be calculated as

$$PV(\text{Electricity Bill}) = E\left[\frac{1-(1+r)^{-n}}{r}\right] \quad (1\text{-}13)$$

where r is the discount rate for the period, and n is the number of periods in which bill payments will be made. Applying the inputs given in Table 5.2, Eq. (5-12) becomes:

$$Benefit_{independent\ DSO} = 500 \times \left[\frac{1-(1+(1+0.5\%)^{-48}}{0.5\%}\right] - PV(\text{Lease Payment})$$
$$= 21{,}290 - 15{,}277 = 6{,}013(£k)$$

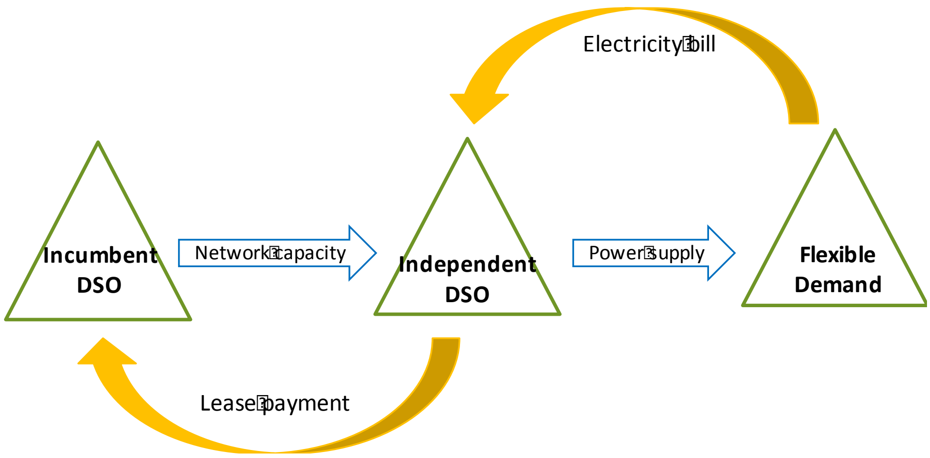


Fig. 5.10. Cash outflow and inflow for independent DSO

The case study above demonstrated that the amount of the lease payment back by independent DSO to incumbent DSO will depend on the current purchase value of the network asset, the residual value of the asset at the end of lease contract, and the appropriate discount rate for the cash flows.

In the demonstration above, we assumed that at the end of the lease contract the independent DSO would return the back-up network asset to the lessor, i.e. the incumbent DSO, who would then obtain the residual market value of the asset of £6,000. In reality, other lease terms are possible. In many cases, the lease allows the lessee to obtain ownership of the asset for some price.

- Fair market value lease (EMV)

An FMV lease gives the lessee the option to purchase the asset at its fair market value at the termination of the lease. Depending on the asset, determining its fair market value may be complicated. The lease will typically stipulate a procedure for doing so, and it often will require estimates of the fair market value to be provided by an independent third party.

- Finance lease

In a finance lease, ownership of the asset transfers to the lessee at the end of the lease for a nominal cost of $1.00. Thus, the lessee will continue to have use of the asset for its entire economic life. The lessee has effectively purchased the asset by making the lease payments. As a result, this type of lease is in many ways equivalent to financing the asset with a standard loan.

- Fixed price lease

In a fixed price lease, the lessee has the option to purchase the asset at the end of the lease for a fixed price that is set upfront in the lease contract. This type of lease is very common for consumer leases (such as for autos). This kind of lease gives the lessee an option: At the end of the lease, if the market value of the asset exceeds the fixed price, the lessee can buy the asset at below its market value; if the market value of the asset does not exceed the fixed price, however, the lessee can walk away from the lease and purchase the asset for less money elsewhere. Consequently, the lessor will set a higher lease rate to compensate for the value of this option to the lessee.

- Fair market value cap lease

In a fair market value cap lease, the lessee can purchase the asset at the minimum of its fair market value and a fixed price (the “cap”). The lessee has the same option as in a fixed price lease, although the option in this case is easier to exercise because the lessee does not have to find a similar asset elsewhere to buy when the fixed price exceeds the market value.

6 CONCLUSIONS

This deliverable has identified the infrastructure context in which P2P energy exchange can offer significant benefits in terms of value creation and capture over the centralized approach. More important, based on the innovative models developed in previous deliverables of this work package, this report has quantified the benefits from introducing such P2P trading mechanism from the perspective of various stakeholders.

This work has examined how the existing and future upgrading smart grid and ICT infrastructures might support the realization of P2P trading practices. On the smart grid side, the upgrade to a P2P trading environment affects deeply the operation of the distribution networks as they evolve from passive to active networks. The power system will need to become smarter at balancing demand and supply in local levels. In order to achieve a regional energy trading mechanism, customers' demand behaviour responding to available energy resources in local areas needs to be considerably simulated. While of the ICT side, the ability to deliver accurate, reliable and secure data to and from the grids becomes even more critical in supporting P2P marketplace function and optimizing operational systems.

The second part of this work has quantified the benefits of the proposed models of P2P platform, Microgrid trader and distribution system operator in a P2P environment. For the platform operation, it has been found that with only boiler heating optimization, the annual savings potential is in the range of 20-30€ annually per platform member, while with joint optimization of boiler heating and wind production, the savings increase to the range of 30-40€. For the Microgrid trader, a bidding simulation model was developed based on the game theory method to investigate the behaviour of energy prosumers in the new market. The results shows that P2P energy trading is able to balance local generation and demand, and more important, has a potential to facilitate a large penetration of renewable energy resources in the power system. For the DSO SNA business model, the financial benefit for both the incumbent and independent DSOs has been quantified, and network configuration scenarios of radial and meshed have been compared. The result shows that for higher security of supply situations, SNA is able to provide even more substantial financial rewards to existing DSO entities, thus affirming the practicalities of the developed SNA business model over current methods in a real world scenario.

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