Model Predictive Control for Scheduling of Flexible Microgrid Systems

Igor Kuzle
University of Zagreb Faculty of Electrical Engineering and Computing
e–mail: igor.kuzle@fer.hr

Ninoslav Holjevac*
University of Zagreb Faculty of Electrical Engineering and Computing
e–mail: ninoslav.holjevac@fer.hr

Tomislav Capuder
University of Zagreb Faculty of Electrical Engineering and Computing
e–mail: tomislav.capuder@fer.hr

ABSTRACT

Microgrids, groups of loads and generators in the same location with centralized control, have the ability to balance the variability and the forecast error of the renewable sources (RES) within them, thus reducing the need for the conventional reserve. The main goal of this paper is to explore the influence of the microgrid components on its ability to operate independently from the distribution grid. A deterministic model using mixed integer linear programming (MILP) is developed to simulate the microgrid operation over one year period and used to determine the optimal microgrid parameters with respect to the amount of unused energy.

In the second part of this paper a developed model is expanded with model predictive control (MPC) approach to capture the behaviour of the microgrid connected to the rest of the distribution grid, modelling the uncertainties of forecasting RES production by stochastic programming. The model is capable of evaluating the impact of variable energy prices and the impact of energy balancing tariffs depending on the amount of balancing energy needed on the operation of flexible units such as electric heat pumps (EHP), micro Combined Heat and Power plants (μCHP) and heat storage (HS).

KEYWORDS

Flexible units, Microgrids, Mixed Integer Linear Programming (MILP), Model Predictive Control (MPC), Renewable Energy Sources (RES), Uncertainty

* Corresponding author: ninoslav.holjevac@fer.hr

1. INTRODUCTION

Integration of renewable energy sources (RES) today is largely driven by governmental incentives, especially for RES on a small domestic scale. As the share of RES increases, the concept of incentives becomes unsustainable and the need to develop new approaches becomes inevitable. Traditionally, there has been a separation between the production and consumption of electricity where consumption has been regarded a passive part with very little capabilities for control. Therefore any generation mismatch caused by variations in RES generation had to be compensated by other generating units. Today the development is shifting towards enabling the flexibility from the consumer, ranging from flexible demand to distributed generation. The range of controllable and RES technologies at the low voltage level covers a wide range of units: photo-voltaic units (PV), wind power plants (WPP), electric heat pumps (EHP), micro combined heat and power units (μCHP), thermal energy storage (HS), battery storage (BS) etc. Aggregating these technologies creates a market entity capable of not only isolated operation but also interaction with the electric system.

Any such system could be integrated with the rest of power grid's control system by means of aggregation and market mechanism. Although ideas of virtual power plants and standalone microgrids are not new [1], there is still a lack of models capable of representing the behaviour and scheduling of such clusters of units. A good model must provide robust response of microgrid to fluctuations of connected RES and, if needed, has to ensure stand-alone operation with minimum to no interaction with the rest of the electrical grid.

The methodology for decision-making on local microgrid level is not simple to find and has many key factors that have to be included. Microgrid comprises of both dispatchable units (e.g. distributed generators) needed to balance the microgrid and uncontrollable units such as RES whose production cannot be precisely estimated. Additionally, flexible loads (FL), energy storage systems (EES) and connection to the rest of the system have to be modelled in order to find optimal control approach. There are several methods found in literature that tackle the problem of finding the best control algorithm. In [2] Sanseverino *et al.* look for a solution of optimal operation of a microgrid using a non-dominated sorting algorithm that includes forecast error. Different approach using MILP (Mixed Integer Linear Programming) for a mid-term virtual power plant dispatch optimization was investigated in [3] by Pandžić *et al.* where uncertainty of the wind and solar power generation is settled using storage in order to provide flexible operation. Day ahead planning horizon is more commonly used when operation of microgrid is considered [4]. Furthermore, complex and computationally demanding approaches such as multiagent modelling presented by Want *et al.* in [5] or evolutionary strategies presented by Basu in [6] do not guarantee global optimality of the solution.

MILP approach coupled with Model Predictive Control (MPC) has recently proved to be an efficient approach since it is based on future predictions as well as present state of the system. This combination provides a good mechanism to deal with uncertainty of predictions. Optimization centred around battery storage is presented in [7] by Malysz *et al.* where battery is used to maximize economic benefits for both the customers and utility operators. Perkovic *et al.* [8] used receding horizon model predictive control for smart management of residential type microgrid while taking into account Plug-in Electric Vehicles (PEV) as energy storage with the goal of maximizing profit. Energy management system using rolling horizon strategy for an isolated renewable-based microgrid is presented by Marietta *et al.* in [9]. Another MPC control algorithm which minimizes the operation cost, tested on a real microgrid, and proves the feasibility of proposed approach was described by Parisio *et al.* in [10].

With respect to different or multi objective functions, the available literature proposes several approaches and possibilities. As stated before, genetic algorithms can incorporate multi-objective optimization and consider both, for example, economic benefits and emission reductions, as in example by Deng *et al.*[11], but the final result is not guaranteed to be the global optimum as it is the case with MILP. Many optimization algorithms set minimization of operational costs or maximization of profit as objective functions which, in most cases, are dual functions. Recently, approach that minimizes emissions and emissions cost has been presented in [12], proposed by Ren *et al.*, trying to reduce environmental impacts of energy production. It is important to notice that there are currently no integrated models including all the important elements (PEV, FL, battery and heat storage, μCHP etc.) and providing a comprehensive study of operational costs, energy usage, energy curtailment, losses, equipment degradation information etc. The focus of this paper is on defining the flexibility that can be gained by optimally coupling heat storage, μCHP, EHP and flexible demand in microgrid operation.

2. MAIN CONTRIBUTIONS

In this paper control-oriented approach for microgrid operation is developed. Two models are developed, deterministic and rolling unit commitment incorporating MPC. These models are used to simulate daily operation of a microgrid for a period of one year. The microgrid consists of 300 households (each modelled by a specific heat and electricity demand profile), multiple DG units (μCHP, EHP, boiler and heat storage), and household installed RES units, in particular solar and wind.

In all the simulations certain assumptions were made:

- microgrid optimization and operation is primarily market driven and voltage and frequency stability are assumed to be controlled on the lower level and are not considered;
- microgrid consists of the following elements: PV arrays, wind turbines, μCHP units, EHP units, flexible and inflexible loads, heat storage, and boiler units. The concept relays only on units widely adopted by the consumers and thus does not include BS or PEV. It should be noted that the model can easily be expanded to include additional technologies;
- central controller is assumed to have all the required information about the present state of the microgrid (boiler, EHP and μCHP operational points, house heat storage unit capacity, market energy prices, RES production);
- energy exchanged with the grid is assumed to be bought/sold at day-ahead market;
- microgrid is small enough to act as a price taker and does not influence the formation of prices on the market;
- connection with the distribution grid is unconstrained;
- flexible consumers are not compensated for rescheduling their output;
- sampling time is constant ($\Delta T\tau = t_k - t_{k-1}$) and the ration between power and energy is therefore also constant.

The first contribution of the paper is defining the value of different flexible components, such as EHP, μCHP and Flexible Load (FL), on microgrids ability to operate in the off grid mode. A mathematical model based on Mixed Integer Linear Programming (MILP) is developed to simulate the off grid operation over one year period, determining the optimal parameters with respect to the amount of unused energy on microgrid level. This series of simulations was done with deterministic input data. A comparison of deterministic model simulation off-grid and on-grid is also given. Determined optimal sizes of installed wind aggregates and PV units for given microgrid configuration are afterwards used to study how much flexibility can be gained by altering heat storage capacity, flexible demand percentage and percentage of specific controllable DG unit installed with consumers. The flexibility is evaluated as the yearly amount of unused energy; curtailed RES electricity and wasted heat.

The second contribution of the paper is the rolling unit commitment model incorporating MPC algorithm optimizing the microgrid operation on a daily basis considering the uncertainties inherent to the RES production and demand forecasting. Adding MPC improves the system's ability to react to prediction errors since the controller takes into account a series of future moments instead of making decision just based on current status of the system. The developed model minimizes day ahead scheduling error of the microgrid as well as the operational cost based on penalizing export/import balancing energy cost and total fuel cost.

It should be noticed that, through a number of analyses, the paper clearly recognizes benefits of coupling and coordinated operation of µCHP and EHP units, supported with HS as heat buffer, in order to compensate for the fluctuating nature of RES production and to minimize, or if possible totally exclude, balancing interaction with distribution network. This way microgrid can operate as independent entity at any time needed, follow the scheduled import/export plan and compensate for unpredictable fluctuations in RES production.

3. MICROGRID SYSTEM COMPONENTS AND MODELING

Basic concept of the modelled microgrid is shown on Figure 1. As it can be seen the microgrid consists of heat and electricity consumers (households), electricity producers (µCHP), heat producers (EHP, µCHP and auxiliary boilers) and buffers decoupling heat and electricity demand - heat storages (HS). The possibility of direct electrical energy storage is not modelled, even though the heat storage in combination with µCHP and EHP units can provide a certain ability to change the electrical power output [13], [14]. All microgrid components are modelled using CPLEX solver FICO Xpress [15]. Data manipulation and results extraction was done using MatLab 2013.

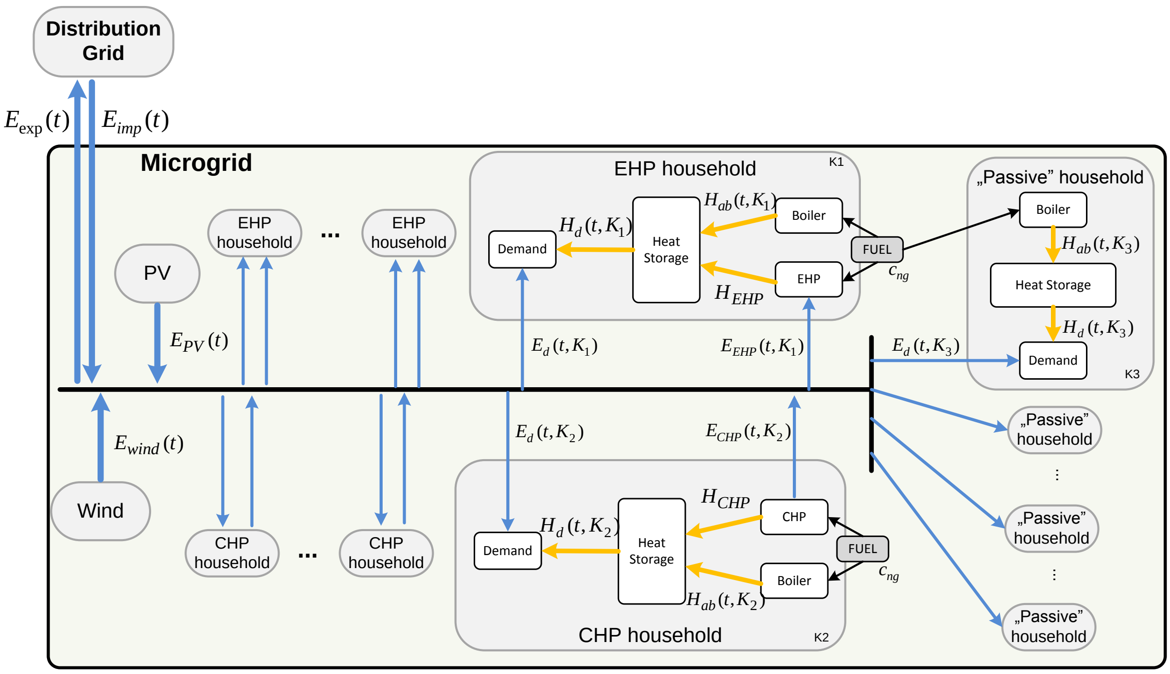

Figure 1. Schematic of a microgrid

In tables 1, 2 and 3 a list of indices, input and decision variables is given for easier understanding of the mathematical formulation parameters used in optimization problem formulation.

Table 1. Parameters of the optimization model

Parameter	**Description**
K	Total number of households
i	Counter referring to *i-th* household
t	Current simulation step
$T_{\max}$	Time horizon of the simulation [hour]
τ	Simulation time step duration [hour]
$c_{ng}(t)$	Natural gas supply price [€/kWh]
P	Penalty factor for waste heat and wind energy
$H_{chp\_\max}(t,i)$	Maximum heat production of μCHP unit [kWh]
$\eta_{chp\_e}(t,i)$	Electric efficiency of μCHP unit
$\eta_{chp\_t}(t,i)$	Thermal efficiency of μCHP unit
$H_{ehp\_\max}(t,i)$	Maximum heat production of EHP unit [kWh]
$COP(t,i)$	Coefficient of performance of EHP unit
$H_{ab\_\max}(t,i)$	Maximum thermal output of a boiler unit[kWh]
$\eta_{ab}(t,i)$	Boiler efficiency
$H_{hs\_\max}(t,i)$	Maximum heat storage capacity [kWh]
$\eta_{hs}(t,i)$	Heat storage efficiency
p_{flex}	Percentage of total electrical load defined as flexible
$C_{flex\_\max}(t)$	Maximum capacity of flexible load being rescheduled [kWh]

Table 2. Forecasts (inputs of the optimization algorithm)

Parameter	**Description**
$H_d(t,i)$	Heat demand of *i-th* household [kWh_t]
$E_d(t,i)$	Electricity demand of *i-th* household [kWh_e]
$E_{wind}(t)$	Standardized per 1 kW installed power hourly wind production [kWh]
$E_{PV}(t)$	Standardized per 1 kW installed power hourly PV production [kWh]
$c_{imp}(t)$	Import electricity price [€/kWh]
$c_{\exp}(t)$	Export electricity price [€/kWh]

Table 3. Decision variables of the optimization model

Parameter	Description
$H_{chp}(t,i)$	Heat production of μCHP unit [kWh]
$H_{hs}(t,i)$	Heat flow through heat storage [kWh]
$C_{hs}(t,i)$	Heat storage capacity at simulation step t [kWh]
$H_{ab}(t,i)$	Heat production of a boiler unit [kWh]
$E_{flex}(t)$	Flexible loads being rescheduled [kWh]
$E_{wind\_gen}(t)$	Used wind energy [kWh]
$E_{wind\_curt}(t)$	Curtailed wind energy [kWh]
X_{wind}	Installed wind power
X_{PV}	Installed PV power
$E_{imp}(t)$	Imported energy from the grid [kWh]
$E_{\exp}(t)$	Exported energy to the grid [kWh]
$F(t)$	Total fuel energy used [kWh]

3.1 Micro Combined Heat and Power unit (μCHP)

A number of households with larger heat consumption use μCHP units as main heat source. μCHP units are modelled with peak power of 8 kW_t and technical minimum of 1,6 kW_t. The coefficient τ is used since technical min/max constraints are expressed in kWh values. This way the model is able to capture different time step resolutions which usually depend on the market structure and settlement periods in the observed market. In all simulations in this paper a 0,5 hour time step is considered.

$$H_{chp\_\min}(i)\cdot\tau \le H_{chp}(t,i) \le H_{chp\_\max}(i)\cdot\tau \tag{1}$$

It is assumed that μCHP units can adjust their output fast enough and no ramp constraints have been introduced. Production of electrical energy of *i-th* μCHP unit in every time step:

$$\mathrm{E}_{chp}(t,i) = \mathrm{H}_{chp}(t,i)\cdot\frac{\eta_{chp\_e}(t,i)}{\eta_{chp\_t}(t,i)} \tag{2}$$

Fuel consumption of all CHP units is:

$$fuel_{chp\_total}(t) \le \sum_{i}^{K}\frac{H_{chp}(t,i)}{\eta_{chp\_t}(t,i)} \tag{3}$$

3.2 Electric Heat Pump unit (EHP)

A number of households have EHP as main heat source. EHP is modelled with its peak heat power of 10 kW_t and coefficient of performance COP which varies throughout the year. Assumed EHP type is air-water and is therefore dependent on the outdoor temperature and temperature difference. Households that have no EHP have the $H_{ehp}(t,i)$ equal to 0.

$$H_{ehp}(t,i) \leq H_{ehp\_\max}(t,i) \cdot \tau \tag{4}$$

Heat production of EHP unit in every time step and household is:

$$\mathrm{E}_{ehp}(t,i) = \frac{\mathrm{H}_{ehp}(t,i)}{COP(t,i)} \tag{5}$$

3.3 Auxiliary boiler (AB) and heat storage (HS)

All households are equipped with gas boiler which is being used when heat demand is too large to be covered by primary heat sources (EHP or μCHP) or when optimization algorithm dispatches it under right circumstances. Boiler has peak power of 10 kW_t and efficiency of fuel conversion is 85%:

$$H_{ab}(t,i) \leq H_{ab\_\max}(t,i) \cdot \tau \tag{6}$$

$$fuel_{ab\_total}(t) \leq \sum_{i}^{K} \frac{H_{ab}(t,i)}{\eta_{ab}(t,i)} \tag{7}$$

Additionally all households have a simple water tank, or heat storage with the capacity $C_{hs\_\max}$ of 6 kWh. To store that amount of heat, assuming water temperature difference of 30 to 35 °C, approximately 150 litters of water are needed. Heat losses on hourly bases are assumed to be 4%, which corresponds to losses of 2% every half an hour. Heat storage has constraints due to its charge/discharge time:

$$H_{hs}(\mathrm{t,i}) \leq C_{\max\_hs}(t,i) \cdot \tau \tag{8}$$

Storage capacity limit and behaviour are described with following inequalities:

$$C_{hs}(t,i) \leq C_{hs\_\max}(t,i) \tag{9}$$

$$C_{hs}(t,i) = \eta_{hs}(t,i) \cdot C_{hs}(t-1,i) - H_{hs}(t,i) \tag{10}$$

3.4 Heat demand

Daily heat demand is modelled with 5 different curves which are evenly assigned among all households (Figure 2). The heat consumption profiles are extracted from data available for United Kingdom [16]. Heat demand throughout the year is modelled with seasonal variations each with its 5 different heat demand profiles.

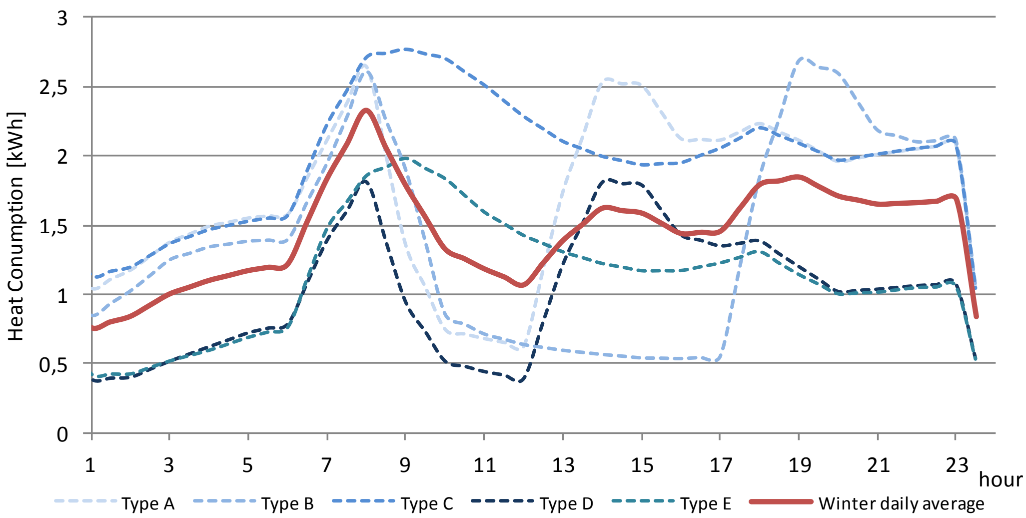

Figure 2. Daily heat consumption for different household types for a winter day

Heat demand of each household is modelled with following inequality:

$$H_d(t,i) \leq H_{chp}(t,i) + H_{ehp}(t,i) + H_{ab}(t,i) + H_{hs}(t,i) \tag{11}$$

To ensure the safe microgrid operation under all circumstances waste of heat is allowed:

$$H_{waste}(t) \leq \sum_{i=1}^{K} H_{chp}(t,i) + H_{ehp}(t,i) + H_{ab}(t,i) + H_{hs}(t,i) \tag{12}$$

3.5 Flexible electrical load

A simple model to represent demand side management is incorporated by defining a percentage of total electrical demand that can provide flexible response. Initially the percentage p_{flex} is set to be 15% of $E_d(t)$ at any give period:

$$-p_{flex} \cdot E_d(t) \leq E_{flex\_total}(t) \leq p_{flex} \cdot E_d(t) \tag{13}$$

$E_{flex}(t)$ is positive for load reduction and negative for load increase.

The information about the total amount of shiftable loads that are being rescheduled at every time step is modelled using flexible load maximum capacity:

$$-C_{flex\_\max}(t,i) \leq C_{flex}(t,i) \leq C_{flex\_\max}(t,i) \tag{14}$$

$$C_{flex}(t,i) \leq C_{flex}(t-1,i) - E_{flex}(t,i) \tag{15}$$

3.6 Renewable energy sources

Input data for RES modelling are measured hourly values over a one year period [17] depicted on Figure 3. The input data is standardized for 1 kW of installed wind or solar power.

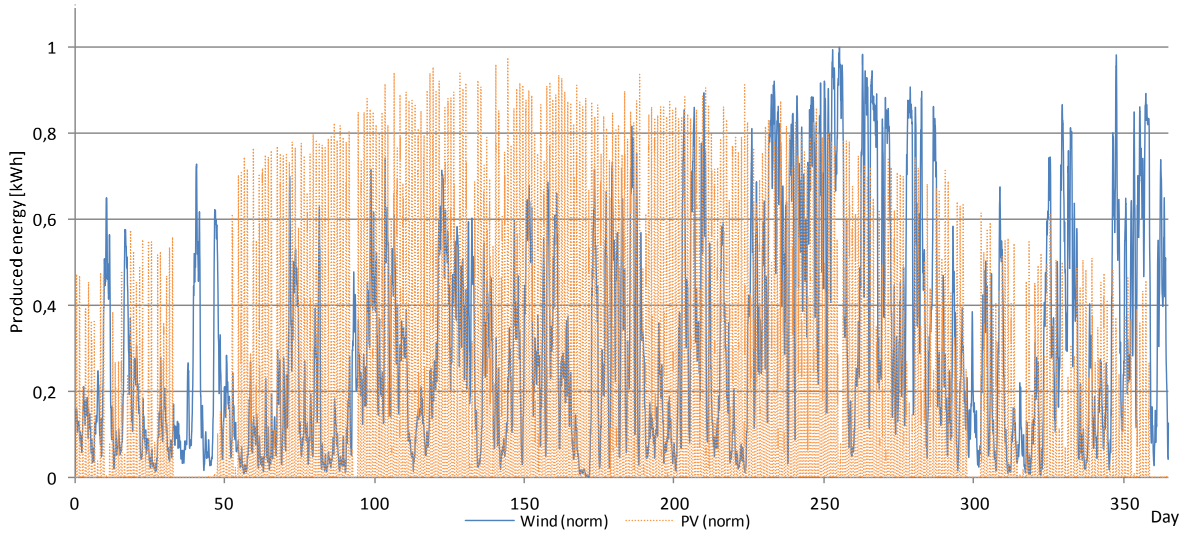

Figure 3. Standardized wind and solar production

One of the goals of deterministic model is to determine optimal installed values of wind turbines and PV and therefore their production is defined as deterministic input data ($E_{wind}(t), E_{PV}(t)$) that is standardized to 1 kW of installed power, multiplied with their installed capacity that is being optimized (X_{wind}, X_{PV}). The resulting number $E_{wind\_real}(t)$ is the actual production of PV and wind renewable energy sources measured in kWh that is obtained by multiplying the standardized to 1 kW input data of wind/PV production ($E_{wind}(t), E_{PV}(t)$) and the actual size of the installed RES capacity (X_{wind}, X_{PV}) that is being optimized. Results obtained from the optimization algorithm are optimally chosen values of installed renewable energy sources capacities.

$$E_{wind\_real}(t) = E_{wind}(t) \cdot X_{wind} \tag{16a}$$

$$E_{PV\_real}(t) = E_{PV}(t) \cdot X_{PV} \tag{16b}$$

The correlation between consumption and PV production is much better than one with wind production. The peak production of PV array occurs during the day when the consumption is higher. Therefore only wind curtailment is introduced:

$$E_{wind\_curt}(t) + E_{wind\_gen}(t) = E_{wind\_real}(t) \tag{17}$$

3.7 Electrical demand

Similarly to heat demand electrical demand is on a daily basis represented with 3 different load consumption profiles (winter, spring/autumn, summer) depicted on Figure 4.

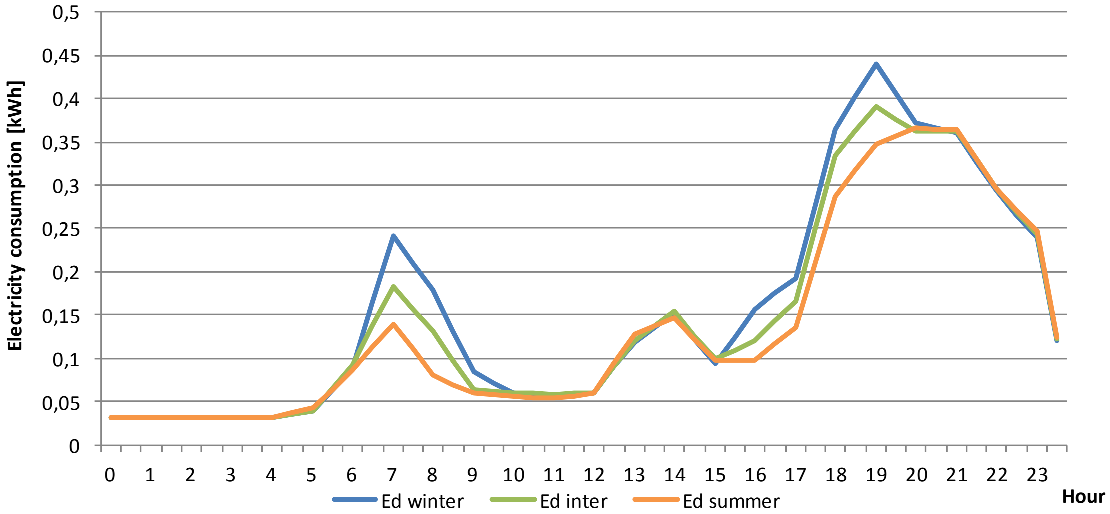

Figure 4. Electrical demand profile for 3 different seasons

Equilibrium between electricity production and consumption must be achieved at every time step:

$$E_d(t,i) + E_{\exp}(t) + \sum_{i=1}^{K} E_{ehp}(t,i) = E_{imp}(t) + E_{pv\_real}(t) + E_{wind\_gen}(t) + \sum_{i=1}^{K} E_{chp}(t,i) + \sum_{i=1}^{K} E_{flex}(t,i) \tag{18}$$

3.8 Cost function

Total fuel used is equal to fuel used by boiler and CHP units:

$$F(t) = fuel_{chp\_total}(t) + fuel_{ab\_total}(t) \tag{19}$$

Day ahead market prices and are taken from the ELEXON (EEX) [18]. The prices are therefore real prices of electricity in €/kWh that change every time step (half an hour). No price forecasting is done and prices are taken to be known for the observed period.

Minimization of total microgrid operation cost is the objective function of the optimization model:

$$COST = \sum_{t=1}^{T_{\max}} \left(\begin{array}{l} F(t) \cdot c_{ng}(t) + E_{imp}(t) \cdot c_{imp}(t) - E_{\exp}(t) \cdot c_{\exp}(t) \\ + P \cdot E_{wind\_curt}(t) + P \cdot H_{waste}(t) \end{array} \right) \tag{20}$$

Penalty factor P is used to highlight the importance of avoiding energy waste and losing potential wind production. Factor 300 was used in off-grid simulation of a deterministic model when optimal RES installed values were determined.

4. DETERMINISTIC MODEL RESULTS

The deterministic model described in the preceding section is run for $i_{\max} = 17520$ steps representing half an hour periods during one year time. All parameters are shown in the following table (Table 4).

Table 4. Simulation parameters initial values

Parameter	Unit	Value
Simulation time $T_{\max}$	[hour]	8760
Simulation time step duration τ	[hour]	0,5
Number of households K	--	300
Penalty factor for unused energy P	--	300
Natural gas price c_{ng}	[€/kWh]	0,025
Export electricity price $c_{\exp}(t)$ [18]	[€/kWh]	Varies every time step
Import electricity price $c_{imp}(t)$ [18]	[€/kWh]	Varies every time step
Household heat storage capacity $C_{hs\_\max}$	[kWh$_t$]	6
Flexible load share p_{flex}	[%]	15
Maximum flex load capacity $C_{flex\_\max}$	[kWh]	50
Electric efficiency of μCHP unit η_{chp_e}	--	0,38
Thermal efficiency of μCHP unit η_{chp_t}	--	0,55
Maximum thermal output of CHP unit $H_{chp\_\max}$	[kWh$_t$]	8
Maximum thermal output of EHP unit $H_{ehp\_\max}$	[kWh$_t$]	10
Share of households with CHP based heating	[%]	45
Share of households with EHP based heating	[%]	45
Share of households with only boiler based heating	[%]	10
Coefficient of performance of EHP unit $COP(t)$	--	3,5 summer 3 inter 2,5 winter
Maximum thermal output of a boiler unit $H_{ab\_\max}$	[kWh$_t$]	10
Boiler efficiency η_{ab}	--	0,85
Maximum heat storage capacity $C_{hs\_\max}$	[kWh$_t$]	6
Heat storage efficiency η_{hs}	--	0,98
Heat storage discharge/charge rate per time step $E_{hs\_\max}$	[kWh$_t$]	$C_{hs\_\max} \cdot \tau$

Off-grid operation is simulated where $E_{imp}(t), E_{\exp}(t)$ are equal to 0.

Optimal values of installed wind and solar power were calculated:

- $X_{wind\_opt} = 65$ and $X_{PV\_opt} = 113$.

Therefore the optimal installed capacity of wind is 65 kW and PV is 113 kW. These results are obtained in the deterministic environment.

These calculated values are later used as input parameters (reference) in MPC model where uncertainty is introduced.

As described before high penalty factor P, in the objective function for waste energy, achieves that only 0,31% (12.989 kWh) of total energy spent has to be spilt (Figure 5). Heat waste occurs in off-grid mode when there is not enough electrical energy (EE) production to cover the demand (little to no wind or sun); in those cases μCHP units have to produce more and consequently increase heat production which is not needed and cannot be stored in HS.

Additionally, similar case happens when there is a surplus of electrical energy (high wind and sun generation) so optimization algorithm increases EHP heat production to balance the microgrid. Wind is curtailed in periods when there is a surplus of EE and there is no option of it being indirectly stored (indirectly in HS).

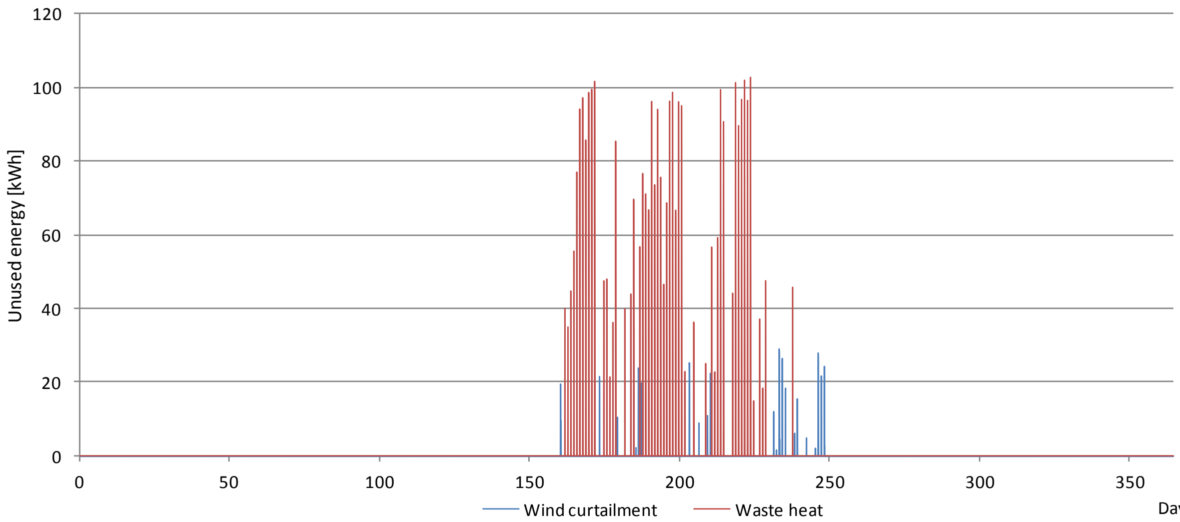

Figure 5.Curtailed wind energy and surplus of produced heat energy

Sensitivity analysis of the change in installed wind and solar capacity was performed in order to show how non optimal values increase the total amount of curtailed wind and surplus of heat energy (Figure 6). While one parameter was being changed the other was set at the optimal value.

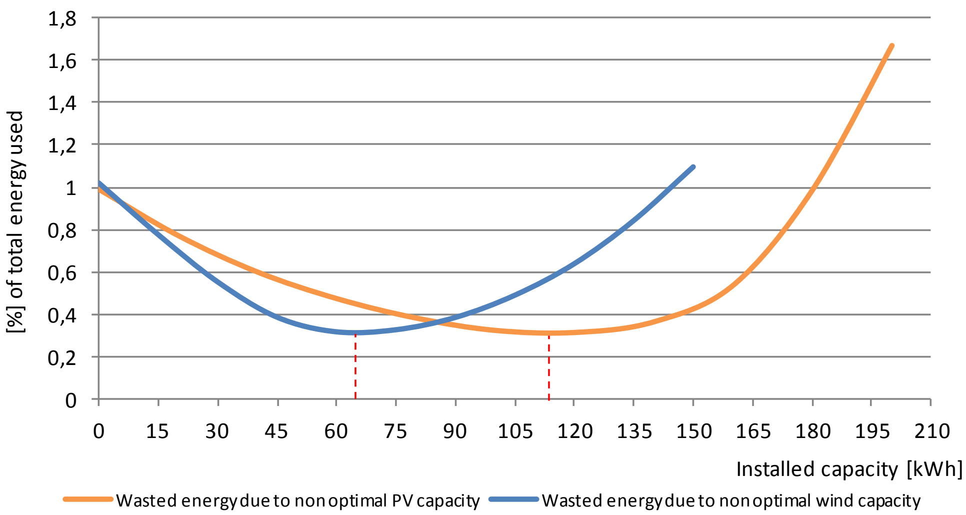

Figure 6.Connection between installed RES capacity and unused energy

The possibility of storing heat energy is one of the elements that provide flexibility in grid operation. With large enough storage units μCHP units do not have to follow the demand exactly. Furthermore, larger storage capacity can compensate for the non optimally dimensioned microgrid elements like installed power of RES. The results of the sensitivity analysis depicted on Figure 7. shows dependency of storage size and total unused energy from RES. Installing a storage unit of 12 kWh_t (6 kWh_t is initial storage size) in every household can reduce total unused energy below 0,31% margin for 50% more RES that calculated as the optimal values.

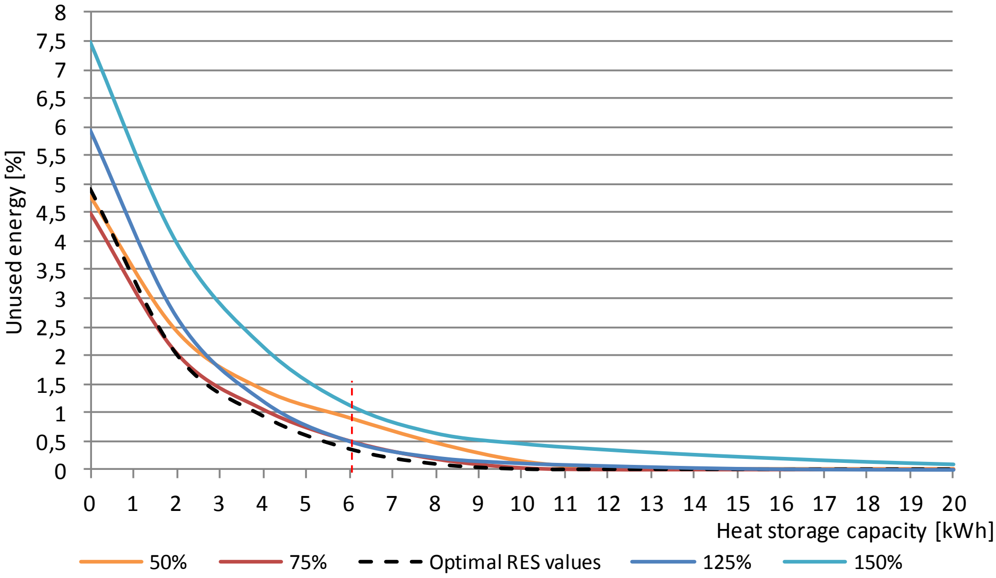

Figure 7.Connection between HS capacity and unused energy

Similar analysis was conducted for flexible load share. Reference is the simulation with optimal values (Figure 8).

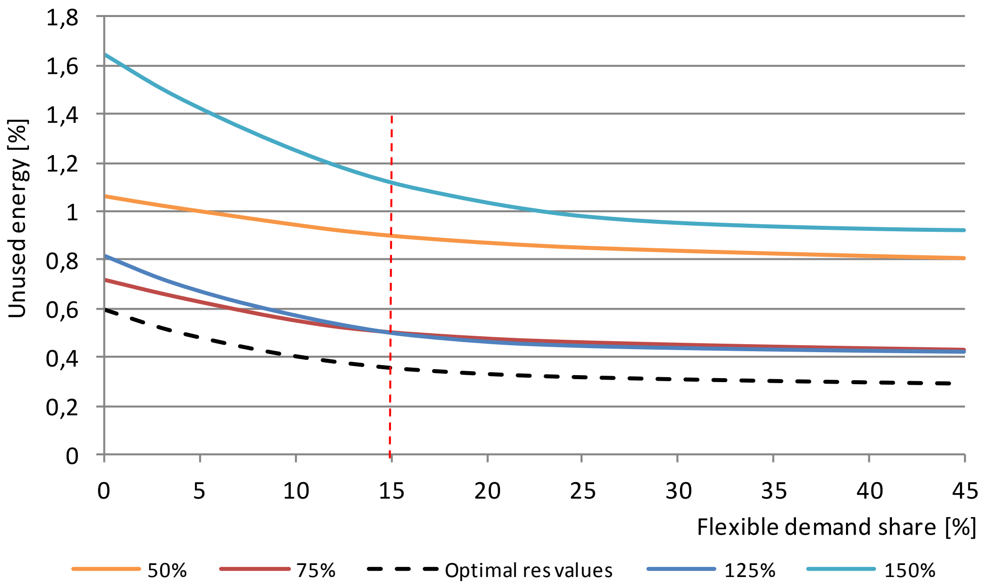

Figure 8.Connection between flexible demand share and unused energy

Flexible demand has smaller influence on the unused energy compared to heat storage capacity. The differences in unused energy for different FL shares are not stressed and curves get to the saturation point quickly.

Interesting information is provided by the analysis conducted to determine what impact different ratios of heating types (μCHP/EHP) has on the amount of unused energy. μCHP and EHP units complement each other in operation as seen in the wasted energy analysis, and together can provide a certain amount of flexibility. Results (Figure 9.) show that the least value of unused energy is achieved if 60% of households have μCHP and 40% EHP based heating. Boiler based household heating type share is set to 0 during this sensitivity analysis meaning each household has either EHP or μCHP installed.

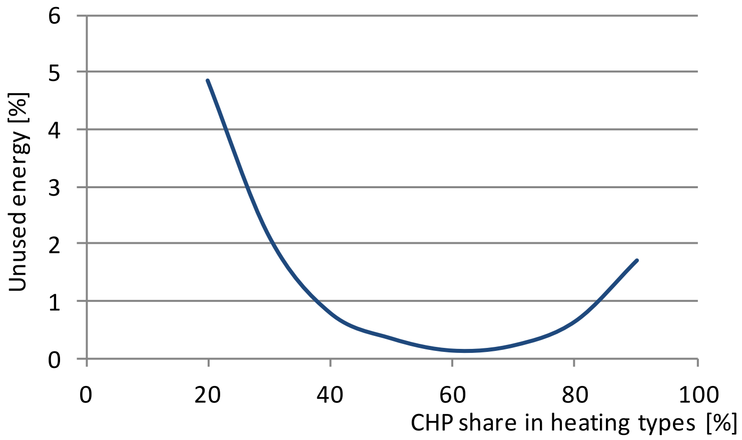

Figure 9. Impact of CHP share in heating types on unused energy

For a μCHP share of 10% in the off-grid mode the units have to be pushed to operate at their maximum point in order to produce enough EE and this results in a lot of wasted heat. As the share moves beyond 60% there is not enough EHP electrical demand to balance periods of high RES generation and energy is wasted again.

4.1 On-grid simulation

The results have shown that the modelled microgrid can operate independently with very little unused energy. In case there is a connection with the rest of the distribution system the microgrid can exchange electrical energy with the system and its operation is driven by market signals. Results of an on-grid operation are shown in Table 5.

Table 5. On-grid and off-grid operation comparison

Microgrid operation indicator	**Off-grid** $P = 300$	**Off-grid** $P = 1$	**On-grid** $\forall P$ **
Total energy produced [kWh]	4.190.934	4.192.833	4.177.944
Total EE used [kWh_e]	764.926	764.926	764.926
Total heat used [kWh_t]	3.559.675	3.559.675	3.413.018
Wind curtailment [kWh]	1.301	1.333	0,00
Wasted heat [kWh]	11.689	13.557	0,00
Imported EE [kWh]	0,00	0,00	266.934
Exported EE [kWh]	0,00	0,00	547.112
Unused energy [%]*	**0,31**	**0,36**	**0,00**
Boiler production [kWh]	**453.621**	**453.697**	**87.756**
Boiler fuel cost [€]	**13.341**	**13.344**	**2.581**
TOTAL COST [€]	**99.320**	**99.625**	**68.477**

** Percentage of total energy used*
***Value of penalty factor P has no effect on on-grid operation mode.*

In case when the microgrid operates connected to the rest of the system there is no unused energy. Additionally the boilers are forced to produce much less heat compared to off-grid mode where they are used to balance the heat production and demand. Consequently amount of fuel and the operational cost in boilers is reduced drastically.

The operational cost results presented in Table 5 do not take emissions into account. Additionally, investment costs could be introduced to get more precise information about the profitability of installing different microgrid units (battery storage, heat storage, RES, greater flexible load share, plug-in electric vehicles integration etc.). These expansions are a part of future work.

5. THE ROLLING UNIT COMMITMENT MODEL INCORPORATING MPC

If a microgrid operates connected to the rest of the system, it participates in the energy market and its operation will be driven by market signals. In order to simulate dynamic behaviour of a microgrid the paper observes the microgrid as a single market entity/player. As such it has to ensure self balancing and comply with the contracted exchange schedule at the day ahead market. To be able to do that it has to consider forecasting errors and be able to reschedule, changing the operating points of flexible units as new information on uncertainty parameters becomes available. For this reason the extension of previously described deterministic model is made. The main goal was to investigate in what amount forecast uncertainties impact the microgrid operation and is the microgrid flexible enough to compensate the stochastic nature of RES installed. It is expected and desired that microgrid has at least neutral impact on grid (respecting proposed export/import schedules). All production and consumption variations should be balanced internally with controllable microgrid elements that can provide flexibility.

5.1 Model Predictive Control (MPC) framework

The results of a deterministic model have shown that the modelled microgrid can operate independently with very little unused energy in deterministic environment. In case there is a connection with the rest of the distribution system the microgrid can exchange electrical energy and energy waste is avoided. This interaction is even more important in stochastic environment where the need for balancing energy grows due to forecast errors.

The MILP unit commitment control algorithm employs MPC to minimize the impact of forecast errors. MPC is a control method which is used for discrete control; during one simulation step control signals do not change. The MPC concept and developed unit commitment algorithms flowchart are depicted on Figure 10.

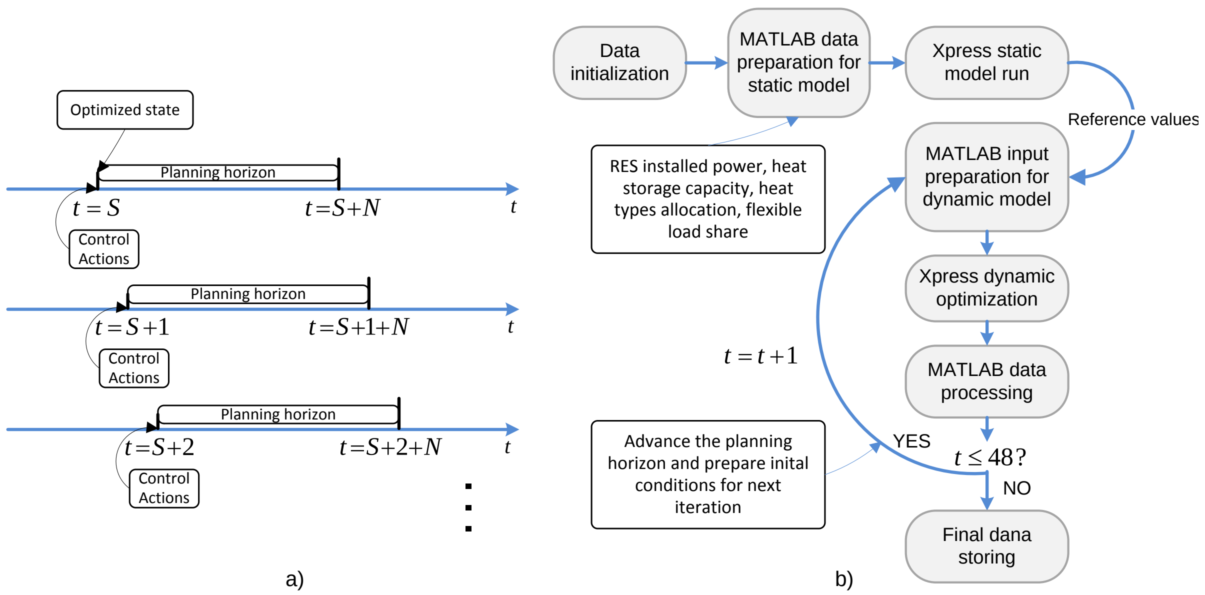

Figure 10. a) MPC rolling horizon concept b) Flowchart of the MPC optimization model

At every time step t the algorithm estimates the next N system states and reaches an optimal desired state. Control actions are applied and the state stays unchanged until the start of a new iteration. At the start of next time step $t+1$ again N system states are estimated based on new forecasts that include realized input data for preceding iteration. In the developed model the horizon is 24 hours because the microgrid participates in is day-ahead market. $S \in [1, 48]$ represents the current time period of the ongoing day. During one day, 48 half an hour time steps are simulated and in each, according to planning horizon, optimal state is specified. The solution to the optimization problem determines the power levels throughout the whole planning horizon considering the forecast uncertainty.

5.2 MPC model formulation

When introducing a stochastic element to the model, a range of error is defined for each forecasted data series. The bases for this were predictions from the deterministic model that were modified by random number generator of normal distribution with standard deviation linearly increasing with the distance from current time step. That way maximum error occurs at the end of planning horizon (24 hours ahead). Additionally, for PV production 10% possibility to lose 90% of current power was added. Figure 11 shows how the forecast error increases towards the end of planning horizon. Figure 12. depicts RES production for a single day.

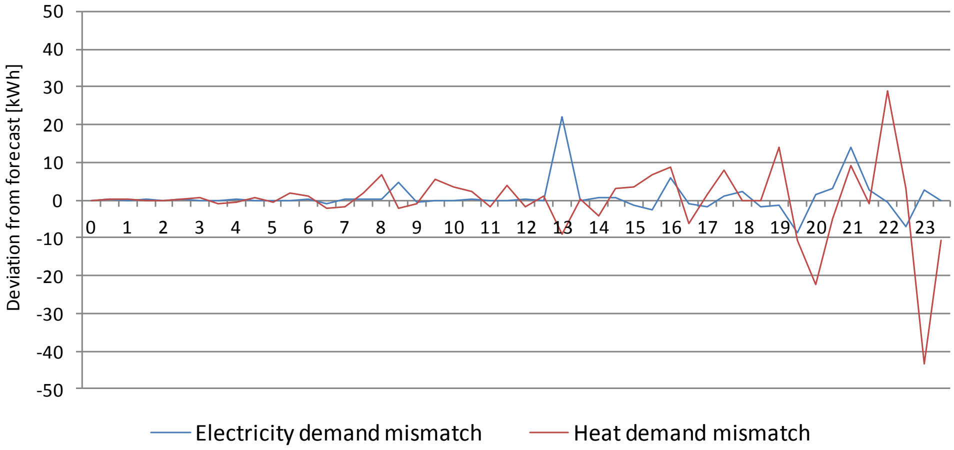

Figure 11. Mismatch between realized and forecasted heat and electricity production

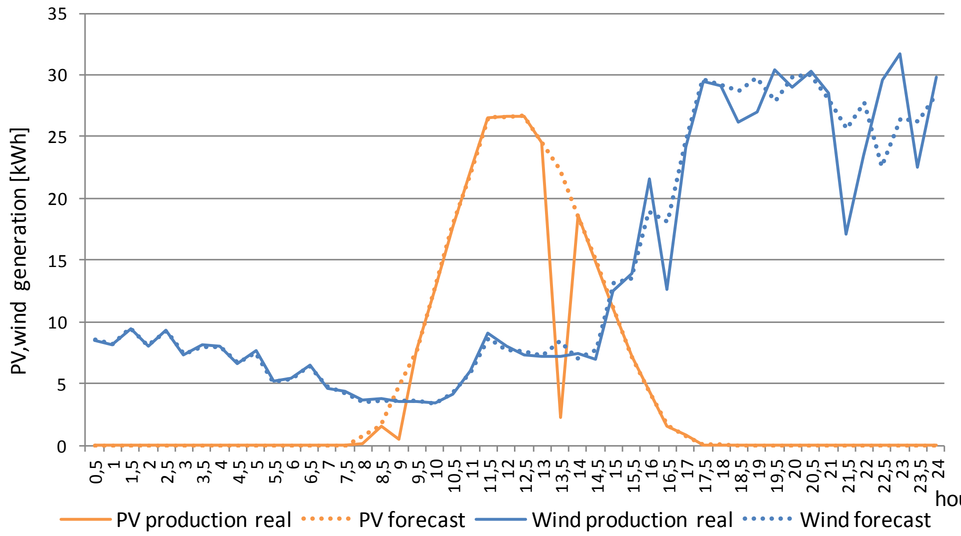

Figure 12. Forecasted and realized RES production for first planning horizon ($S=0$)

Proposed microgrid operation is modelled in the following way:

1. Controller collects forecast data ($E_d, H_d, E_{pv}, E_{wind}$) and estimates optimal microgrid operation. The planned import/export schedule is then sent to the distribution system operator (DSO);
2. In the first hour of the day controller acquires updated forecasts (for planning horizon) and accordingly deploys rolling unit commitment MPC model and adjusts control variables (operational set points of flexible units) to minimize operational cost. The mismatch from initially contracted exchange with the system is penalized;
3. In the next hour (next iteration) optimization is run again with updated forecast and planning horizon is shifted forward;
4. Step 2 and step 3 are repeated until the end of the day.

Additional cost, coming from the forecast error, can be divided in two main components: (i) mismatch compensation for not following the announced and contracted import/export schedule with the market; (ii) fuel cost increase (e.g. more frequent boiler use). Total cost function is updated as the rolling horizon moves to the end of the day, making adjustments and taking into account the mismatch compensation for the realized periods and estimating costs from current hour till the end of the day (Equation 21). The final operational cost at the end of the day is calculated based on actual, adjusted operating points. Therefore objective function being minimized is:

$$COST = \sum_{t=1}^{24\cdot\tau^{-1}-S} \left[F(t)\cdot c_{ng} + E_{imp0}(t)\cdot c_{imp}(t) - E_{\exp 0}\cdot c_{\exp}(t) + P\cdot E_{wind\_curt}(t) + P\cdot H_{waste}(t) \right] + \dots$$

$$\dots + \begin{bmatrix} (-)short_{imp}(t)\cdot(1-\mathrm{M})\cdot c_{\exp}(t) + long_{imp}(t)\cdot(1+M)\cdot c_{imp}(t) + \\ short_{\exp}(t)\cdot(1+\mathrm{M})\cdot c_{imp}(t) - long_{\exp}(t)\cdot(1-\mathrm{M})\cdot c_{\exp}(t) \end{bmatrix} + \dots$$

$$\dots + \sum_{t=24\cdot\tau^{-1}+1-S}^{24\cdot\tau^{-1}} \left[F(t)\cdot c_{ng} + E_{imp}(t)\cdot c_{imp}(t) - E_{\exp}\cdot c_{\exp}(t) + P\cdot E_{wind\_curt}(t) + P\cdot H_{waste}(t) \right] \tag{21}$$

S marks how many iterations have passed from the start of the day, $E_{imp0}, E_{\exp 0}$ mark scheduled import/export of EE. Variable $short_{imp}$ is defined for negative mismatch in import, $short_{\exp}$ for negative mismatch in export, $long_{imp}$ for positive mismatch in import and $long_{\exp}$ for positive mismatch in export. The planned exchange is based on day ahead market prices $c_{imp}, c_{\exp}$. Differences resulting from microgrids incapability to balance the uncertainty and variability of RES are penalized by a percentage M reducing price for both import and export. Penalty percentage M used in the simulations is 25%. For the simplicity of later sensitivity analysis the same percentage was used to modify the used prices.

5.3 Results of the model incorporating MPC

Total operating cost from the deterministic model is the reference value. MPC model achieves only 2% worse result (Figure 13.). Compared to the per-hour management where analysis is based solely on the state in the current hour and decisions are made not considering the future planning horizon MPC achieves 7% better results. To elaborate; if there was no microgrid controller capable of adjusting the operation of flexible units, the microgrid acts as a variable source from the system perspective. Incapable of communicating intra-day exchange with the system it constantly, throughout the day, creates an imbalance and practically acts as an uncontrollable market entity, very similar to RES units.

On secondary axis increase in total costs compared to the reference deterministic model is shown. Cumulatively costs with in case no MPC is used are increased 8%.

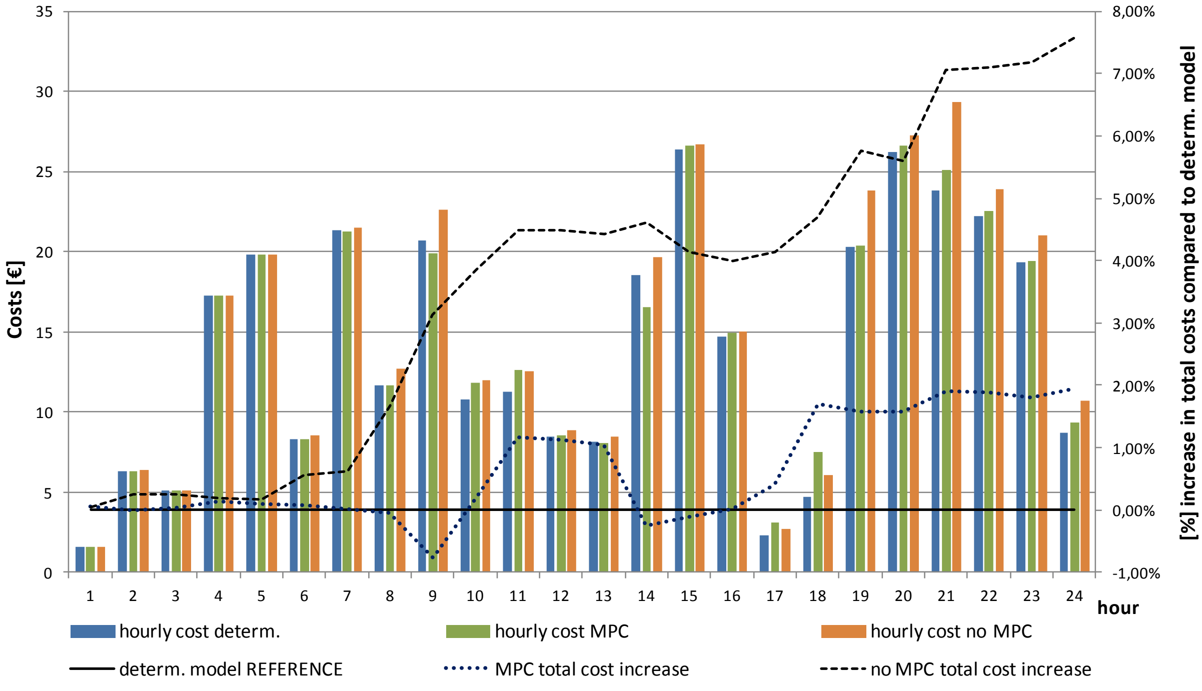

Figure 13. μCHP unit dispatch in the MPC model with and without heat storage

In case no MPC is implemented boiler unit needs to be used much more frequently to balance the heat demand (Figure 14.). It is important to note that MPC model also uses high penalty factor to inhibit the waste of energy.

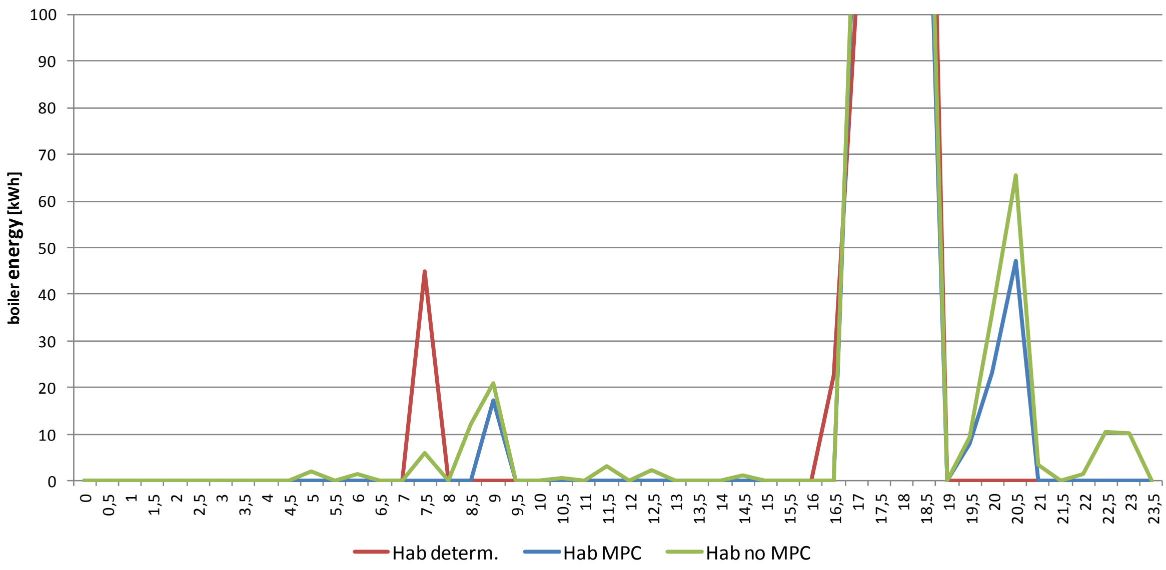

Figure 14. Boiler unit operation

To investigate if microgrid is capable to totally neutralize the RES forecast error penalty factor M was changed. The amounts of imported and exported energy were observed (Figure 15.) and their difference from planned values. The optimization problem was run 50 times for every value of M and averaged import and export values were taken.

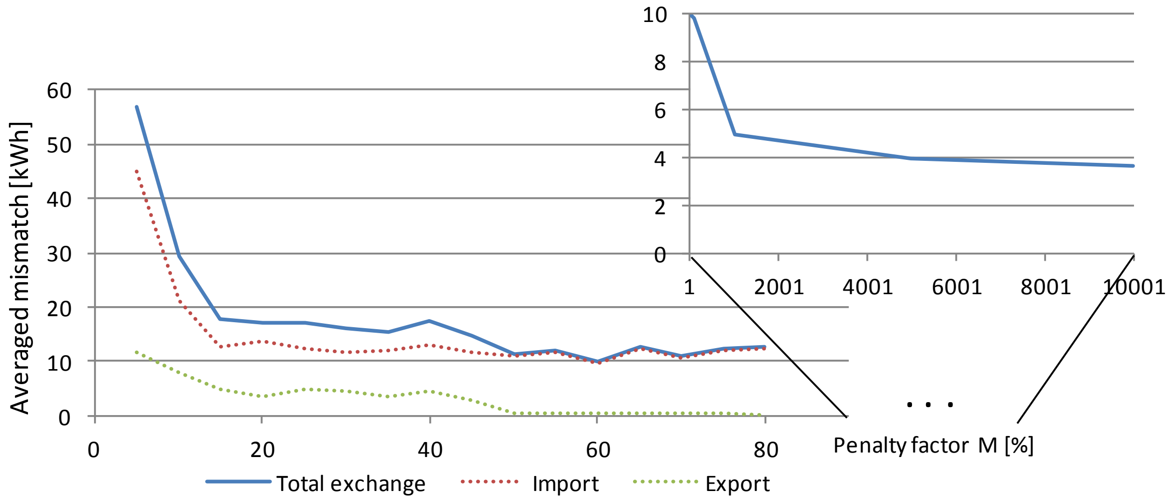

Figure 15. µCHP unit dispatch in the MPC model with and without heat storage

Already a small penalty factor reduces the amount of not planned exchange energy. Furthermore, imported part is smaller and can be reduced to 0 which means microgrid can more easily compensate surplus of energy produced by its components. Exported amount saturated around 10 kWh value which represents only 0,4% of daily used energy. Even with drastically increased penalty factors that totally inhibit the exchange of energy microgrid could not achieve perfect error compensation.

6. CONCLUSION AND FUTURE WORK

A novel concept based on MILP for modelling and optimization of microgrid operation has been presented. Deterministic model was developed to investigate what impact different units have on microgrids ability to operate in the off grid mode. It was shown that defining optimal sizes of installed wind and PV in a microgrid means very little of energy has to be wasted. Additionally, it was shown that capacity of heat storages and ratio of CHP to EHP units will units has bigger impact than flexible loads on the amount of wasted heat and curtailed wind.

To potentially compensate inevitable disturbances and forecast errors, model predictive control with rolling horizon was developed simulating market driven behaviour of system connected microgrid. The MPC strategy achieves better results (lower costs) than simple deterministic day ahead unit commitment strategy. It was shown that, with implemented MPC strategy, microgrid can almost totally balance the RES uncertainty by intraday adjustment of operational set points of flexible units.

Further work will focus on how a microgrid can achieve complete independence from distribution grid under stochastic framework. As it can be concluded from the work presented including battery storage systems seems to a valuable source of flexibility in off grid operation. However it should be taken into account that economics behind installing them only for energy arbitrage will not be sufficient to justify them. In term, more detailed model capable of addressing frequency flexibility is needed. Adding emissions and emissions cost to the model will also be one of the goals with a goal of defining decarbonisation potential of the microgrids.

ACKNOWLEDGMENT

This work has been supported by the European Community Seventh Framework Programme under grant No. 285939 (ACROSS).

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