Optimal Cooperative Scheduling of Multi-Energy Microgrids Under Uncertainty

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***Abstract*—With the restructuring of the power system, household level end-users are becoming active participants in the electricity market. Since their size is negligible versus the size of the whole system, they are encouraged to group into energy communities such as microgrids (MG). They operate parallel to the rest of the system and their operation is driven by market signals with the goal of minimizing energy costs for MG stakeholders by utilizing available resources in their portfolio. The complexity of optimizing MG operation increases with the introduction of additional energy vectors and their interaction with the electricity sector, but also with the possibility to provide services on multiple markets and on different time horizons. In the paper we consider different decarbonization strategies of several MGs, modelling 3 main cases: full electrification, gas-heat-electricity and electricity-hydrogen coupling. While each of these options can separately achieve savings, cooperation between different MGs can bring additional benefits for all involved parties. To evaluate these benefits we propose a stochastic two-stage mixed integer linear model for multi MG cooperation and bring the conclusions on the value of their joint market participation through several exchange scenarios. This is expressed through operational costs savings on annual and daily basis as well as through other metrics such as self sufficiency and CO2 savings.**

***Index Terms*—microgrid, stochastic optimization, cooperation, multi-energy**

NOMENCLATURE

Indices and Variables

Ψ, ψ	Set and index for scenarios
M, m	Set and index for microgrids
T, t	Set and index for hours
$b_{\psi,m,t}$	Boiler input power in scenario ψ, MG m and time t
$p_{\psi,m,t}$	PtH input power in scenario ψ, MG m and time t
$c_{\psi,m,t}$	CHP input power in scenario ψ, MG m and time t
$h_{\psi,m,t}$	FC input power in scenario ψ, MG m and time t
$\nu_{\psi,m,t}$	HP input power in scenario ψ, MG m and time t
$r_{\psi,m,t}$	Room temperature in scenario ψ, MG m and time t
$\Delta r_{\psi,m,t}$	Room temperature deviation in scenario ψ, MG m and time t
$f_{\psi,m,t}$	Floor temperature in scenario ψ, MG m and time t
$w_{\psi,m,t}$	Water temperature in scenario ψ, MG m and time t
$d_{\psi,m,t}$	Heat demand in scenario ψ, MG m and time t
$\overline{\alpha}_{\psi,m,t}$	Input power of heat storage in scenario ψ, MG m and time t
$\underline{\alpha}_{\psi,m,t}$	Output power of heat storage in scenario ψ, MG m and time t
$\overline{\beta}_{\psi,m,t}$	Input power of battery storage in scenario ψ, MG m and time t
$\underline{\beta}_{\psi,m,t}$	Output power of battery storage in scenario ψ, MG m and time t
$\overline{\gamma}_{\psi,m,t}$	Input power of hydrogen storage in scenario ψ, MG m and time t
$\underline{\gamma}_{\psi,m,t}$	Output power of hydrogen storage in scenario ψ, MG m and time t
ω_m	Volume of gas bought from day-ahead market in MG m
$\overline{\epsilon}_{m,t}$	Volume of electricity bought from day-ahead market in MG m and time t
$\underline{\epsilon}_{m,t}$	Volume of electricity sold to day-ahead market in MG m and time t
$\overline{\rho}_{\psi,m,t}$	Volume of electricity bought from local MG market in scenario ψ, MG m and time t
$\underline{\rho}_{\psi,m,t}$	Volume of electricity sold to local MG market in scenario ψ, MG m and time t

Parameters

η^{b}	Efficiency coefficient for boiler
η^{p}	Efficiency coefficient for PtH
$\eta^{c,el}$	Efficiency coefficient for CHP electricity output
$\eta^{c,heat}$	Efficiency coefficient for CHP heat output
$\eta^{h,el}$	Efficiency coefficient for FC electricity output
$\eta^{h,heat}$	Efficiency coefficient for FC heat output
COP	Coefficient of performance for HP
$A_{m,t}$	Ambient temperature of MG m and time t
R^{max}	Room temperature upper bound
R^{min}	Room temperature lower bound
W^{max}	Water temperature upper bound
N_m	Number of household in MG m
$L_{\psi,m,t}$	Household load in scenario ψ, MG m and time t
$PV_{\psi,m,t}$	PV production in scenario ψ, MG m and time t
$\pi_{\psi,m,t}$	Price of electricity in scenario ψ, MG m and time t
G	Gas price
λ_ψ	Probability of scenario ψ
μ	Penalty for temperature deviation
τ	Transmission system cost
γ	Distribution system cost

I. INTRODUCTION

A. Motivation and Background

Renewable energy sources (RES) connected to low or medium voltage distribution grid are taking the lead in decarbonization of the power systems and, by coordinating their operation with local controllable assets, unlocks new flexibility options on the side of end-users [1]. This can be further increased when energy vectors, such as electricity, gas and hydrogen, are coupled and operate in an integrated way. In general, multi energy systems (MESs) incorporate different energy vectors so that they function together and complement each other through shifting and virtually storing energy in different energy forms [2]. MES flexibility can be exercised through demand response (DR), battery energy storage systems (BESSs), combined heat and power unit (CHP), heat pumps (HP), power-to-hydrogen (P2H), and can have the scale of local end-users [3], district level clustered options such as MGs [4], virtual power plants [5] or energy communities at the city or national scale.

Microgrid is a cluster of distributed energy sources, energy storage systems, and controllable and uncontrollable loads, presented as a single entity towards the grid. They can operate parallel to the grid, but can also function autonomously in island mode [6]. The goal of the MG operation is to provide the most benefits to its stakeholders through security of supply, better resource management and lower operation cost. The rule of thumb says that the more flexibility the MG possess the better it will be in achieving previously mentioned goals. Ideally MG would have a device suitable for any occasion that appears on the market and incorporates a wide variety of different energy vectors. Realistically, devices are chosen based on their investment costs, rate of return, MG operator or stakeholders preferences, etc. In other words MG will contain a set of devices, e.g. photovoltaic system (PV), BSS and HP. This example might be sensitive to electricity prices or BSS capacity during low PV production periods (e.g in winter months). Collaboration of that MG with other MGs which have alternative ways of producing electricity (e.g. CHP plant) could be beneficial. A group of such MGs cooperating together can greatly increase their overall flexibility and reduce sensitivity on market changes and unfavourable periods. The general concept of MES MG cooperation is shown in fig. 1 where three MGs cooperate together on local MG market and also jointly participate in a global power exchange. Square shapes represent energy conversion devices and tank shapes present storage units, while flow of energy is defined with colored lines: blue for electricity, orange for gas, yellow for heat, grey for hydrogen and red for local MG market. The developed MES MG operational model considers the uncertainty in RES production, MG consumption and electricity prices. Imperfections in predictions of production and consumption can lead to mismatch of import/export of electricity which may lead to penalties. Electricity price predictions are used for positioning MG on electricity day-ahead market. Cooperation of different MGs will thus lead to a reduction in the risk of uncertainty. For real-world operational and market implementations the modelling aspect would be adjusted to capture realistic aspects of critical information privacy and/or different entity ownerships. The following Section provides a systematic literature review and detects gaps in the current research body. It ends with a proposal of contributions that address the identified issues.

B. Relevant Literature

Cooperation of multiple different MGs in an uncertain environment (electricity market, RES production and energy consumption) has been a topic of interest, however there are still gaps in the literature, especially in terms of MES MGs and interaction of different energy vectors. Reference [7] proposes a chance-constrained optimization model of MG cluster. Four different trading models are presented for 16 MGs with same architecture but varying in size. Uncertainty parameters considered are electricity prices and PV production. A case of multi MG coordination is shown in [8] with multiple objectives of cost minimization and independence from grid maximization. It incorporates RES production as a stochastic parameter, but does not incorporate other energy vectors besides electricity. Free energy trading multi MG approach, where every MG achieves same percentage of cost savings is presented in [9]. MGs are only considered to have electricity production from PV and wind to achieve 100% renewable production. The model is created as a hybrid version of IGDT (Info-gap decision theory) and stochastic programming with RES production as stochastic parameter. In [10] the authors present a local competitive peer-to-peer market for energy trading (electricity, heat, cooling) of multi-carrier energy hubs. Each energy hub separately optimize its day-ahead schedule and then they compete on the local energy market. In the day-ahead scheduling, energy hubs consider uncertainty in price, generation and demand. A different approach is used in [11] where multi-energy retailer competes in various energy markets with the goal of selling energy bilaterally to consumers. This approach transfers market risk from consumer to the retailer. The retailer uses a hybrid robust-stochastic approach for dealing with electricity price and consumption uncertainty. Lyapunov optimization approach for energy trading of multi-energy MGs is presented in [12]. Energy trading is designed as double-auction mechanism where MG submits purchase/selling prices and volumes to external auctioneer, who then by trading rules decide the accepted prices and allocates energy to MGs.

Multi-energy systems are fairly researched area through different concepts and model, from methods for sizing and resource planing of MES [13] to energy management and flexibility potential [14]. Reference [15] provides detailed overview of MES concepts from various perspectives and with different evaluation methods. Techno-economic analysis on flexibility of MES considering investment cost and environmental benefits is presented in [16]. Framework and benefits of MES as an ancillary service provider are explored in [17]. Numerous other paper deal with optimal unit sizing and energy management of MG [18], [19] or dynamics of MG [20].

C. Contributions and Organization

Most of the literature consider very similar MGs in their research thus failing to show importance of different energy vectors. Also, they fail to emphasise benefits of MG cooperation in risk reduction from uncertainty. Thus the contributions proposed in this paper are summarised as follows:

- Define the benefits of multiple multi-energy microgrids cooperation based on optimization of joint market participation as compared to the individual case. The model will incorporate mutual trading under local price signals but also will discuss benefits of mutual energy exchange with no charges.
- The paper develops a two-stage stochastic mixed integer linear optimization model for day-ahead and real-time scheduling of multiple microgrids where the interplay of different multi-energy microgrids is enabled and compared to individual market performance.

Rest of the paper is organized as follows: Model formulation is presented in section II; case study description in section III; results are presented in section IV; and section V concludes the paper.

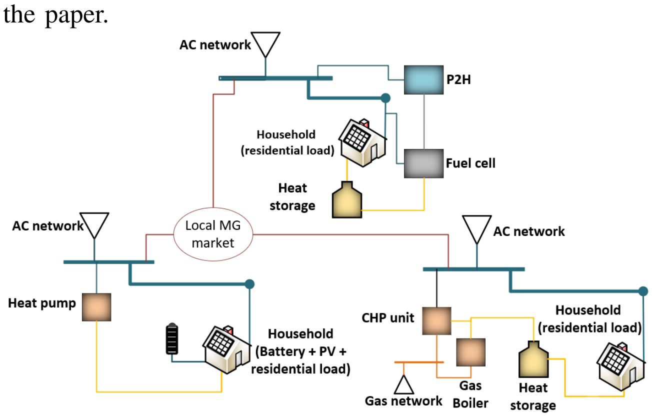

Fig. 1. Layout of proposed multi-energy MGs

II. Model Formulation

In this chapter the proposed model for multi MG cooperation will be explained. It is cast as a two-stage stochastic mixed integer linear model. Uncertainty in stochastic optimization is presented through scenarios (ψ) and their probability of occurrence (λ_{ψ}). The optimization is done in two stages. In the first stage a decision must be made before the realization of uncertainty and in the second stage we optimize MGs behaviour after the realization of uncertainty but considering first stage decisions. Each stage has its own set of variables. All equations are valid for each scenario, MG and hour unless stated otherwise.

A. Mathematical model

The goal of the optimization is to reduce the expected operational costs considering uncertainty scenarios. The objective function is shown in (1) as a weighted (λ_{ψ}) sum of electricity and gas bought/sold from/to the day ahead market, energy exchanged between MGs, CHP and boiler start up cost and penalty for temperature deviation.

$$\sum_{j=1}^{\Psi}\sum_{i=1}^{T}(\overline{\epsilon}_{m,i}\cdot(\pi_{j,m,i}+\tau+\gamma)\cdot\lambda_j-\underline{\epsilon}_{m,i}\cdot\pi_{j,m,i}\cdot\lambda_j$$
$$+\overline{\rho}_{j,m,i}\cdot(\pi_{j,m,i}+\gamma)\cdot\lambda_j-\underline{\rho}_{j,m,i}\cdot\pi_{j,m,i}\cdot\lambda_j$$
$$+\Delta r_{j,m,i}\cdot\mu\cdot\lambda_j+Start_{j,m,i}\cdot\lambda_j)+\omega_m\cdot \tag{1}$$

Each MG contains a specific set of devices which is defined prior to the optimisation. If the device is present in the current MG the belonging constrains and variables are included in the specific MG model. Most of the devices are constrained with the minimum and maximum input power as shown in (2), including: heat pump (HP), combined heat and power unit (CHP), boiler, power to hydrogen unit (PtH) and fuell cell (FC). In (2) "var" represents a continuous variable of production/consumption for a specific device and "Xvar" represents a binary variable which indicates if the device is online. The boiler and the CHP are modelled with the start up cost, so they need extra binary variables and constrains (3), which set binary variable to "1" if the device is started. The relation between device's input and output depends on a device. Output of devices such as boiler and PtH is reduced depending on its efficiency as shown in (4) and (5). Superscript "O" denotes output variable. Please note that these output variables are virtual i.e. they are not used in optimisation, instead corresponding expressions (4)-(8) are used to reduce the number of variables. CHP and FC have two different outputs: electricity and heat. Their outputs are calculated using electrical and heat efficiency as shown in (6) and (7). HP uses coefficient of performance to calculate output power shown in (8).

$$min\cdot Xvar_{\psi,m,t}\leq var_{\psi,m,t}\leq max\cdot Xvar_{\psi,m,t} \tag{2}$$
$$Xvar_{\psi,m,t}-Xvar_{\psi,m,t-1}\leq start_{\psi,m,t} \tag{3}$$
$$b^{O}_{\psi,m,t}=\eta^{b}\cdot b_{\psi,m,t} \tag{4}$$
$$p^{O}_{\psi,m,t}=\eta^{p}\cdot p_{\psi,m,t} \tag{5}$$
$$c^{O,el}_{\psi,m,t}=\eta^{c,el}\cdot c_{\psi,m,t},\ c^{O,heat}_{\psi,m,t}=\eta^{c,heat}\cdot c_{\psi,m,t} \tag{6}$$
$$h^{O,el}_{\psi,m,t}=\eta^{h,el}\cdot h_{\psi,m,t},\ h^{O,heat}_{\psi,m,t}=\eta^{h,heat}\cdot h_{\psi,m,t} \tag{7}$$
$$\nu^{O}_{\psi,m,t}=COP\cdot\nu_{\psi,m,t} \tag{8}$$

We model different types of storage by following the same logic where all are modeled in the same way. There are three types of storage that MGs can have: battery storage system, heat storage and hydrogen storage. Each storage has to keep track of the amount of energy stored (SOE) shown in (9). Variables "in" and "out" correspond to input and output amounts to the storage and "η^{in}" and "η^{out}" are efficiencies. Variables that are used for input and output amounts, as well as for state of storage use equation (2) to constrain their bounds, with the exception that the state of storage does not need binary variables. Initial value of SoS is predefined and set in the hour "0" and SoS in the last hour must be greater or equal than initial state.

$$SOE_{\psi,m,t}=SOE_{\psi,m,t-1}+in_{\psi,m,t}\cdot\eta^{in}-\frac{out_{\psi,m,t}}{\eta^{out}} \tag{9}$$

Microgrids will also employ energy storage in form of smart household heating. Model calculates various temperatures in a house, a keeps them within the predefined threshold. This approach enables load shifting of heating units while maintaining the end-user comfort. It is based on the heat capacity and heat transfer coefficients between room air, floor, heating water and ambient based on its temperature. Equation (10) calculates the room temperature of the building based on its previous state, floor and ambient temperature. Similarly (11) calculates the floor temperature from its previous state, room and water temperature and (12) calculates water temperature from its previous state, floor temperature and heat input. Equations (13) and (14) keep the room temperature between certain predefined thresholds. The variable $\Delta r_{\psi,m,t}$ is used for deviation of the temperature from this threshold in order to increase the model feasibility, but it is severely penalized in the objective function. The water temperature also has an upper bound, which is constrained with (15). Initial values for temperatures are predefined and set in hour "0". Also, we consider that water temperature in the last hour must at least be the same as the initial value. This model is a slight adaptation of models taken from [21] and [22]. Thee referenced model considers only one device for heating which is incorporated in equation (12). Instead our model is expanded by introducing the heat input variable ($d_{\psi,m,t}$) which can be produced by a variety of different devices/units within the MG.

$$r_{\psi,m,t} = a_{11}\, r_{\psi,m,t-1} + a_{12}\, f_{\psi,m,t-1} + e\, A_{m,t} \tag{10}$$

$$f_{\psi,m,t} = a_{21}\, r_{\psi,m,t-1} + a_{22}\, f_{\psi,m,t-1} + a_{23}\, w_{\psi,m,t-1} \tag{11}$$

$$w_{\psi,m,t} = a_{32}\, f_{\psi,m,t-1} + a_{33}\, w_{\psi,m,t-1} + D\, d_{\psi,m,t-1} \tag{12}$$

$$r_{\psi,m,t} - \Delta r_{\psi,m,t} \leq R^{max} \tag{13}$$

$$r_{\psi,m,t} + \Delta r_{\psi,m,t} \geq R^{min} \tag{14}$$

$$w_{\psi,m,t} \leq W^{max} \tag{15}$$

After the devices have been defined, they need to be interconnected. Each MG can be composed of one or more different energy types: electricity, gas, heat and hydrogen. For each of these, a balancing constrain will be used. In case the energy vector or a certain device is not present in the modelled MG, equations or variables associated with it will be omitted. Equation (16) is a heat demand balance equation. Some devices are specific for a certain household, like HP, while others are centralised for the entire MG. Devices that are in each house have their value multiplied by the number of households. Hydrogen that is produced must either be stored or consumed as written in (17). Gas is bought from a day ahead market in a single 24 hour bid as shown in (18). Lastly, (19) is the balance equation for each hour. Variables for gas bid "ω_m" and electricity bids "$\overline{\epsilon}_{m,t}$" and "$\underline{\epsilon}_{m,t}$", are first stage decisions variables and as such must be valid in each scenario. All other variables are second stage variables and are different in all scenarios. Trading between MGs is implemented using (20), where variable $\overline{\rho}_{\psi,m,t}$ is used if MGs buy electricity from each other and $\underline{\rho}_{\psi,m,t}$ if they sell electricity to each other. Trading is implemented so that the purchased volumes are equal to the sold volumes.

$$\begin{aligned} N_m \cdot d_{\psi,m,t} = N_m \cdot \nu^{O}_{\psi,m,t} - \overline{\alpha}_{\psi,m,t} + \underline{\alpha}_{\psi,m,t} \\ + c^{O,heat}_{\psi,m,t} + b^{O}_{\psi,m,t} + h^{O,heat}_{\psi,m,t} \end{aligned} \tag{16}$$

$$p^{O}_{\psi,m,t} - \overline{\gamma}_{\psi,m,t} + \underline{\gamma}_{\psi,m,t} - h_{\psi,m,t} = 0 \tag{17}$$

$$\omega_m = \sum_{i=1}^{T} (c_{\psi,m,i} + b_{\psi,m,i}) \tag{18}$$

$$\begin{aligned} N_m \cdot L_{\psi,m,t} = N_m \cdot PV_{\psi,m,t} - N_m \cdot \overline{\beta}_{\psi,m,t} + N_m \cdot \underline{\beta}_{\psi,m,t} \\ - N_m \cdot \nu_{\psi,m,t} + c^{O,el}_{\psi,m,t} - p_{\psi,m,t} + h^{O,el}_{\psi,m,t} \\ + \overline{\epsilon}_{m,t} - \underline{\epsilon}_{m,t} + \overline{\rho}_{\psi,m,t} - \underline{\rho}_{\psi,m,t} \end{aligned} \tag{19}$$

$$\sum_{j=1}^{M} \overline{\rho}_{\psi,j,t} = \sum_{j=1}^{M} \underline{\rho}_{\psi,j,t} \tag{20}$$

III. Case study

The case study will incorporate three different MGs shown in Fig. 1:

- The first MG will be fully electrified with heat pumps, battery storage systems and photovoltaics in every household.
- The second MG will use gas devices such as CHP unit and boiler in combination with heat storage. Each household will possess a photovoltaic unit.
- The third MG is hydrogen based with PtH electrolyzer, hydrogen storage and FC. Each household will possess a photovoltaic unit.

Gas and hydrogen devices are centralised which means there is only one of each in a MG. Rated power of each PV unit in every household is 2 kW and will have 30 households. Each battery has charging and discharging power of 1 kW and the capacity of 5 kWh, with charging and discharging efficiency of 0.9. HPs have input power of 4 kW and a COP of 2.5. Input power of the central CHP unit is 450 kW with electric efficiency of 22% and heating efficiency of 70%. Backup boiler to that CHP has input power of 360 kW and the efficiency of 85%. Heat storage can store up to 100 kWh with input and output power of 50 kW and efficiency of 90%. PtH is based on alkaline water electrolysis with input power of 152 kW and efficiency of 66%. Central FC has a rated power of 600 kW with electric efficiency of 37% and heating efficiency of 52%. Hydrogen storage can store up to 1200 kWh with input and output power of 600 kW and efficiency of 90%. Devices that produce heating energy are sized so that they have around 10 kW of thermal output per household. Specific emissions of electricity from grid is 0.177 kg/kWh and for gas is 0.202 kg/kWh. Sizing of devices and other mentioned parameters are taken from [23]. Room temperature must be kept between 19 °C and 24.7 °C based on research from [21] and water temperature must not surpass 80 °C. Penalty for deviation of room temperature is 30 €\°C. Three different ambient temperatures (one for each MG) are taken for winter day in Mediterranean Croatia. Gas price is not volatile as electricity price so it will be used as deterministic value and is equal to 28 €\MWh according to statistics from [24] for Croatia.

Stochastic parameters used in the model are: PV production, day-ahead electricity price and electrical demand of the households. Nine scenarios are used in stochastic optimization with different parameters arrays. Three arrays of values of each stochastic parameters were generated for each MG and then combined in nine different scenarios, considering equal probability of occurrence. The day-ahead electricity prices are predicted using SARIMA (seasonal autoregressive integrated moving average) model for Croatian power exchange [25] from which price scenarios are created. The final cost of MG buying electricity also includes transmission and distribution network fees/tariffs which are set as fixed values. When MGs are trading between themselves only the distribution network fee is payed and when the MGs sell electricity either to electricity market or between themselves they earn day-ahead price. Electricity load profiles are generated using [26] and PV production profiles using [27].

To analyse benefits of MG cooperation, five cases will be examined:

- MGC - three different MGs with trading between MGs enabled.
- TM - three different MGs with trading between MGs disabled (variables $\overline{\rho}_{\psi,m,t}$, $\underline{\rho}_{\psi,m,t}$ and constrain (20) are removed).
- EE - three fully electric MGs with trading between MGs enabled.
- Gas - three gas MGs with trading between MGs enabled.
- H2 - three hydrogen MGs with trading between MGs enabled.

IV. Results

The model is written in Python 3.8 and solved using Gurobi 9 optimization solver [28]. PC specifications are AMD Ryzen 5 3600 6-Core 3.59 GHz processor and 16 GB of RAM. Computational time is of the order of 10 seconds.

Table I shows the values of the objective functions for the MG cooperation model (MGC), the testing model (TM) and for the cases with same MG types per MG. The savings are expressed with regards to the MGC model. The total cost of MGC is around 4.4% better than the TM on a daily basis, meaning this is the value of intra MG trading option. Interestingly, although the overall costs are lower, the third MG has higher cost in the MGC model than in the TM model. This comes as a result of how the optimization is set; it is trying to lower the overall cost of the MGs and not their individual costs. To even this out and provide incentives for each of the MGs to participate in the trading arrangements, the central entity optimizing all MGs would need to incorporate a cost sharing mechanism similar to [29]; this is outside of the scope of this paper. Fig. 2 presents accumulated electricity trade in the day ahead market for all cases. Total gas volumes bought are 15.5 kWh for MGC, 590 kWh for TM and 2273 kWh for gas case. In addition to cost saving, MGC also lowered total energy import by 22%. Decrees in import means that MGs in MGC are more self-sufficient, because they are less dependant on external sources of energy. In tearms of CO_2 emissions MGC managed to have 25% lower emissions than TM. Trade between MGs is mainly used to lower uncertainty risk, which can be seen from fig. 3. There is significant change in trade between scenarios as the MGs are trying to adjust their operation based on their day-ahead schedule decision and realization of a certain scenario.

Although MGC shows better results than the TM, the value of multi-energy cooperation is not shown when comparing with the case of three EE MG, which have 7% lower cost than the MGC. The explanation is rather simple as: i) the price of electricity is low; ii) the EE has the most efficient and most flexible electricity storage system and iii) heat pump is, most of the time, the cheapest heat producer. The H2 case is very similar to MGC, being only being 1% worse. The cost is higher in H2 case because the roundtrip efficiency for storing electricity as hydrogen is much lower than that of the battery storage system and because electricity production of fuel cell is dependant on heat consumption. The worst case is Gas being almost 14% more expensive than MGC and is even more expensive than TM. Gas case lacks flexibility because electricity production of CHP and its heat storage are highly dependant on heat consumption. Lack of flexibility is somewhat mitigated with high amount of local electricity trading seen in fig. 3. EE and H2 cases need the least amount of flexibility from local energy trading, but sill utilize it for the purpose of mitigating risk from uncertainty. Investment cost analysis could improve results shown in this chapter, but was not part of this paper.

Last analysis will show how are saving between MGC and EE, Gas and H2 effected by price increase. Electricity prices are incresed by 25%, 50% and 100% as shown in first column of table II. EE and H2 cases seas their percentage difference increased from the original case. Gas case becomes more competitive as the electricity price rises, being very similar to MGC at 100% multiplier.

TABLE I
Value of objective function for all examined cases

MG	MGC	TM	EE	Gas	H2
1	32.93	33.51	32.79	43.95	34.17
2	43.44	53.9	47.69	54.87	48.27
3	51.28	46.06	38.71	49.29	46.39
Total	127.65	133.46	119.19	148.1	128.83
Savings		4.35%	-7.1%	13.8%	0.91%

TABLE II
Percentage difference between MGC and EE, Gas, H2 based on price increases

Price Multiplier	EE	Gas	H2
1.25	-6.83%	8.23%	1.03%
1.5	-6.69%	5.56%	1.1%
2	-4.89%	0.42%	2.64%

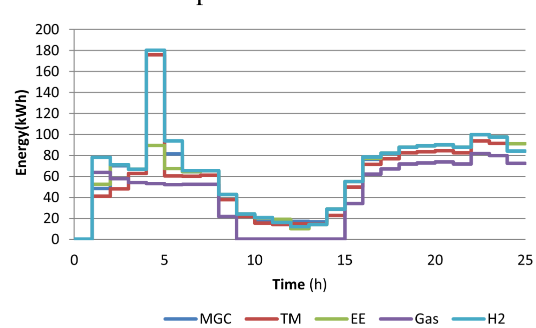

Fig. 2. DAM bid in all cases (MGC, TM, EE, Gas, H2)

V. Conclusion

The goal of this paper was to show how multiple different microgrids can cooperate together. Three different microgrids

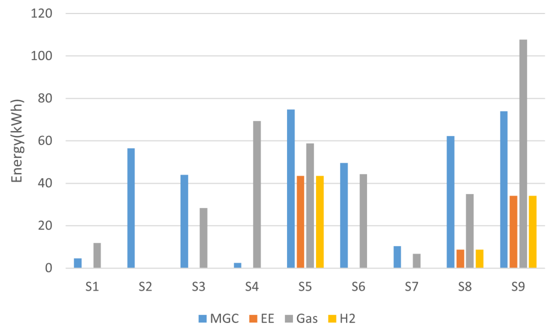

Fig. 3. Trade between MGs in all cases (MGC, EE, Gas, H2) and scenarios

are created: fully electrified, gas based and hydrogen based. Trading between microgrids is done in a way so neither participant is at a loss. Additionally, competing in a day-ahead electricity market is considered. The uncertainties are modeled through two-stage stochastic optimization, capturing day-ahead electricity price, electricity load and PV production. The cooperation model utilizing local energy trading was found to be 4.3% better than a model without cooperation and it also improved self sufficiency of MGs by lowering import volumes by 22% and CO_2 emissions by 25%. The case with three electric MGs was found to be better than case where all MGs were different, case with three hydrogen MGs was slightly worst and case with three gas MGs had the worst performance. The local energy trading was mostly used by the models to mitigate risk of uncertainty and to better adjust operation of MGs.

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References

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

[2] P. Mancarella and G. Chicco, "Real-time demand response from energy shifting in distributed multi-generation," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1928–1938, 2013.

[3] N. Good, E. Karangelos, A. Navarro-Espinosa, and P. Mancarella, "Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users' discomfort," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2333–2342, 2015.

[4] N. Holjevac, T. Capuder, N. Zhang, I. Kuzle, and C. Kang, "Corrective receding horizon scheduling of flexible distributed multi-energy microgrids," *Applied Energy*, vol. 207, pp. 176 – 194, 2017, transformative Innovations for a Sustainable Future – Part II.

[5] T. Capuder and P. Mancarella, "Assessing the benefits of coordinated operation of aggregated distributed multi-energy generation," in *2016 Power Systems Computation Conference (PSCC)*, 2016, pp. 1–7.

[6] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, 2018.

[7] M. Daneshvar, B. Mohammadi-Ivatloo, S. Asadi, A. Anvari-Moghaddam, M. Rasouli, M. Abapour, and G. B. Gharehpetian, "Chance-constrained models for transactive energy management of interconnected microgrid clusters," *Journal of Cleaner Production*, vol. 271, p. 122177, 2020.

[8] H. Karimi and S. Jadid, "Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework," *Energy*, vol. 195, p. 116992, 2020.

[9] M. Daneshvar, B. Mohammadi-ivatloo, K. Zare, S. Asadi, and A. Anvari-Moghaddam, "A novel operational model for interconnected microgrids participation in transactive energy market: A hybrid igdt/stochastic approach," *IEEE Transactions on Industrial Informatics*, pp. 1–1, 2020.

[10] M. Khorasany, A. Najafi-Ghalelou, R. Razzaghi, and B. Mohammadi-ivatloo, "Transactive energy framework for optimal energy management of multi-carrier energy hubs under local electrical, thermal, and cooling market constraints," *International Journal of Electrical Power Energy Systems*, 01 2021.

[11] M. Zare Oskouei, M. A. Mirzaei, B. Mohammadi-Ivatloo, M. Shafiee, M. Marzband, and A. Anvari-Moghaddam, "A hybrid robust-stochastic approach to evaluate the profit of a multi-energy retailer in tri-layer energy markets," *Energy*, vol. 214, p. 118948, 2021.

[12] D. Zhu, B. Yang, Q. Liu, K. Ma, S. Zhu, and C. Ma, "Energy trading in microgrids for synergies among electricity, hydrogen and heat networks," *Applied Energy*, vol. 272, p. 115225, 08 2020.

[13] J. Sachs and O. Sawodny, "Multi-objective three stage design optimization for island microgrids," *Applied Energy*, vol. 165, pp. 789 – 800, 2016.

[14] A. Parisio, C. Del Vecchio, and A. Vaccaro, "A robust optimization approach to energy hub management," *International Journal of Electrical Power Energy Systems*, vol. 42, no. 1, pp. 98 – 104, 2012.

[15] P. Mancarella, "Mes (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1 – 17, 2014.

[16] T. Capuder and P. Mancarella, "Techno-economic and environmental modelling and optimization of flexible distributed multi-generation options," *Energy*, vol. 71, pp. 516 – 533, 2014.

[17] P. Mancarella, G. Chicco, and T. Capuder, "Arbitrage opportunities for distributed multi-energy systems in providing power system ancillary services," *Energy*, vol. 161, pp. 381 – 395, 2018.

[18] N. Holjevac, T. Capuder, and I. Kuzle, "Defining key parameters of economic and environmentally efficient residential microgrid operation," *Energy Procedia*, vol. 105, pp. 999 – 1008, 2017.

[19] C. Shilaja, T. Arunprasath, and P. Priya, "Day-ahead optimal scheduling of microgrid with adaptive grasshopper optimization algorithm," *International Journal of Communication Systems*, p. e4133, 2019.

[20] A. Karimi, Y. Khayat, M. Naderi, T. Dragičević, R. Mirzaei, F. Blaabjerg, and H. Bevrani, "Inertia response improvement in ac microgrids: A fuzzy-based virtual synchronous generator control," *IEEE Trans. Power Electron.*, vol. 35, no. 4, pp. 4321–4331, 2020.

[21] M. Zugno, J. Morales González, P. Pinson, and H. Madsen, "A bilevel model for electricity retailers' participation in a demand response market environment," *Energy Economics*, vol. 36, pp. 182–197, 2013.

[22] R. Halvgaard, N. K. Poulsen, H. Madsen, and J. B. Jørgensen, "Economic model predictive control for building climate control in a smart grid," in *2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2012, pp. 1–6.

[23] L. Herenčić, M. Melnjak, T. Capuder, I. Andročec, and I. Rajšl, "Techno-economic and environmental assessment of energy vectors in decarbonization of energy islands," *Energy Conversion and Management*, vol. 236, p. 114064, 2021.

[24] "EU-28: industrial prices of natural gas 2019 — Statista."

[25] "CROATIAN ENERGY EXCHANGE." [Online]. Available: https://www.cropex.hr/en/

[26] N. Pflugradt, "Load profile generator v8.9," https://www.loadprofilegenerator.de/.

[27] S. Pfenninger and I. Staffell, "Long-term patterns of european pv output using 30 years of validated hourly reanalysis and satellite data," *Energy*, vol. 114, pp. 1251–1265, 2016. [Online]. Available: https://www.renewables.ninja/

[28] "Gurobi." [Online]. Available: https://www.gurobi.com/

[29] M. Grzanić, J. M. Morales, S. Pineda, and T. Capuder, "Electricity cost-sharing in energy communities under dynamic pricing and uncertainty," *IEEE Access*, vol. 9, pp. 30 225–30 241, 2021.