Multi-Energy Industrial Prosumer as a Flexibility Service Provider

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***Abstract*—While the latest energy regulatory framework is putting the the focus on inclusion of the household level end-users into active power system participation, large consumers such as industrial facilities are still not fully exploiting the opportunities that market participation can offer in reducing their energy costs and making their energy consumption related end-products more competitive. They are able to lower risk from market participation with flexibility from the interaction of different energy vectors. An additional value can be found in optimal price-driven scheduling of the product chain timing which, from the perspective of the market participant, behaves as a demand response service. Thorough literature review on multi-energy systems and industrial plants is conducted. A few gaps were found and solutions are proposed for some of them. The uncertainty market aspects are modelled by both robust optimization and two-stage stochastic optimization. The validation of the model is shown on a case study of a multi-energy industry facility and the results indicate that cost savings of up to 18 % can be achieved compared to the passive and deterministic, mass flow based, business as usual behaviour.**

***Index Terms*—demand response, energy flow modelling, flexibility, industry facility, multi-energy system, uncertainty optimization**

I. Introduction

With the deregulation of the power system, end-users are encouraged to become more active participants. Current European Union (EU) policies tend towards lowering greenhouse gas emission and decarbonised power system [1]–[3]. To help in achieving these goals a lot of renewable energy sources (RES) are being installed. Even smaller end-users are participating with e.g. installing photovoltaics (PV) on the building roofs. With high penetration of RES, the power system is changing away from its classic structure. RES such as wind and PV are intermittent in their nature and unpredictable in the short term, thus power system will require more flexibility to balance them. In the past, conventional power plants (e.g gas-powered thermal power plants) were the main flexibility provider, but many of them are being shut down in favour of RES. With fewer available convectional power plants power system will require new sources of flexibility. End-users are more and more considered and incentivized to be new flexibility providers [4], [5]. Smaller, household-level end-users are negligible on their own, but when grouped together could make a significant impact [6]. On the other hand, energy-intensive end-users (such as industrial plants) could be better suitable for providing such services. This can further be increased with the cooperation of different energy vectors, such as electricity and gas when operating optimally in an integrated way. Additionally, large end-users are more suited for competing on a wholesale electricity market, mainly the day-ahead electricity market (DAM). In DAM producers and consumers place bids ahead of delivery time. After the gate closure when bids are processed, volumes and prices are announced publicly and participants must obey them in real-time. In the EU market, all deviations which occur in real-time are subject to imbalance prices reducing the profit of participant [7]–[9]. Large end-users can mitigate their imbalance through demand response by shifting its consumption and multi-energy flexibility by shifting between different energy vectors [10], [11].

II. Multi-Energy Systems

Multi-energy system (MES) is a group of different energy vectors such as electricity, gas and hydrogen operating together. In general, MES incorporate different energy vectors so that they function together and complement each other through shifting and virtually storing energy in different energy forms [12]. It can be anything from building to a country. Such systems can be a great way for decarbonization of the energy sector and for variability mitigation of renewable energy sources such as wind and solar [13]. Example of MES district (microgrid, MG) is shown on fig. 1. It contains multiple households with electricity and heat load. Both loads can be satisfied from multiple sources. Combined heat and power unit (CHP) uses gas to produce electricity and heat, heat pump (HP) uses electricity to produce heat. Heat can be stored in heat storage and distributed to households when needed. Each household also has a photovoltaic (PV) system for producing electricity and a battery storage system (BSS) for electricity storing. MG can also buy or sell a shortage or surplus of electricity from the market. This interchange between energy vectors provides MG with high flexibility to deal with unfavourable periods and achieve benefits to its stakeholders.

Reference [13] provides an overview of concepts for MES. Also, it presents different tools for analysis of MES and evaluation methods used in literature. Energy assessment criteria are based on relative energy efficiency that compares MES performance compared to some reference case. This assessment criterion is used in [14] for performance analysis

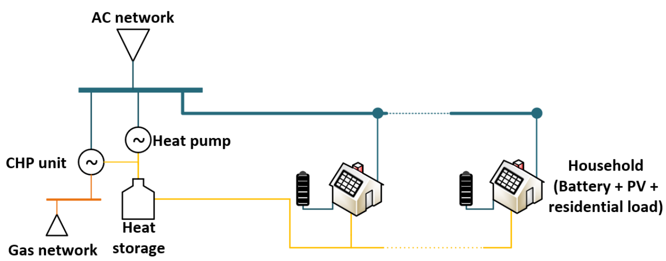

Fig. 1. Example of MES

of CHP plant. Second assessment criteria are environmental. It focuses on the environmental impact of different energy vectors. Assessment of emission impact of CHP plant is presented in [15]. Last and most used assessment criteria are economic. It usually refers either to an operational aspect where operational strategies for MES are devised or to planing aspects where best technologies, size and topology are identified. Operational aspects of the trigeneration system (combined cooling heat and power) optimization using graph theory concept is presented in [16]. Assessment criterion is the minimization of operational costs subject to multi-energy demand. Two-stage stochastic optimization of a multi-energy industrial plant is presented in [17] where multi-energy flexibility is used to compensate for uncertainty in demand and electricity prices. The goal of the model is to find the optimal bidding strategy for competing on electricity and gas day-ahead market and thus to lower the energy cost. Planing aspect is presented in [18] with the sizing of CHP and heat storage. In [19] environmental and economic assessment criterion is used. Unit sizing is done based on a daily and annual operational cost of MES and carbon footprint was calculated for each case. There are other assessment metrics that can be taken into account. For example in [20], the discomfort of end-users is analyzed and assessed. There are multiple modelling approaches and aggregation concepts of MES, three most commonly used are energy hubs, microgrids and virtual power plants. Energy hub approach is used for analyzing multi-energy conversion from input-output perspective and interaction of different hubs with different energy vectors. Day-ahead nonlinear optimization of renewable based energy hub is presented in [21]. It uses a Monte-Carlo simulation approach for RES scenario generation. Optimal expansion planing of existing energy hub is proposed in [22]. The system is evaluated through reliability, energy efficiency and emission metrics. Microgrid is a cluster of distributed energy sources, energy storage systems, and controllable and uncontrollable loads presented as a single entity towards the grid that can operate in parallel to the grid or in the off-grid mode (island mode). Paper [23] provide a detailed evaluation of flexibility in multi-energy microgrids. It analyses different MG configurations capturing different technologies and their interaction. Multi-energy microgrid's resilience and transitioning to islanding mode is researched in [24]. Also, it evaluates increase in cost when the microgrid is always able to transition to islanding mode as opposed to its normal operation. Virtual power plants are a flexible aggregation of distributed energy resources that are coordinated in an optimal way, are capable to compete in the energy market, and offer services in the same way as a conventional large-scale power plant. Reference [25] aggregates distributed multi-energy generation units such as CHP, electric heat pumps (EHP), boilers and thermal storage. It introduces the aggregation benefit matrix as a way of assessing benefits from coupling different energy vectors together.

As seen from the literature review, MES are fairly researched area which shows its importance. It is a great way for mitigating variability from RES [26], lowering operational cost [27] and providing flexibility services to the system operator [28], thus helping in the decarbonization of the energy sector. Nevertheless, there are still some gaps in the literature. Most papers only consider two energy vectors, thus lowering their flexibility. The market environment is also underutilized and should be further researched. The sheer amount of inherent flexibility that MES possesses would put it in a better position compared to the competition. Modelling uncertain aspects of the market environment such as electricity prices and load consumption are often overlooked in the literature opting for simpler and faster models. Lastly, energy-intensive MES such as industrial plants is also underdeveloped in literature.

III. Optimization Under Uncertainty

Deterministic models consider all parameters as known. In reality, there are a lot of things subjected to uncertainty. In those cases deterministic models might not give plausible solution and uncertainty should be taken into account. Parameters that usually cause uncertainty are production from renewable sources, consumption of loads or electricity market prices. There are a lot of ways for dealing with uncertainty two of which will be presented in this chapter: two-stage stochastic optimization and robust optimization. Both approaches are observed from a mixed-integer linear perspective.

A. *Two-Stage Stochastic Optimization*

In two-stage stochastic optimization (SO) decision is made at two stages and uncertainty is presented through a set of scenarios and their probability of occurrence. Here we have two types of variables: first stage decision variables (here-and-now) and second stage decision variables (wait-and-see). In the first stage, a decision must be made before the realization of uncertainty and in the second stage, we optimize our behaviour after the realization of uncertainty. Decisions made in the second stage depend on the decisions made in the first stage and on the realization of the uncertain parameter. This is solved simultaneously in a single optimization problem to ensure that all decisions are optimal and that all relationships among decision variables are accounted for. For a more detailed overview of stochastic optimization in electricity markets, we refer to [29]–[31]. The decision making is shown in fig. 2 through scenario tree and summarised as follow:

- First stage decision x is made before the realization of the stochastic process λ. This decision is shown as a root node on fig. 2.
- Stochastic process λ is realised as $\lambda(\omega)$. On fig. 2 branches represent different realization of stochastic process.
- Second stage decision $y(x,\omega)$ is made after the realisation of stochastic process λ. This decision is shown as a leaf node connected to root node on fig. 2.

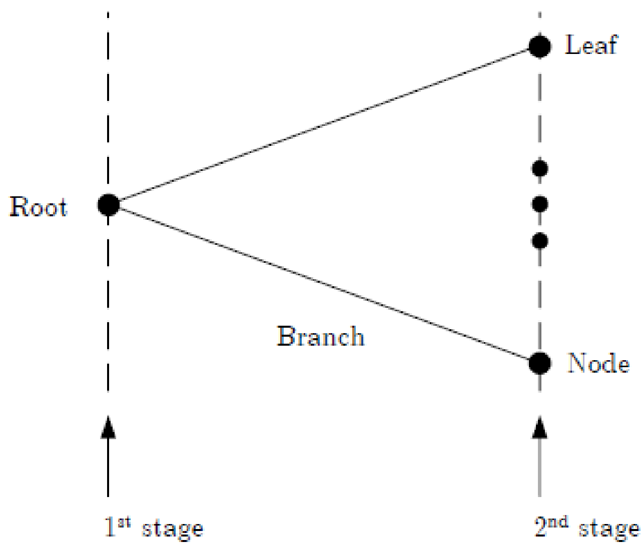

Fig. 2. Scenario tree for a two-stage problems [29]

General formulation of SO model is shown in (1)-(4). Decision variable vectors are denoted as x and $y(\omega)$ and c, $q(\omega)$, b, $h(\omega)$, A, $T(\omega)$ and $W(\omega)$ are parameter vectors and matrices. Any parameter vector can depend on the realization of the uncertainty set. Please note that the two-stage model can be expanded to a multi-stage problem.

$$\min_{x,y(\omega)} c^T x + \sum_{\omega\in\Omega} \pi(\omega) q(\omega)^T y(\omega) \tag{1}$$

$$Ax = b \tag{2}$$

$$T(\omega)x + W(\omega)y(\omega) = h(\omega),\, \forall\omega\in\Omega \tag{3}$$

$$x \in X,\, y(\omega)\in Y,\, \forall\omega\in\Omega \tag{4}$$

B. Robust Optimization

In robust optimization (RO) we are trying to make optimal decision based on the worst-case scenario of the uncertain parameter. Uncertain parameters are modelled as uncertainty sets whose probability distribution does not have to be known, unlike in SO. It is assumed that the objective and constrains belongs in the function space of the uncertainty set. The goal is to make a decision that is feasible for the whole uncertainty set and optimal for the worst-case objective function. Uncertainty sets are defined so that every uncertain parameter u_i in vector $u \in U$ may deviate from a reference value u_i^{ref} by at most $\pm u_i^{\Delta}$. The formulation is shown in (5). Note that this formulation can also be replaced by a more general polyhedral constrain consisting of linear combinations of the elements of u. Also, uncertain parameters u_i can be correlated across time and space. Uncertainty budget is used for constraining the variation in uncertainty set. Its primary purpose is to reduce the level of conservatism in RO. A formulation for uncertainty budget is shown in (6), where Γ denotes a value of uncertainty budget. General formulation of RO model is shown in (7) and (8), where x is decision variable vector, u is uncertainty set and A and B are parameters matrices and vectors. To solve this type of a problem, an inner maximization must be converted to minimization. If the inner problem is linear we can use duality theorem and change maximization problem to its dual form. Maximization in primal form is changed to minimization in dual form, so objective function becomes min-min or just minimization. Also, it solves the bilinear term problem of $u^T x$. In this state, it can be solved with any MILP solver. For a more detailed overview of robust optimization and duality theorem we refer to [32]–[35].

$$u_i \in [u_i^{ref} - u_i^{\Delta} \quad u_i^{ref} + u_i^{\Delta}],\, \forall i \tag{5}$$

$$\sum_{i=1}^{n} \frac{|u_i - u_i^{ref}|}{u_i^{\Delta}} \le \Gamma \tag{6}$$

$$\min_{x} \max_{u\in U} u^T x \tag{7}$$

$$Ax = B \tag{8}$$

IV. Multi-Energy Industrial Prosumer

Industrial plants are very complex systems comprised of multiple interconnected processes and devices. They usually incorporate multiple energy vectors and local electricity and heat production. Since they are energy-intensive, energy cost takes a major part in their production expenditures. Thus proper energy consumption management can lead to an increase in profit and to a more competitive product. Industry in EU accounts for around 25% of total electricity consumption [36]. Large industrial consumers such as cement industry, paper industry and metal processing industry can have rated power of the order of tens of megawatts for both electricity and heat [37]–[43].

A. Literature Review

Gaps in the literature of MES industrial prosumers are similar to those mentioned in chapter II. Mainly, the area of energy-intensive MES is under researched and its market participation options are underdeveloped, especially in terms of uncertainty modelling. Also, to the author's knowledge all papers using a linear model for steam/heat industry facilities relay on a mass flow modelling approach. It is a simple and easy way to calculate, but neglects losses in the process which results in unrealistic operational states and may lead to penalties. References [44]–[46] fall into this category. They are different MILP optimization of industrial steam and power system. In [44] only steam part of the system is considered. They use four different optimization types (objective functions) such as fuel minimisation and electricity production maximization. Reference [45] is a simple optimization model of a steam plant whose results are compared to a real operation of a certain plant. With a conclusion that their tool is good in a steady state condition. In [46] optimization of CHP plant is presented. It is based on the maximization of profits from selling electricity and heat. Their emphasis on a more detailed linear model of gas boilers and heat recovery steam generators. They are modelled with start-up costs, minimum uptime and downtime, different efficiency regions and different fuels. Other than using MILP optimization there are other approaches. One way would be to use a mixed-integer nonlinear program (MINLP) like in papers [47] and [48]. MINLP models are less limited in terms of modelling but are more difficult to solve. Both papers emphasize detail modelling of multiple extraction steam turbines. Authors of paper [49] present approach of dealing with efficiency parameters considering them as an uncertain parameter. They use adaptive robust formulation to optimize for the worst case of efficiency parameters. A way of dealing with bilinear turbine constrains by fixing certain variables as parameters is shown in [50]. Parameters are fixed using the iterative approach were after every optimization, simulation is used for parameter adjusting until convergence is achieved. Our proposed approach is explained in section IV-B. It was chosen because of its simplicity and low computational time, while still accounting for losses.

Another gap in the literature discuss opportunities for industrial facilities to reduce their costs by adjusting their operation to dynamic prices. To the author's knowledge, only two papers that deal with this topic [51] and [52]. Reference [51] uses a bit simpler process formulation for load scheduling. The goal of their model is to achieve more efficient optimization of CHP operation through process scheduling. Paper doesn't use any form on dynamic pricing but has a single price of electricity and whole for the whole optimization horizon. Also, it should be mentioned that their turbines use mass flow model with constant enthalpy similar to other papers mentioned in this chapter. The second paper [52] presents a formulation for load control of batch processes. The formulation is in part similar to that in our proposed model. Their optimization goal is profit maximization from the production of the final product and they only consider electricity as an expenditure. Their electricity pricing is deterministic and based on different smart pricing schemes like time-of-use and peak pricing. Paper [53] is prior work from the same authors on this subject and is based on a case study of real industrial plant.

Literature review clearly shows that the existing literature does not recognize the opportunities offered by optimal process scheduling and multi-energy flexibility within industrial facility operating as a market entity.

B. Energy Flow

This paper proposes a linear optimization approach for steam systems in industrial plants. The problem arises from a fact that relations need to stay linear which greatly limits modelling. Most of the state-of-the-art literature in relevant area utilizes mass-flow for steam system modeling [44]–[46], [51]. In such turbine models, input and output flows are equal and have a linear relation for output electricity or constant enthalpy of input and output steam is assumed. The same modelling is used for valves but without electricity output. Since the mentioned approach does not incorporate losses adequately, this paper proposed a new approach. Equation (9) represents the law of conservation of energy for a turbine, which says that input energy is equal to the sum of output heating energy, mechanical energy and losses inside the turbines. Where $T^{in}, T^{out}, T^{mh}, T^{loss}$ are input power, output power, mechanic power and losses inside the turbine, respectively. Mechanical energy is defined with a heat to power ratio (HtP) and losses with a efficiency coefficient (η^T) as shown in (10) and (11) respectively. Combining equations (9)-(11) heating input-output relation is created as shown in (12). Equation (13) calculates electricity output from generator which is mechanical output multiplied by generator efficiency (η^{gen}). Valve is a much simpler device so its input-output energy is calculated using efficiency as shown in (14), where V^{out} and V^{in} are input and output power, respectively. During operation boiler input-output is shown in (15), B^{out} and B^{in} are input and output power and B^k and B^l are conversion coefficients.

$$T^{in} = T^{out} + T^{mh} + T^{loss} \tag{9}$$

$$T^{mh} = T^{out} \cdot HtP \tag{10}$$

$$T^{loss} = T^{in} \cdot \eta^T \tag{11}$$

$$T^{out} = T^{in} \cdot \frac{1 - \eta^T}{1 + HtP} \tag{12}$$

$$T^{el} = T^{mh} \cdot \eta^{gen} \tag{13}$$

$$V^{out} = V^{in} \cdot \eta^v \tag{14}$$

$$B^{out} = B^{in} \cdot B^k + B^l \tag{15}$$

Difference in these two approaches can be seen in figures 3 and 4. Figure 3 show energy and mass flow through the turbine and fig. 4 through valve. Numbers on these figures are normalized so they can be easier to compare. Firstly, there is a difference between gas consumption in energy flow when using different devices as opposed to identical gas consumption in case of mass flow. Secondly, it can be seen that electricity production affects both turbine input and gas consumption in energy flow. The last thing to notice is a difference in gas consumption of boilers. In the case of mass flow, it is lower because losses are neglected and electricity production is not taken into account. All these effects create a more accurate and detailed model.

C. Model Description

Industrial plants usually consist of multi-stage operations were material goes through several transformations/refinements to reach the final product, e.g. cement production as in [38]. Our industrial facility model is based on the scheduling of batch and continuous process units as shown in fig. 5. The first number in the square is an ordinal number of the process and the second number (in brackets) indicates the

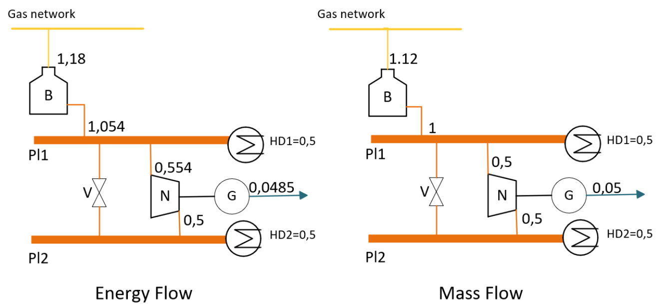

Fig. 3. Energy and Mass Flow Through Turbine

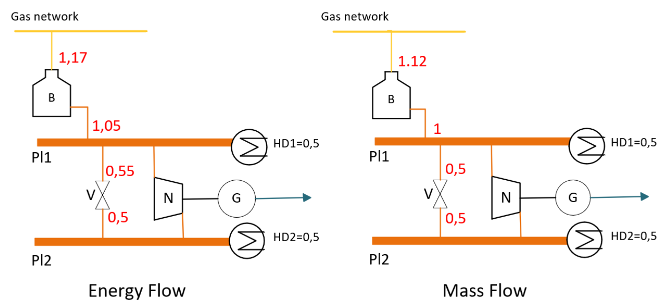

Fig. 4. Energy and Mass Flow Through Valve

length of the process in hours. There are two process chains on the figure: 1-2-3 and 1-2-4-5. Batch units take input material at the beginning of each batch cycle and output product at the end of the cycle, while continuous process inputs and outputs are fed and produced continuously. Mathematically, for the purpose of the proposed model, continuous processes will be the same as a batch but with a length of 1 hour. On fig. 5 process 2 and 5 are a continuous process and processes 1, 3 and 4 are batch. These units are chained together to simulate the operation of industrial plant. Process units may have a different type of loads (electrical, thermal and mechanical) which are satisfied using different devices. Heating part of the system used to satisfy the thermal load is shown in fig. 6 and it consists of a gas boiler, backpressure steam turbine and letdown valves. The mechanical load is satisfied with gas and electric motors and electrical load can be satisfied from either generator connected to the turbines or from the electricity grid and bought on the market. As mentioned we consider that our plant buys electricity and gas from their respective day-ahead markets. Prices on the day-ahead market are unknown beforehand, so the model will have to deal with this uncertainty. Since they are subject to predictions, they can be prone to errors. The gas price is assumed to be known since its variability is negligible. Three different models are created. The first model uses robust optimization formulating and second, is using two-stage stochastic formulation. The third model represents business as usual approach (BaU). It won't employ demand response or multi-energy flexibility. BaU's primary purpose is for comparison with other models and is it made as a robust model for a better comparison with the robust model. Models are named as follows:

- Robust model without demand response (BaU_1) and multi-energy flexibility (BaU_2)
- Two-stage stochastic model with demand response (SO)
- Robust model with demand response (RO)

Values for uncertainty budget in RO are: 0 (mean values), 7 ($\approx$ 30% variation), 17 ($\approx$ 70% variation) and 24 (100% variation). In SO three price scenarios will be used which correspond to the mean, upper and lower value of prices in RO.

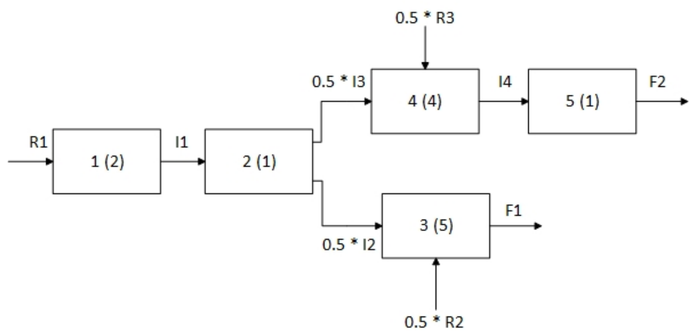

Fig. 5. Industrial processes

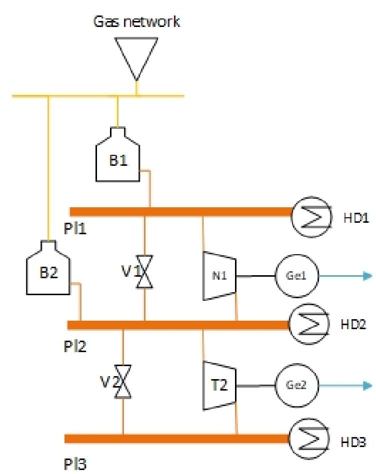

Fig. 6. Heat system

D. Results

The model is coded in Python 3.7 and is using Gurobi 9 optimization solver [54]. PC specifications are AMD Ryzen 5 3600 6-Core 3.59 GHz processor and 16 GB of RAM. First, we will compare the RO and SO approach. Table I shows computational time in seconds and value of the objective function in EUR (€) of RO and SO approach. Number in brackets denotes uncertainty budget in RO. We can see that SO has a lot higher computational time (5-15 times) than RO while using only three scenarios. Adding more scenarios would further increase the computational time. SO and RO (0) have the same optimization results both in terms of objective function and variables. Because of all this, we have chosen RO as a superior approach to our problem.

TABLE I
RO AND SO COMPUTATIONAL TIME AND OBJECTIVE FUNCTION VALUE

	RO (0)	RO (7)	RO (17)	RO (24)	SO
Computational time	145	594	1826	115	9595
Objective function	10476	11892	12793	12798	10476

In the RO model, there are two types of flexibility: from multiple energy vectors and demand response. In fig. 7 we can see electricity bids of RO for each uncertainty budget and in fig. 8 gas bids. On these figures, we can see how electricity and gas volumes change following the changes in the uncertainty of electricity prices. As the uncertainty rises, volumes of electricity are reduced in favour of gas. This happens mostly due to changes in the scheduling of electric and gas motors and is a result of multi-energy flexibility. Figure 9 shows a number of processes active in a certain hour of a certain case. It shows how processes were arranged by the optimization. Schedule of processes changes as the uncertainty increases, which is results of demand response flexibility. For example, in the uncertainty budget 17, the volumes of electricity are more evenly spread out than in other cases. This trend is also seen in fig. 7 as electricity bid curve follows process schedule. In short; multi-energy flexibility is expressed through changes in overall consumption of electricity and gas and demand response flexibility is expressed through changes of volumes in each hour.

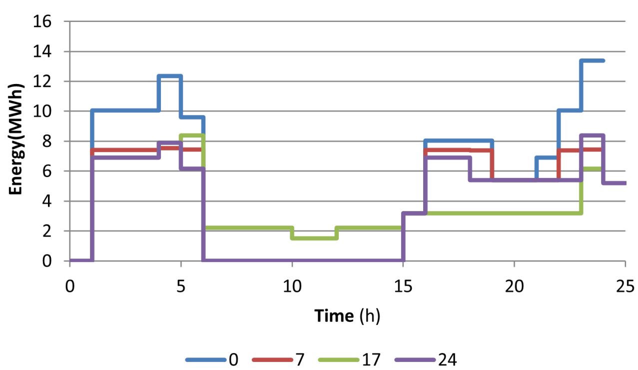

Fig. 7. Electricity bids in RO

Lastly, we will compare the RO and BaU models. Table II shows the objective value functions of RO, both cases of BaU and percentage difference between them. Figures 10 and 11 shows electricity and gas bids for BaU_1 for each uncertainty budget. Bids schedule changes slightly when uncertainty increases. Electricity volumes are lowered in favour of gas, similar to the trend seen in RO. The change in bids exclusively comes from multi-energy flexibility such as changing electric to gas motors. RO is better than BaU_1 for about 7% to 11%. Savings the RO achieves here are mainly tied with demand response flexibility. Figure 12 shows electricity (left graph) and gas (right graph) bids for BaU_2. Bids are the same for all cases of uncertainty budget because BaU_2 has no flexibility. RO achieve a saving of 14% to 18% when compared to BaU_2. The savings are achieved both with multi-energy flexibility and demand response.

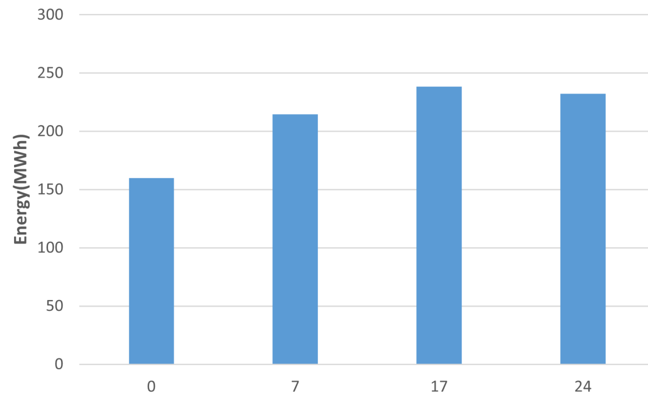

Fig. 8. Gas bids in RO

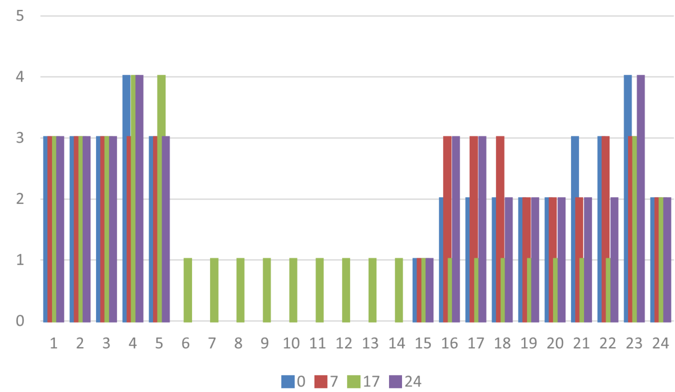

Fig. 9. Process schedule in RO

TABLE II
RO AND BAU OBJECTIVE VALUE COMPARISON

Uncertainty budget	0	7	17	24
RO	10476	11892.62	12793.43	12798.02
BaU_1	11826.74	12862.47	13781.31	13781.31
Savings (BaU_1)	11.42%	7.54%	7.17%	7.13%
BaU_2	12805.11	13876.77	14867.55	14867.55
Savings (BaU_2)	18.19%	14.3%	13.95%	13.92%

V. CONCLUSION

The presented paper gives an overview of the state-of-the-art literature and identifies gaps in it. Mainly in considering how MES can manipulate multiple energy vectors interaction to achieve benefits on the market. Another gap is modelling uncertainty from electricity prices, RES production and load consumption. Also, most of the literature focuses on smaller MES usually residential while bigger energy-intensive MES, such as industrial plants are mostly neglected. In the review

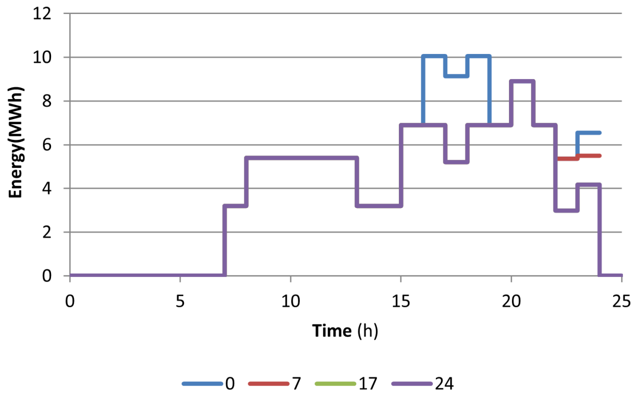

Fig. 10. Electricity bids in BaU_1

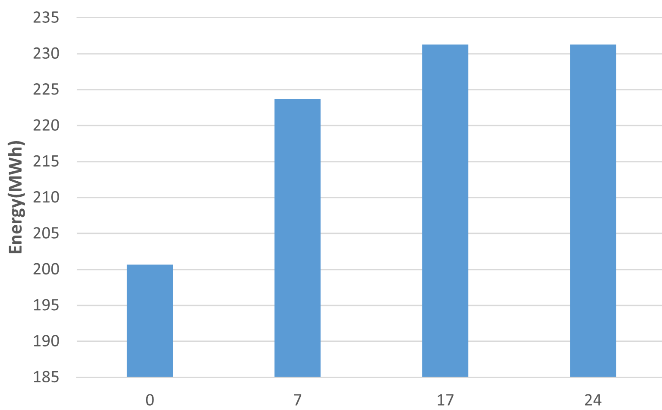

Fig. 11. Gas bids in BaU_1

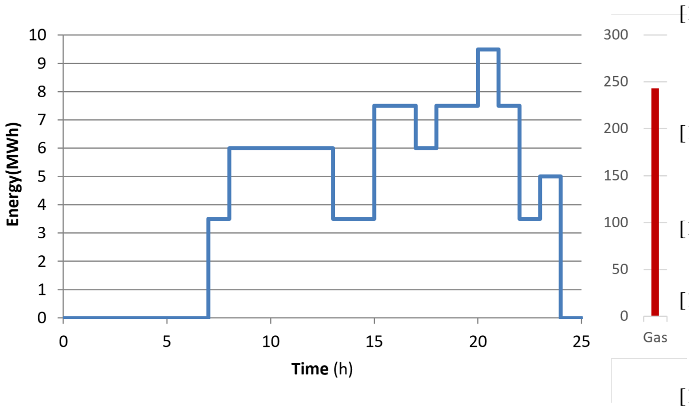

Fig. 12. Electricity and gas bids in BaU_2

of literature considering industrial plants, similar gaps were found. Additionally, we proposed an alternative way for modelling steam/heating system not found in the literature. Two different uncertainty models were created based on two-stage stochastic optimization and robust optimization. Electricity prices are considered as an uncertainty and load uncertainty is dealt with by load scheduling though price-responsive demand response. RO was deemed as a better model mainly because of much faster computational time. Robust optimization model ended up being 7%-11% better than case 1 of the testing model and 14% to 18% better than case 2 of the testing model.

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References

[1] "European Climate Law — Climate Action." [Online]. Available: https://ec.europa.eu/clima/policies/eu-climate-action/law_en

[2] "2030 climate & energy framework — Climate Action." [Online]. Available: https://ec.europa.eu/clima/policies/strategies/2030_en

[3] "2050 long-term strategy — Climate Action." [Online]. Available: https://ec.europa.eu/clima/policies/strategies/2050_en

[4] M. H. Albadi and E. F. El-Saadany, "Demand response in electricity markets: An overview," in *2007 IEEE Power Engineering Society General Meeting*, 2007, pp. 1–5.

[5] G. De Zotti, S. A. Pourmousavi, J. M. Morales, H. Madsen, and N. K. Poulsen, "Consumers' flexibility estimation at the tso level for balancing services," *IEEE Transactions on Power Systems*, vol. 34, no. 3, pp. 1918–1930, 2019.

[6] A. Caramizaru and A. Uihlein, *Energy communities : an overview of energy and social innovation*, 2019. [Online]. Available: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/energy-communities-overview-energy-and-social-innovation

[7] 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.

[8] M. Shahidehpour, H. Yamin, and Z. Li, *Market Overview in Electric Power Systems*, 2002, pp. 1–20.

[9] ENTSO-E, "ENTSO-E MARKET REPORT 2019," Tech. Rep. [Online]. Available: https://www.entsoe.eu/news/2019/09/03/two-new-entso-e-reports-on-market-network-codes-implementation-now-released/

[10] R. Heffron, M.-F. Körner, J. Wagner, M. Weibelzahl, and G. Fridgen, "Industrial demand-side flexibility: A key element of a just energy transition and industrial development," *Applied Energy*, vol. 269, p. 115026, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261920305389

[11] Z. Jiang, R. Hao, Q. Ai, Z. Yu, and F. Xiao, "Extended multi-energy demand response scheme for industrial integrated energy system," *IET Generation, Transmission Distribution*, vol. 12, no. 13, pp. 3186–3192, 2018.

[12] 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.

[13] P. Mancarella, "Mes (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1 – 17, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544213008931

[14] C. A. Frangopoulos, "A method to determine the power to heat ratio, the cogenerated electricity and the primary energy savings of cogeneration systems after the european directive," *Energy*, vol. 45, no. 1, pp. 52 – 61, 2012, the 24th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy, ECOS 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S036054421100870X

[15] P. Mancarella and G. Chicco, "Global and local emission impact assessment of distributed cogeneration systems with partial-load models," *Applied Energy*, vol. 86, no. 10, pp. 2096 – 2106, 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261908003516

[16] G. Chicco and P. Mancarella, "Matrix modelling of small-scale trigeneration systems and application to operational optimization," *Energy*, vol. 34, no. 3, pp. 261 – 273, 2009, wESC 2006 Advances in Energy Studies. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544208002429

[17] M. Kostelac, I. Pavić, and T. Capuder, "Mathematical model of flexible multi-energy industrial prosumer under uncertainty," in *2020 International Conference on Smart Energy Systems and Technologies (SEST)*, 2020, pp. 1–6.

[18] A. Pini Prato, F. Strobino, M. Broccardo, and L. Parodi Giusino, "Integrated management of cogeneration plants and district heating networks," *Applied Energy*, vol. 97, pp. 590 – 600, 2012, energy Solutions for a Sustainable World - Proceedings of the Third International Conference on Applied Energy, May 16-18, 2011 - Perugia, Italy. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261912001377

[19] 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. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544214005283

[20] 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.

[21] M. Daneshvar, B. Mohammadi-ivatloo, S. Asadi, K. Zare, and A. Anvari-Moghaddam, "Optimal day-ahead scheduling of the renewable based energy hubs considering demand side energy management," in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, 2019, pp. 1–6.

[22] X. Zhang, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, "Optimal expansion planning of energy hub with multiple energy infrastructures," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2302–2311, 2015.

[23] 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. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261917307973

[24] T. Capuder, M. Kostelac, M. Krpan, and I. Pavić, "Multi-energy microgrid ability to provide flexibility services to the system operator and security of supply to end-users," in *2020 International Conference on Smart Energy Systems and Technologies (SEST)*, 2020, pp. 1–6.

[25] 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.

[26] W. Huang, N. Zhang, J. Yang, Y. Wang, and C. Kang, "Optimal configuration planning of multi-energy systems considering distributed renewable energy," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1452–1464, 2019.

[27] W. Liu, J. Zhan, C. Y. Chung, and Y. Li, "Day-ahead optimal operation for multi-energy residential systems with renewables," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 4, pp. 1927–1938, 2019.

[28] V. Kleinschmidt, T. Hamacher, V. Perić, and M. Reza Hesamzadeh, "Unlocking flexibility in multi-energy systems: A literature review," in *2020 17th International Conference on the European Energy Market (EEM)*, 2020, pp. 1–6.

[29] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*, ser. International Series in Operations Research & Management Science. Boston, MA: Springer US, jan 2010, vol. 153, no. 1. [Online]. Available: https://www.tandfonline.com/doi/full/10.1057/jors.2014.93 http://link.springer.com/10.1007/978-1-4419-7421-1

[30] A. Prékopa, *Stochastic Programming*. Dordrecht: Springer Netherlands, 1995. [Online]. Available: http://link.springer.com/10.1007/978-94-017-3087-7

[31] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*, ser. Springer Series in Operations Research and Financial Engineering. New York, NY: Springer New York, 2011. [Online]. Available: http://link.springer.com/10.1007/978-1-4614-0237-4

[32] A. Ben-Tal and A. Nemirovski, "Selected topics in robust convex optimization," *Math. Program.*, vol. 112, pp. 125–158, 03 2008.

[33] A. Ben-Tal, L. El Ghaoui, and A. Nemirovski, *Robust Optimization*, ser. Princeton Series in Applied Mathematics. Princeton University Press, October 2009.

[34] D. Bertsimas, D. B. Brown, and C. Caramanis, "Theory and applications of robust optimization," 2010.

[35] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[36] European Commission, *EU energy in figures - Publications Office of the EU*, 2020. [Online]. Available: https://op.europa.eu/es/publication-detail/-/publication/87b16988-f740-11ea-991b-01aa75ed71a1

[37] M. Suhr, G. Klein, I. Kourti, M. Rodrigo Gonzalo, G. Giner Santonja, S. Roudier, and L. Delgado Sancho, *Best Available Techniques (BAT) Reference Document for the Production of Pulp, Paper and Board*, 2015. [Online]. Available: http://eippcb.jrc.ec.europa.eu

[38] F. Schorcht, I. Kourti, B. M. Scalet, S. Roudier, and L. D. Sancho, *Best Available Techniques (BAT) Reference Document for the Production of Cement, Lime and Magnesium Oxide*, 2013. [Online]. Available: http://eippcb.jrc.ec.europa.eu/reference/BREF/CLM_Published_def.pdf

[39] G. G. Santonja, P. Karlis, T. , Brinkmann, and S. Roudier, *Best Available Techniques (BAT) Reference Document on Food, Drink and Milk Industries*, 2019. [Online]. Available: http://eippcb.jrc.ec.europa.eu/reference/brefdownload/download_FDM.cfm

[40] T. Brinkmann, G. Giner Santonja, F. Schorcht, S. Roudier, and L. Delgado Sancho, *Best Available Techniques Reference Document for the Production of Chlor-alkali*, 2014. [Online]. Available: http://eippcb.jrc.ec.europa.eu

[41] R. Remus, S. Roudier, M. A. Aguado-Monsonet, and L. Delgado Sancho, *Best available techniques - iron and steel production*, 2013, vol. BREF-IS.

[42] G. Cusano, M. R. Gonzalo, F. Farrell, R. Remus, S. Roudier, and L. D. Sancho, *Best Available Techniques (BAT) Reference Document for the Non-Ferrous Metals Industries*, 2017. [Online]. Available: http://eippcb.jrc.ec.europa.eu/reference/BREF/NFM/JRC107041_NFM_Bref_2017.pdf

[43] K. He and L. Wang, "A review of energy use and energy-efficient technologies for the iron and steel industry," *Renewable and Sustainable Energy Reviews*, vol. 70, pp. 1022 – 1039, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1364032116310620

[44] Y.-K. Yeo, H.-D. Roh, I.-W. Kim, I. Moon, and Y. Chung, "Optimal operation of utility systems in petrochemical plants," *Korean Journal of Chemical Engineering*, vol. 20, pp. 200–206, 03 2003.

[45] E. G. de Magalhães, T. Fronza, K. Wada, and A. R. Secchi, "STEAM AND POWER OPTIMIZATION IN A PETROCHEMICAL INDUSTRY," *IFAC Proceedings Volumes*, vol. 39, no. 2, pp. 839–844, 2006. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1474667016354350

[46] S. Mitra, L. Sun, and I. E. Grossmann, "Optimal scheduling of industrial combined heat and power plants under time-sensitive electricity prices," *Energy*, vol. 54, pp. 194 – 211, 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544213001448

[47] X. Luo, B. Zhang, Y. Chen, and S. Mo, "Modeling and optimization of a utility system containing multiple extractions steam turbines," *Energy*, vol. 36, no. 5, pp. 3501 – 3512, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544211002246

[48] Z. Li, W. Du, L. Zhao, and F. Qian, "Modeling and optimization of a steam system in a chemical plant containing multiple direct drive steam turbines," *Industrial & Engineering Chemistry Research*, vol. 53, no. 27, pp. 11 021–11 032, 2014. [Online]. Available: https://doi.org/10.1021/ie402438t

[49] L. Zhac, C. Ning, and F. You, "Industrial steam systems optimization under uncertainty using data-driven adaptive robust optimization," in *2019 American Control Conference (ACC)*, 2019, pp. 2127–2132.

[50] P. Varbanov, S. Doyle, and R. Smith, "Modelling and optimization of utility systems," *Chemical Engineering Research and Design*, vol. 82, no. 5, pp. 561 – 578, 2004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0263876204725289

[51] M. H. Agha, R. Thery, G. Hetreux, A. Hait, and J. M. Le Lann, "Integrated production and utility system approach for optimizing industrial unit operations," *Energy*, vol. 35, no. 2, pp. 611 – 627, 2010, eCOS 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544209004666

[52] A. Gholian, H. Mohsenian-Rad, and Y. Hua, "Optimal industrial load control in smart grid," *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2305–2316, 2016.

[53] A. Gholian, H. Mohsenian-Rad, Yingbo Hua, and Joe Qin, "Optimal industrial load control in smart grid: A case study for oil refineries," in *2013 IEEE Power Energy Society General Meeting*, 2013, pp. 1–5.

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