2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe) | 978-1-6654-8537-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/EEEIC/ICPSEUROPE54979.2022.9854642

A Risk-Averse Energy Management System for Optimal Heat and Power Scheduling in Local Energy Communities

Maryam Mohiti
Department of Electrical Engineering
Chalmers University of Technology
Gothenburg, Sweden
maryamar@chalmers.se

Mohammadreza Mazidi
Department of Electrical Engineering
Chalmers University of Technology
Gothenburg, Sweden
mazadi@chalmers.se

David Steen
Department of Electrical Engineering
Chalmers University of Technology
Gothenburg, Sweden
david.steen@chalmers.se

Le Anh Tuan
Department of Electrical Engineering
Chalmers University of Technology
Gothenburg, Sweden
tuan.le@chalmers.se

***Abstract*—Local energy communities (LECs) facilitate energy distribution, supply, consumption, storage, and trading for the communities and their members. This paper proposes a risk-averse energy management system (EMS) for optimal heat and power scheduling in LECs. Three approaches namely high accuracy forecast models, advanced optimization models, and providing flexibility sources are followed to handle uncertainties of photovoltaic power and load. To this end, the load demand and photovoltaic power as uncertain variables are predicted using machine learning methods and the problem is modeled under uncertainties by information-gap decision theory (IGDT). This method doesn't require probability distribution functions of uncertain variables which makes it valuable in cases with high levels of uncertainties or lack of sufficient historical data. The advantage of flexibility in increasing robustness is studied by adjusting desired indoor and hot water temperatures. The effectiveness and efficiency of the proposed model are evaluated on the LEC at Chalmers University of Technology campus, Gothenburg, Sweden.**

Keywords— Local energy community, forecast, flexibility, information-gap decision theory, heat and power scheduling.

Nomenclature

Indices

t	Index of time

Parameters

η_e, η_{th}	CHP electrical/thermal efficiency coefficients
η_d, η_{ch}	Battery energy storage (BESS) charge/discharge efficiency
η_{th}^{B}	Boiler efficiency
λ_t^{DH}	District heating energy price [sek/kW]
λ_t^{peak}	Peak power charge for electricity [sek/kW]
λ_t^{Elec}	Spot market price
λ_t^{fuel}	CHP fuel price (sek/kW)
C^A	Heat capacity of building indoor air [$kWh/$℃]
C^W	Specific heat of water [$kWh/lit.$℃]
P_{ramp}^{CHP}	CHP ramp rate
$H_{min}^{CHP}, H_{max}^{CHP}$	Minimum/Maximum allowed thermal power of CHP [kW]
H_t^{dem}	Thermal power demand [kW]
P_t^{Dem}	Electrical power demand [kW]
$P_{min}^{CHP}, P_{max}^{CHP}$	Minimum/Maximum allowed electrical power of CHP [kW]
$Pd_{max}^{BES}, Pc_{max}^{BES}$	Minimum/Maximum allowed electrical power of CHP [kW]
R	Thermal resistance of building shell [℃$/kW$]
SOC_{min}, SOC_{max}	Minimum/Maximum capacity of BESS
T_t^{CW}	Temperature of cold water entering to the storage to replace the consumed hot water
T_t^{OB}	Outdoor temperature [℃]
$T_{min}^{HW}, T_{max}^{HW}$	Minimum/maximum desired hot water temperature [℃]
$T_{min}^{IB}, T_{max}^{IB}$	Minimum/maximum desired indoor temperature [℃]
V^{Tot}	Total volume of water storage [lit].

Variables

α	Uncertainty horizon of wholesale market price in IGDT method.
β	Uncertainty horizon of load demand in IGDT method.
SOC_t	Capacity of BESS (kWh)
$P_{s,t}^{CHP}$	CHP electrical power (kW)
P_t^{Im}, P_t^{Ex}	Import, Export electrical power with grid.
uc_t^{BES}, ud_t^{BES}	Discharging /charging status of the BESS
H_t^B	Boiler thermal power
H_t^{CHP}	CHP thermal power
H_t^{IB}	Thermal power needed to set the building temperature
P^{peak}	Peak load [kW]
$\widetilde{P_t^{Dem}}$	Forecasted value of electrical power [kW]
u_t^{CHP}	CHP commitment status
Pd_t^{BES}, Pc_t^{BES}	Scheduled discharge /charge power of BESS
T_t^{HW}	Hot water storage temperature [℃]
$T_{s,t}^{IB}$	Building indoor temperature [℃]
H_t^{IB}	Thermal power needed to set the building temperature [kW]

I. INTRODUCTION

The increasing integration of renewable energy sources (RESs) along with other distributed energy sources (DERs) such as battery energy storages (BESSs) and demand response in distribution networks, has highlighted the need of considering them as an entity. To this end the European Commission's has introduced the concept of Local Energy Communities (LECs) in the EU legislation [1]. LECs are clusters of DERS which allow the whole community and their members to actively participate in the energy management system (EMS). However, the uncertainties of RESs and demand imposes serious challenges in developing an efficient EMS for LECs. To deal with uncertainties three approaches can be followed; first, forecast models with high accuracy can be developed to predict the RES generation and load in the forecast horizon, secondly, advanced models should be developed to optimize the scheduling problem of

The work of this paper was supported by funding from: i) SUNSETS project within Solar ERANET program, funded by the Swedish Energy Agency with project number 51197-1; ii) FlexiGrid project under European Union's Horizon 2020 Research and Innovation program under grant agreement No 864048.

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LECs under uncertainties, and third, flexibility sources such as BESSs and demand response can be incorporated to deal with the uncertainties [2].

PV generation and load forecast have been extensively investigated in literature [3]. Although advanced forecasting models based on Machine Learning (ML) approaches are developed to predict PV generation [4, 5] and load , they cannot be precisely predicted beforehand. This arises from the fact the that PV generation as well as load may highly be dependent to exogenous features such as meteorological factors. Many work [6] have utilized the historical measurements of weather parameters as input to their algorithms, in other words they have assumed they have the perfect prediction of weather parameters, however, to exploit the PV and load forecast in EMSs this assumption may not be realistic and in the proposed model similar to some work [7] the forecasting system is based on weather prediction models and predicted weather features are used for training the ML model.

To tackle the uncertainty of RESs and loads several optimization methods have been developed, namely stochastic optimization (SO) [8], robust optimization (RO) [9], and interval optimization (IO) methods [10, 11]. SO methods are based on probability distribution functions (PDFs) of uncertain variables which are used to create numerous scenarios with their probabilities for simulating possible realization of uncertainties [12, 13]. However, the accuracy of SO is dependent to the accuracy of the PDFs, i.e., forecasts, and the number of scenarios. This means lack of sufficient data to establish high accuracy forecast methods, not only degrades the prediction, but also results in inaccurate PDFs and a non-optimized solution. In RO methods the worst-case scenario is realized enforcing a conservative and robust costly solution. To deal with this, IO methods namely IGDT (Information Gap Decision Theory) method which only require forecasted values and lower and upper bands of uncertain variables are utilized in the presented paper. In the proposed IGDT method a pre-specified level of cost is guaranteed while the optimal solution is risk averse.

In the proposed paper a risk-averse energy management system for optimal heat and power scheduling in Chalmers university local Energy community is presented. The proposed paper attempts to investigate the three mentioned approaches of handling uncertainty i.e., forecasts, uncertainty-based optimization methods, and incorporating flexibility sources. First based on the real data a forecast method for PV generation and load of the LEC is presented and evaluated. Based on these forecasted values, the bounds of the uncertain variables i.e., PV generation and load are determined for the IGDT optimization method to provide a risk averse EMS which is robust against uncertainty. In the presented LEC, desired end users' water and indoor temperature are adjusted to provide flexibility and the effect of provided flexibility on the robustness against forecast errors is illustrated.

II. Energy Management System

As shown in Fig. 1, the studied LEC includes various sources which trades electricity and heat with the main grid and district heat network. In this section, the energy management system for the residential LEC is formulated.

A. Objective function

The objective function is to minimize total expected operation cost of LEC which is formulated as following:

$$\begin{aligned} Min\ Cost = \sum_{t=1}^{N_T} \Big(& \lambda_t^{Elec}(P_t^{Im} - P_t^{Ex}) + \lambda_t^{peak} P^{peak} \\ & + \lambda_t^{fuel}(P_{s,t}^{CHP}/\eta_e + H_t^B/\eta_{th}^B) \\ & + \lambda_t^{DH}(H_t^{Im} - H_t^{Ex}) \end{aligned} \tag{1}$$

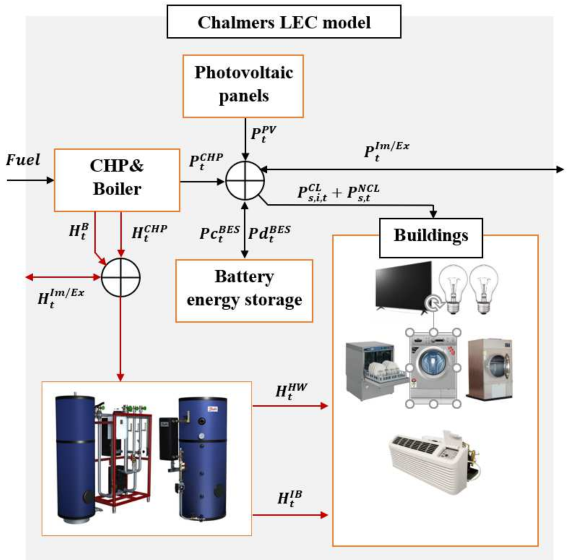

Fig. 1. The residential energy community model

Operation cost of LEC includes cost of export/import of electricity from/to the main grid, cost of fuel consumed by the CHP, cost of heat delivered/exported to the LEC/district heating network, and a separate tariff is also applied on the peak load drawn from the electricity grid.

B. Constraints

1) Constraints on CHP and boiler: The heat produced by the boiler is related to the efficiency of the boiler and is reflected in the third term of (1). The electrical and thermal power of the CHP are related as (2) and limited as (3) and (4). Note that since Chalmers CHP is primarily designed for heat production, the maximum electric capacity is coupled to its maximum heat capacity by the electrical to heat ratio (η_e/η_{th}):

$$P_t^{CHP} = \frac{\eta_e}{\eta_{th}} H_t^{CHP} \tag{2}$$

$$u_t^{CHP}.P_{min}^{CHP} \le P_t^{CHP} \le u_t^{CHP}.P_{max}^{CHP} \tag{3}$$

$$u_t^{CHP}.H_{min}^{CHP} \le H_t^{CHP} \le u_t^{CHP}.H_{max}^{CHP} \tag{4}$$

The ramp rate constraints are as following:

$$-P_{ramp}^{CHP} \le P_t^{CHP} - P_{t-1}^{CHP} \le P_{ramp}^{CHP} \tag{5}$$

$$-\frac{\eta_{th}}{\eta_e}.P_{ramp}^{CHP} \le H_t^{CHP} - H_t^{CHP} \le \frac{\eta_{th}}{\eta_e}.P_{ramp}^{CHP} \tag{6}$$

2) Constraints on BESS: The BESS is charged and discharged considering the following constraints:

$$0 \le Pc_t^{BES} \le uc_t^{BES}.Pc_{max}^{BES} \tag{7}$$

$$0 \le Pd_t^{BES} \le ud_t^{BES}.Pd_{max}^{BES} \tag{8}$$

$$uc_{s,t}^{BES} + ud_t^{BES} \le 1 \tag{9}$$

$$SOC_t = SOC_{t-1} - Pd_t^{BES}/\eta_d + Pc_t^{BES}.\eta_{ch} \tag{10}$$

$$SOC_{min} \leq SOC_t \leq SOC_{max} \tag{11}$$

3) Constraints on thermal comfort of buildings: The CHP supplies thermal power to a water storage tank which supplies hot water of buildings. Also, the space heating thermal power demand to control inside temperature of buildings is drawn from the water storage. The water storage is assumed to be always full and the consumed hot water is replaced with the same volume of cold water in each time interval. The temperature of water storage can be calculated as follows [14]:

$$T_{t+1}^{HW} = \frac{V_t^{CW}.\left(T_t^{CW} - T_t^{HW}\right) + V^{Tot}.T_t^{HW}}{V^{Tot}} + \frac{H_t^{dem} - H_t^{IB}}{V^{Tot}.C^{W}} \tag{12}$$

The first term in (12) indicates the equilibrium temperature of storage water, which is due to combination of cold input water and hot water remaining in the water storage. The second term represents the temperature deviation of thermal storage due to the difference between the input heat from the heat supply (CHP, boiler and district heating) and the output heat for controlling the inside temperature of buildings which can be obtained as following [15]:

$$T_{t+1}^{IB} = T_t^{IB}.exp(-1/(R.C^A)) + (R.H_t^{IB} + T_t^{OB}).\left(1 - exp(-1/(R.C^A))\right) \tag{13}$$

To adhere these constraints, hot water and inside temperatures of buildings should be maintained within predefined ranges:

$$T_{min}^{HW} \leq T_{s,t}^{HW} \leq T_{max}^{HW} \tag{14}$$

$$T_{min}^{IB} \leq T_{s,t}^{IB} \leq T_{max}^{IB} \tag{15}$$

4) Constraints on electrical and heat power balance: The electrical load demand of LEC should be supplied by resources and the main grid which is considered as (16). As previously mentioned, the heat demand is composed of hot water demand and space heating demand which is supplied by the CHP, boiler and district heating as in (17).

$$P_t^{im} - P_t^{Ex} + P_t^{PV} + P_t^{CHP} + Pd_t^{BES} - Pc_t^{BES} = P_t^{Dem} \tag{16}$$

$$H_t^{im} - H_t^{Ex} + H_t^{CHP} + H_t^{B} = H_{s,t}^{Dem} \tag{17}$$

III. Proposed Risk averse EMS

In this section, the forecast methods of load demand and PV power is introduced and then, the risk-averse EMS based on IGDT method for the LEC is developed.

A. Load and PV prediction

The PV site is located on rooftop of a building at Chalmers university of Technology campus, Gothenburg, Sweden. In the proposed model the forecasting system is based on weather prediction models and predicted weather features are used for training the machine learning (ML) algorithms. MEPS High Resolution Numerical Weather Prediction (NWP) model which is a 10-member short-range convection permitting ensemble prediction system and collected from Application Programming Interface (API) of [16] is utilized for weather predictions. This model was selected because of its low update cycle and spatial resolution which covers Chalmers location. ML algorithms based on Artificial Neural Network (ANN) and dynamic Recurrent Neural Network (DRNN) were implemented and tested on the real data of the PV site. The results of the 24-hour ahead PV generation and load forecast of the ANN and DRNN are presented in Table. I and Table . II, respectively. The results are compared by terms of Mean Absolute Error (MAE), root Mean Squared Error (RMSE) and coefficient of determination (R^2). As can be seen the ANN out-performs the DRNN, therefore, this method was selected for the 24-hour ahead PV and load forecast with the inputs as illustrated in Fig.2. Note that with respect to the results of the feature engineering while PV generation has a high correlation with meteorological features such as direct downward solar radiation and humidity, the load data had very low correlation with meteorological features and consequently, no metrological feature was utilized in the load prediction.

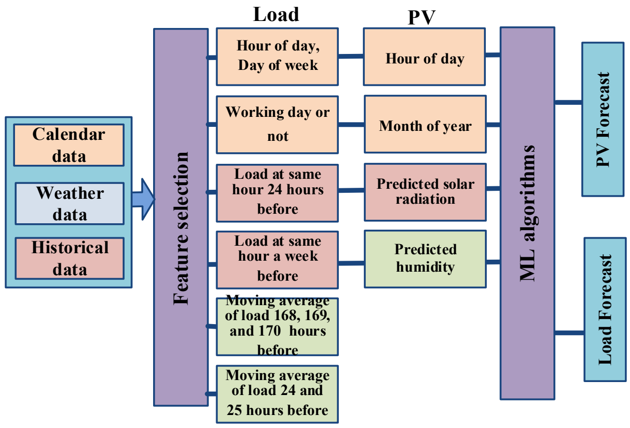

Fig. 2. Feature engineering for PV generation and load forecast

TABLE I. PV generation forecast results

	MAE (kW)	RMSE (kW)	R^2 (%)
ANN	0.63	1.45	94.85
DRNN	1.76	2.19	93.46

TABLE II. Load forecast results

	MAE (kW)	RMSE (kW)	R^2 (%)
ANN	4.69	5.94	89.38
DRNN	5.68	5.98	88.35

B. Risk-averse EMS based on IGDT method for the LEC

The IGDT method is based on the gap between the true value and forecasted value of uncertain variables, i.e., load demand and PV generation:

$$RR_{LD}\left(\alpha_{ld}, \widetilde{P_t^{Dem}}\right) = \left\{P_t^{Dem} \middle| -\alpha_{ld} \leq \left(P_t^{Dem} - \widetilde{P_t^{Dem}}\right)/\widetilde{P_t^{Dem}} \leq \alpha_{ld}, \alpha_{ld} \geq 0\right\} \tag{18}$$

$$RR_{PV}\left(\alpha_{pv}, \widetilde{P_t^{PV}}\right) = \left\{P_t^{PV} \middle| -\alpha_{pv} \leq \left(P_t^{PV} - \widetilde{P_t^{PV}}\right)/\widetilde{P_t^{PV}} \leq \alpha_{pv}, \alpha_{pv} \geq 0\right\} \tag{19}$$

The robustness region (RR) for load demand and PV power are indicated in (18) and (19), respectively. The objective of IGDT method is to maximize the robustness bands, i.e., α_{ld} and α_{pv} , while a prespecified operation cost (TOC) is achieved:

$$Max\ (\alpha, \beta) \tag{20}$$

Subject to:

$$TOC \leq \overline{TOC} \times (1 + UB) \tag{21}$$

$$(2)-(17) \tag{22}$$

$$\begin{aligned} TOC = Min \sum\nolimits_{t=1}^{N_T} &\left(\lambda_t^{Elec}(P_t^{Im} - P_t^{Ex}) + \lambda_t^{peak} P^{peak} \right. \\ &+ \lambda_t^{fuel}(P_{s,t}^{CHP}/\eta_e + H_t^B/\eta_{th}^B) \\ &\left. + \lambda_t^{DH}(H_t^{Im} - H_t^{Ex}) \right) \end{aligned} \tag{23}$$

Subject to:

$$-\alpha \le \left(P_t^{Dem} - \widetilde{P_t^{Dem}}\right)/\widetilde{P_t^{Dem}} \le \alpha, \alpha \ge 0 \tag{24}$$

$$-\beta \le \left(P_t^{PV} - \widetilde{P_t^{PV}}\right)/\widetilde{P_t^{PV}} \le \beta, \beta \ge 0 \tag{25}$$

The problem in (20)-(25) is a two-stage optimization problem that can be converted to the single-stage by considering the worst realization of uncertain variables:

$$Max\ (\alpha, \beta) \tag{26}$$

Subject to:

$$(21)-(22) \tag{27}$$

$$\begin{aligned} TOC = \sum\nolimits_{t=1}^{N_T} &\left(\lambda_t^{Elec}(P_t^{Im} - P_t^{Ex}) + \lambda_t^{peak} P^{peak} \right. \\ &+ \lambda_t^{fuel}(P_{s,t}^{CHP}/\eta_e + H_t^B/\eta_{th}^B) \\ &\left. + \lambda_t^{DH}(H_t^{Im} - H_t^{Ex}) \right) \end{aligned} \tag{28}$$

$$\widetilde{P_t^{Dem}} = (1 + \alpha_{ld})P_t^{Dem}, \alpha_{ld} \ge 0 \tag{29}$$

$$\widetilde{P_t^{PV}} = (1 - \alpha_{pv})P_t^{PV}, \alpha_{pv} \ge 0 \tag{30}$$

The optimal solution of (26)-(30) represents the risk-averse heat and power scheduling for the LEC.

IV. Case Study

A. Test system

The proposed model is implemented on a LEC located at the campus of Chalmers University of Technology. The CHP capacity located at Chalmers is scaled down to make it consistent with the size of the LEC. The hot water and electrical demand in the LEC are shown in Fig. 3. The electricity spot price and district heating price are depicted in Fig. 4. The fuel price of the CHP is assumed 0.353 sek/kW. The outdoor temperature is shown in Fig. 5. Other required data are presented in Table III. Two PV sites with the forecasted generation of Fig. 4 are in the LEC.

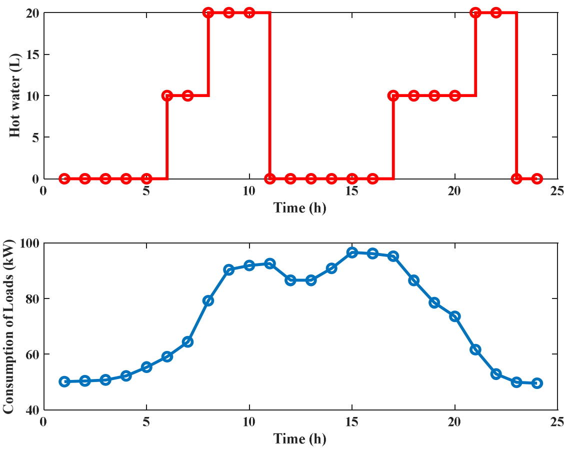

Fig. 3. Hot water demand and consumption of loads

B. Simulation results

The Pareto optimal solutions of α_{pv} and α_{ld} for different values of UB are shown in Fig. 6. As can be seen, Pareto front is extended with increasing the value of UB which means more robustness is provided against forecast errors of PV and load. Also, the results indicate that variations of α_{pv} are greater than α_{ld} which is due to the low penetration of PV in the LEC. Thus, in the studied LEC, the accuracy of load prediction is more important with respect to prediction of PV power. The best solution among Pareto optimal front can be selected based on the accuracy of the forecast method or using fuzzy set theory [10].Accordingly, the optimal power and heat

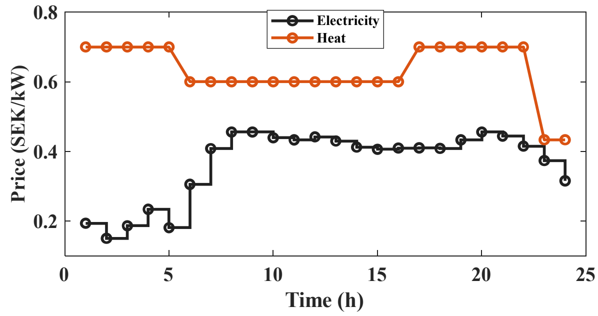

Fig. 4. Electricicty and district heat price and generation power of PVs

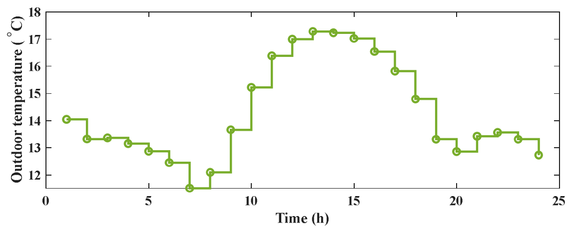

Fig. 5. Outdoor temperature of building

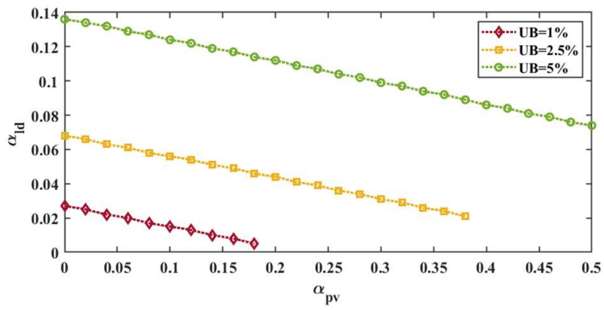

Fig. 6. Pareto optimal solutions of α_{pv} and α_{ld} for different values of UB

TABLE III. Requirement data of EMS

$P_{max}^{CHP}, P_{min}^{CHP}$	$H_{max}^{CHP}, H_{min}^{CHP}$	P_{ramp}^{CHP}	η_e, η_{th}	$Pd_{min}^{BES}, Pc_{max}^{BES}$	SOC_{min}, SOC_{max}
0,0.4	0, 0.5	2.5	0.2,0.8	1.5	0.2,0.9
η_{di}, η_{ch}	C^A, C^W	R	V^{Tot}	$T_{max}^{HW}, T_{min}^{HW}$	$T_{max}^{IB}, T_{min}^{IB}$
0.95	0.525, 0.000116	18	150	80, 60	27, 23

scheduling results for $UB = 5\%$ are shown in Figs. 7 and 8, respectively. As can be seen, the CHP is mainly scheduled to meet the power and heat of the LEC. Likewise, the BESS is discharged at high price hours and charged at low price hours, especially, when the demand is high. To decrease the operation cost of LEC, the power is exported to the grid at high price hours, namely during hours 21 to 24 when the load is the lowest. As shown in Fig.9, the provided heat for the LEC is increased by increasing the hot water demand and decreasing the outside temperature to maintain thermal comfort of the building. The indoor and hot water temperatures during the scheduling horizon are shown in Fig. 9. As can be seen, thermal comfort of the building is satisfied by the optimal heat scheduling. The robustness curves of net load demand (demand minus PV power) is shown in Fig. 10. As can be seen, more robustness can be reached with increasing UB i.e., the operation cost of LEC. However, by utilizing flexibility, a same level of robustness can be provided without increasing the operation cost of LEC. In this paper, the flexibility is increased by tuning wider deviation intervals for desired indoor and water temperatures. The effect of flexibility on the robustness against forecast errors is illustrated in Fig. 11. As can be seen, higher flexibility covers greater ranges of α_{pv} and α_{ld} and therefore more robustness is provided against forecast errors while thermal comfort of the building is met during scheduling horizon without increasing the operation cost of LEC.

To verify the robustness, a Monte-Carlo (MC) simulation approach has been conducted. To this end, considering the PDF of forecasted errors of load demand and PV power retrieved from the conducted forecasts, 500 scenarios are generated, and then, the operation cost of LEC is computed for each scenario. In this case, based on the variance of forecasted errors, the robustness bands of load demand and PV power are selected 0.26 and 0.10, respectively. The results are shown in Fig. 12. Note that the negative operation cost means a profit. As can be seen, the profit is always higher than the 1818 SEK which indicates that with selecting the appropriate robustness bands, the earned profit is guaranteed.

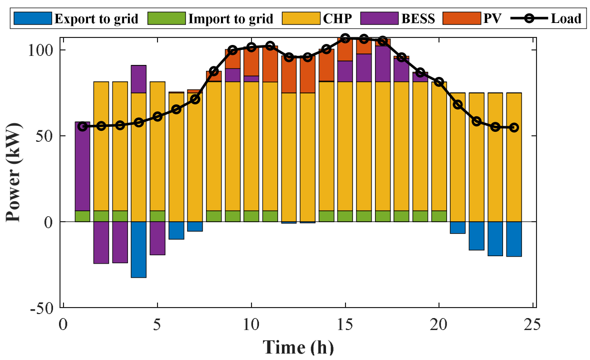

Fig. 7. Optimal power scheduling results during scheduling horizon

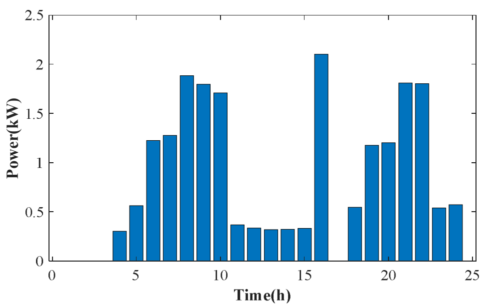

Fig. 8. Optimal heat scheduling results during scheduling horizon

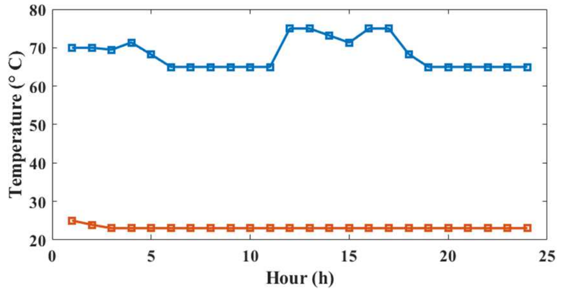

Fig. 9. Temperatures of indoor and hot water during scheduling horizon

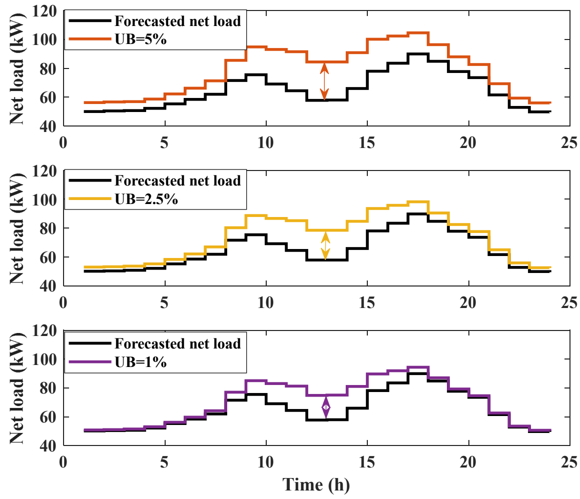

Fig. 10. The robustness curves of net load demand under different UBs

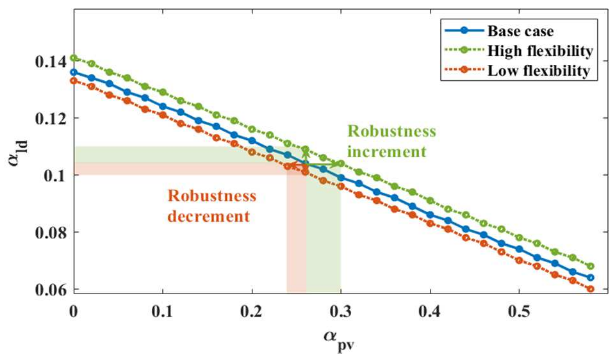

Fig. 11. The effect of flexibility on the robustness against forecast errors

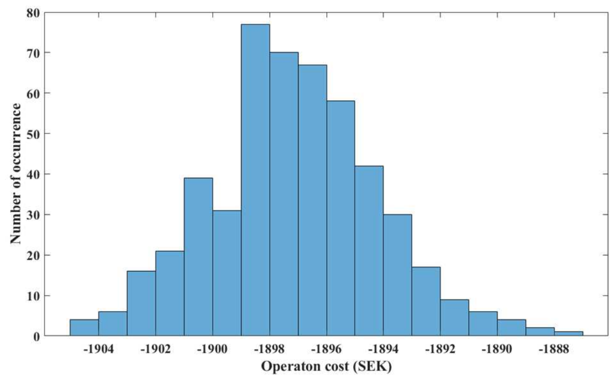

Fig. 12. Monte Carlo simulation results for robustness verification

V. CONCLUSIONS

This paper has presented a risk-averse EMS for optimal heat and power scheduling in LECs. Unlike most works, PV and load forecasts were performed based on weather predictions collected from NWPs. The uncertainties of PV and load were modeled by IGDT method and the Pareto front optimal solutions showed with increasing the UB more robustness is provided against forecast errors of PV and load. The best solution among Pareto optimal front was selected based on the accuracy of the conducted forecasts and the results were presented. It was shown by utilizing the flexibility offered by adjusting the hot water and indoor temperatures the robustness against uncertainties can be increased without imposing additional costs. Furthermore, a Monte-Carlo simulation was conducted with considering the PDFs of forecasted errors of load demand and PV power retrieved from the forecasts. It was shown that with selecting the appropriate robustness bands, the earned profit is guaranteed.

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