Robust Scenario-Based Approach for the Optimal Scheduling of Energy Hubs

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***Abstract*—Energy hubs are defined as energy systems that receive various energy carriers and convert or store them to serve different types of load demands. Stochastic scheduling methods can be used to optimally manage the energy hubs. However, in the stochastic approach, the main deficiency is that there exists the risk of experiencing the worst scenario, so a viable solution is needed to address this possibility. This paper addresses the two-stage operation scheduling of energy hubs based on the worst scenarios. A novel robust scenario-based approach is proposed and compared to the stochastic approach. A robustness parameter is defined to control the compromise between the expected operating costs and the model robustness. It can be seen that the model is robust against all the realization of worst scenarios.**

***Keywords*—Robust approach, Energy hubs, Scheduling, Uncertainty.**

NOMENCLATURE

	Indices
t	Time periods, t= 1, 2, …, T
i	Energy carriers nodes, i= 1, 2, …, I
n	CHPs, n= 1, 2, …, N
bo	Boilers, bo= 1, 2, …, BO
m	Diesel generators, m= 1, 2, …, M
hs	Heat storages, hs= 1, 2, …, H
b	Batteries, b= 1, 2, …, B
s	Scenarios, s= 1, 2, …, S
wt	Wind turbines wt=1, 2, …, WT
hp	Heat pumps hp=1, 2, …, HP
g/e	Natural Gas/Electricity
h	Heat
ch	Charge/Store energy
dis	Discharge/Withdraw energy
DA/RT	Day-ahead/Real-time
max/min	Upper/lower limits
	Variables and parameters
P	Power of energy carriers [MW]
Q	Reactive Power [MVar]
ES	Stored energy in heat storages [MWh]
SOC	State of charge in batteries [MWh]
SUC/SDC	Start-up/Shut-down cost [$]
ELC	Electrical energy not supplied [MWh]
TLC	Thermal energy not supplied [MWh]
EL	Electric load [MW]
TL	Thermal load [MW]
η	Efficiency of components
KU/KD	Start-up/shut down cost constant [$]
π	Hourly prices [$/MWh]
$VoLL_e$	Value of loss of electrical load [$/MWh]
$VoLL_h$	Value of loss of thermal load [$/MWh]
ρ_s	Probability of scenario s
u	Binary variable for the status of storages

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I. INTRODUCTION

Microgrids can be described as a group of distributed energy resources that works in both grid-connected and island modes to meet the electrical and heat load demands [1]-[2]. Capturing the interactions among the electricity and the natural gas networks in natural gas-fired units, multiple energy carriers (MEC) microgrids are defined.

In such microgrids, electrical and heat loads are supplied through energy hubs in the context of natural gas and electricity networks. Recently, a considerable amount of researches has been published on the short-term scheduling of energy hub-based systems [3]-[4].

In [5], a method for the energy flow problem is proposed. The energy hubs are formulated as a mixed-integer linear programming (MILP) optimization problem. The extension of [5] is proposed in [6] as risk-averse operation scheduling of the MEC system.

In this reference, the conditional value at risk (CVaR) method [7] quantifies the risk associated with uncertainties in the electrical and heat loads and the real-time price of electricity. Reference [8] presents the optimal operation of an energy hub. In [9], optimal stochastic operation of MEC system is addressed in the presence of electrical and heat demand response programs, electricity and heat energy market, renewables and storage.

Previous studies of operation scheduling in MEC systems have employed stochastic methods to deal with uncertain data. The major deficiency of the stochastic approaches is that there exists the risk of experiencing the worst scenario while the expected objective function is optimized.

To overcome such drawbacks, this paper aims to propose a robust solution for operation scheduling of MEC microgrids that immunizes against all realizations of uncertainties. Recently, researchers have shown an increased interest in the field of robust optimization approaches.

Several methodologies in the context of robust optimization problems have been proposed based on dealing with representing uncertainties. In general, robust optimization can be classified according to the representation of uncertainty as either scenario-based robust optimization or set-based robust optimization.

Mulvey et al. [10] proposed the model of scenario-based robust optimization, which expresses uncertainty as a set of scenarios that relates to realizations of uncertainties. On the other hand, set-based robust optimization expresses uncertainties.

In the context of set-based robust optimization, a robust counterpart is proposed under the assumption of an ellipsoidal uncertainty set by Ben-Tal and Nemirovski [11-13] or as a budget of uncertainty by Bertsimas and Sim [14, 15].

Among these techniques, we have employed the scenario-based approach to operation scheduling of MEC microgrids based on the Mulvey model.

This is due to its implementation simplicity, short computation of time, as well as the accuracy of results, once compared to the set-based approach [16].

The contributions are given by:

- A novel scenario-based robust optimization model for operation scheduling of MEC microgrids is proposed.

- A robust weighting factor is defined to specify the trade-off between the operation cost and solution robustness.

The rest of this paper is organized as follows. The proposed problem description and formulation are defined in section II. A case study and results are provided in sections III and IV, respectively. Finally, the results are concluded in section V.

II. Problem Description and Formulation

A. Framework

The general framework of the proposed robust model is represented in Figure 1. In this model, the decisions are obtained based on the worst scenario.

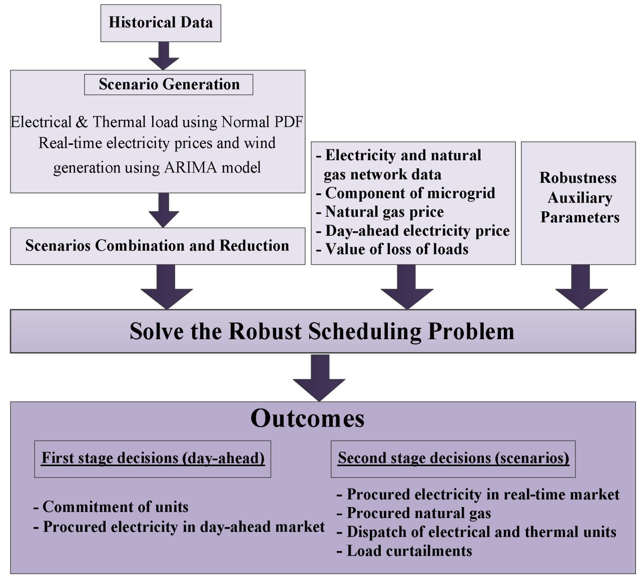


Fig. 1. Robust operation scheduling framework

B. Uncertainty Model

The microgrid operator encounters several uncertainties in the scheduling process.

To generate scenarios for wind and real-time market price, the Autoregressive integrated moving average (ARIMA) formulation is utilized. The ARIMA model is a time series model that generates scenarios based on historical data sets [17].

The load uncertainty is modeled by a Normal probability distribution function (PDF), and the corresponding scenarios are given using this model.

Generating scenarios by the models as mentioned above, a vector of scenarios for all times $X_s^t = [EL_s^t, TL_s^t, \pi_{RT,s}^t, P_{wt,s}^t]$ is supplied with the same probability. As a result of a large number of generated scenarios, the computation time of the optimal scheduling problem will increase significantly.

To cope with this challenge, a well-known scenario reduction called the Forward Method with SCENRED tool [18] in GAMS software [19] is implemented to reduce the primary set of scenarios.

C. General Form of the Proposed Robust Model

The general model of the above mentioned two-stage stochastic linear programming problem is as the followings:

$$Minimize_{x,y_s} \quad \boldsymbol{z} = \boldsymbol{c}^{\top}\boldsymbol{x} + \textstyle\sum_{s\in S} \rho_s \boldsymbol{q}_s^{\top}\boldsymbol{y}_s \tag{1}$$

$$Subject\ to \quad \boldsymbol{F}\boldsymbol{x} \le \boldsymbol{f}\,, \tag{2}$$

$$\boldsymbol{H}\boldsymbol{y}_s \le \boldsymbol{h}, \tag{3}$$

$$\boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y}_s \le \boldsymbol{g} \tag{4}$$

$$\forall\, \boldsymbol{x} \in \boldsymbol{X}, \boldsymbol{y}_s \in \boldsymbol{Y}, s \in S$$

where $\boldsymbol{x}$ and $\boldsymbol{y}_s$ are the vector of first and second-stage variables, respectively, and $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{c}, \boldsymbol{F}, \boldsymbol{q}, \boldsymbol{f}, \boldsymbol{g}, \boldsymbol{h}$ and $\boldsymbol{H}$ are the known coefficient vectors. In this proposed approach, the following constraints are included in the stochastic model to reflect the robustness against the uncertain data

In this paper, equations (5)-(7) are incorporated into the constraints to enforce the worst-case costs within a specified level.

$$\boldsymbol{\alpha} + \boldsymbol{\beta} \sum_{s\in S} \rho_s \boldsymbol{\psi}_s \le \boldsymbol{z}/\boldsymbol{\gamma} \tag{5}$$

$$\boldsymbol{c}^{\top}\boldsymbol{x} + \boldsymbol{q}_s^{\top}\boldsymbol{y}_s - \boldsymbol{\alpha} - \boldsymbol{\psi}_s \le \boldsymbol{0} \tag{6}$$

$$\boldsymbol{\psi}_s \ge \boldsymbol{0} \tag{7}$$

The parameter $\boldsymbol{\alpha}$ is a measure computed as the minimum cost value. Also, $\boldsymbol{\gamma}$ is an auxiliary parameter and $\boldsymbol{\psi}_s$ is employed in (5) and (6) to determine the worst scenario.

D. Objective Function and Constraints

This model is a scenario-based robust programming problem. The stochastic objective function is shown in (8) subject to constraints in (9)-(30). The first term is the total cost for the procured power from day-ahead market.

The second term is the start-up and shut-down cost of units ($\omega\epsilon\Omega = Diesel\ Gen., CHP, Boiler, Heat\ pump$) in the microgrid. The 3rd to 5th terms are the estimated cost of the obtained power from electricity market, natural gas utility, and diesel generators.

$$
\begin{aligned}
CF = &\sum_{t=1}^{T}\{P_{DA}^{t}.\pi_{DA}^{t} + \sum_{\omega\epsilon\Omega}[SUC_{\omega}^{t} + SDC_{\omega}^{t}] \\
&+\rho_{s}.\sum_{s=1}^{S}\ \{[P_{RT,s}^{t}.\pi_{RT,s}^{t}] + [P_{g,net,s}^{t}.\pi_{g}] \\
&+\sum_{m=1}^{M}[u_{m}^{t}.\pi_{m}^{nl} + P_{m,s}^{t}.\pi_{m}] \\
&+\sum_{i=1}^{I}[VoLL_{e}.ELC_{i,s}^{t} + VoLL_{h}.TLC_{i,s}^{t}]\}\}
\end{aligned} \tag{8}
$$

Based on this robust approach (5)-(7), constraints (9)- (11) are presented to express the robustness into the stochastic model.

$$\alpha + \beta\sum_{s=1}^{S}\rho_{s}.\psi_{s} \leq \gamma.CF \tag{9}$$

$$
\begin{aligned}
&\sum_{t=1}^{T}\{P_{DA}^{t}.\pi_{DA}^{t} + \sum_{\omega\epsilon\Omega}[SUC_{\omega}^{t} + SDC_{\omega}^{t}] \\
&+\sum_{s=1}^{S}\ \{P_{RT,s}^{t}.\pi_{RT,s}^{t} + P_{g,net,s}^{t}.\pi_{g} \\
&+\sum_{m=1}^{M}[u_{m}^{t}.\pi_{m}^{nl} + P_{m,s}^{t}.\pi_{m}] \\
&+\sum_{i}^{I}[VoLL_{e}.ELC_{i,s}^{t} + VoLL_{h}.TLC_{i,s}^{t}]\}
\end{aligned} \tag{10}
$$

$$
\begin{aligned}
&-\alpha - \psi_{s} \leq 0 \\
&\psi_{s} \geq 0
\end{aligned} \tag{11}
$$

Constraint (12) guarantees the generation limits of units (ω). Start-up and shut-down costs are described in (13) and (14). The energy storage constraints are defined in (15)-(24). Constraints (25) and (26) define the balance of active and reactive power at nodes, respectively.

Equation (27) describes the thermal energy balance in energy nodes. Constraints (28) and (29) ensure the amount of thermal and electrical load curtailments. The amount of purchased natural gas and its limitation are represented as (30). More details about these equations are obtained from [6].

$$P_{\omega}^{min}.u_{\omega}^{t} \leq P_{\omega,s}^{t} \leq P_{\omega}^{max}.u_{\omega}^{t} \tag{12}$$

$$SUC_{\omega}^{t} \geq 0, SUC_{\omega}^{t} \geq KU_{\omega}.(u_{\omega}^{t} - u_{\omega}^{t-1}) \tag{13}$$

$$SDC_{\omega}^{t} \geq 0, SDC_{\omega}^{t} \geq KD_{\omega}.(u_{\omega}^{t-1} - u_{\omega}^{t}) \tag{14}$$

$$ES_{hs,s}^{t} = ES_{hs,s}^{t-1} + \eta_{hs}^{st}.P_{hs,s}^{t,st} - 1/\eta_{hs}^{wd}.P_{hs,s}^{t,wd} \tag{15}$$

$$ES_{hs}^{min} \leq ES_{hs,s}^{t} \leq ES_{hs}^{max} \tag{16}$$

$$u_{hs,s}^{t,st} + u_{hs,s}^{t,wd} \leq 1 \tag{17}$$

$$0 \leq P_{hs,s}^{t,st} \leq P_{hs}^{st,max}.u_{hs,s}^{t,st} \tag{18}$$

$$0 \leq P_{hs,s}^{t,wd} \leq P_{hs}^{wd,max}.u_{hs,s}^{t,wd} \tag{19}$$

$$SOC_{b,s}^{t} = SOC_{b,s}^{t-1} + \eta_{b}^{ch}.P_{b,s}^{t,ch} - 1/\eta_{b}^{dis}.P_{b,s}^{t,dis} \tag{20}$$

$$SOC_{b}^{min} \leq SOC_{b,s}^{t} \leq SOC_{b}^{max} \tag{21}$$

$$u_{b,s}^{t,ch} + u_{b,s}^{t,dis} \leq 1 \tag{22}$$

$$P_{b,s}^{t,ch} \leq P_{b}^{ch,max}.u_{b,s}^{t,ch} \tag{23}$$

$$P_{b,s}^{t,dis} \leq P_{b}^{dis,max}.u_{b,s}^{t,dis} \tag{24}$$

$$
\begin{aligned}
&\left(P_{DA}^{t} + P_{RT,s}^{t}\right) + \textstyle\sum_{n\epsilon N_i} P_{n,e,s}^{t} + \\
&\textstyle\sum_{m\epsilon M_i} P_{m,s}^{t} - \sum_{hp\epsilon HP_i} P_{hp,s}^{t} + \\
&\textstyle\sum_{wt\epsilon WT_i} P_{wt,s}^{t} + \sum_{b\epsilon B_i}\left(P_{b,s}^{t,dis} - P_{b,s}^{t,ch}\right) = \\
&PL_{i,s}^{t} - ELC_{i,s}^{t}
\end{aligned} \tag{25}
$$

$$
\begin{aligned}
&(Q_{DA}^{t} + Q_{RT,s}^{t}) + \textstyle\sum_{n\epsilon N_i} Q_{n,e,s}^{t} + \\
&\textstyle\sum_{m\epsilon M_i} Q_{m,s}^{t} - \sum_{hp\epsilon HP_i} Q_{hp,s}^{t} + ELC_{i,s}^{t,Q} = \\
&QL_{i,s}^{t}
\end{aligned} \tag{26}
$$

$$
\begin{aligned}
&\textstyle\sum_{n\epsilon N_i} P_{n,h,s}^{t} + \sum_{bo\epsilon Bo_i} P_{bo,s}^{t} + \\
&\textstyle\sum_{hp\epsilon HP_i} COP_{hp}.P_{hp,s}^{t} + \sum_{hs\epsilon HS_i}(P_{hs,s}^{t,wd} - \\
&P_{hs,s}^{t,st}) = TL_{i,s}^{t} - TLC_{i,s}^{t}
\end{aligned} \tag{27}
$$

$$TLC_{i,s}^{t} \leq TL_{i,s}^{t} \tag{28}$$

$$ELC_{i,s}^{t} \leq PL_{i,s}^{t} \tag{29}$$

$$0 \leq P_{g,net}^{t} \leq P_{g,net}^{max} \tag{30}$$

E. Solution Methodology

In this paper, the below decomposition algorithm is used to solve the proposed robust operation scheduling model.

Algorithm

1: Set $LB = -\infty, UB = +\infty, k = 0$

2: Solve the master problem in (31)-(35) with determined $\boldsymbol{y_s^*}$

3: Set $LB = \boldsymbol{c^T x^*} + \gamma^*$ where $\boldsymbol{x^*}$ and $\gamma^*$are the solution of the master problem.

4: Solve sub-problem in (36)-(38).

5: Set $UB = \boldsymbol{c^T x^*} + \sum_{s\in S}\rho_s \boldsymbol{q_s^\top}\ \boldsymbol{y_s^*}$ where $\boldsymbol{y_s^*}$ is the solution of the sub-problem

6: If $UB - LB \leq \varepsilon$ terminate the process else add $\boldsymbol{Ax} + \boldsymbol{By_s^*} \leq \boldsymbol{g}$ and $\gamma \geq \sum_{s\in S}\rho_s \boldsymbol{q_s^\top y_s^*}$ to the master problem (31)-(35).

7: Set $k = k + 1$ and go to step 2.

The master and sub-problems are defined as (31)-(35) and (36)-(38), respectively.

Master problem:

$$\min_{x,\gamma} \boldsymbol{c}^{\boldsymbol{T}}\boldsymbol{x} + \gamma \tag{31}$$

$$\text{s.t.} \quad \gamma \geq \sum_{s \in S} \rho_s \boldsymbol{q}_{\boldsymbol{s}}^{\mathrm{T}} \boldsymbol{y}_{\boldsymbol{s}}^{*} \tag{32}$$

$$\boldsymbol{Fx} \leq \boldsymbol{f}\,, \boldsymbol{x} \in \{0,1\} \tag{33}$$

$$\boldsymbol{Hy}_{\boldsymbol{s}}^{*} \leq \boldsymbol{h}, \tag{34}$$

$$\boldsymbol{Ax} + \boldsymbol{By}_{\boldsymbol{s}}^{*} \leq \boldsymbol{g} \tag{35}$$

Sub-problem:

$$\min_{y} \sum_{s \in S} \rho_s \boldsymbol{q}_{\boldsymbol{s}}^{\mathrm{T}} \boldsymbol{y}_{\boldsymbol{s}} \tag{36}$$

$$\boldsymbol{Hy}_{\boldsymbol{s}} \leq \boldsymbol{h}, \tag{37}$$

$$\boldsymbol{Ax}^{*} + \boldsymbol{By}_{\boldsymbol{s}} \leq \boldsymbol{g} \tag{38}$$

III. Case Study and Description of Test System

A. Description of the Test Microgrid

In order to evaluate the proposed robust model, an energy hub is studied as in Figure 2. Table I describes the characteristics of resources in the energy hub, and also the efficiency of energy storage facilities are 0.9 for both charging and discharging modes of operation. Using the normal PDF and the ARIMA model, 1000 scenarios are generated.

Each scenario's probability is 0.001 and consists of four uncertain variables. Using the SCENRED tool, we have fewer (eight) generated scenarios [18]. Figure 3 a-d illustrates the eight scenarios of electrical demand, thermal demand, real-time prices, and wind speed, respectively. It is considered that natural gas price is equal to 20 $/MWh.

IV. Results and Sensitivity Analysis

The proposed operation scheduling approach is a MILP executed in GAMS software and solved by CPLEX solver.

Case 1: Stochastic scheduling approach. In this case, the robustness criterion in the scheduling is not considered.

Case 2: Robust scenario-based scheduling approach. In this case, the robustness criterion is considered.

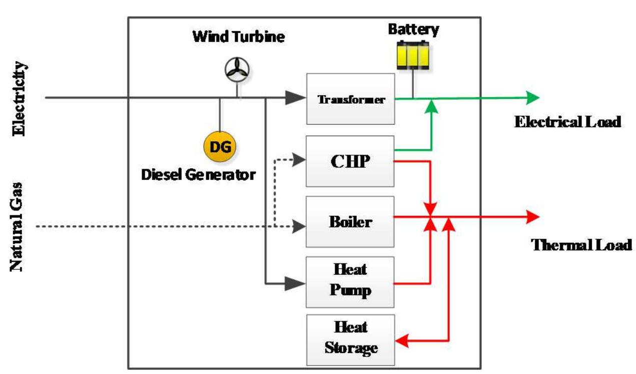


Fig. 2. Model of test energy hub

TABLE I
CHARACTERISTICS OF RESOURCES

Resource				
CHP	$\boldsymbol{\eta_{CHP,e/h}}$ **[%]**	$\boldsymbol{P_{n,e/h}^{min}}$ **[MW]**	$\boldsymbol{P_{n,e/h}^{max}}$ **[MW]**	$\boldsymbol{KU_n}$ **[$]**
	42/47	0.6	6	10
Heat Storage	ES_{hs}^{min} [MWh]	ES_{hs}^{max} [MWh]	$P_{hs}^{st,max}$ [MW]	$P_{hs}^{wd,max}$ [MW]
	0.1	1	0.4	0.6
Boiler	η_{bo} [%]	P_{bo}^{min} [MW]	P_{bo}^{max} [MW]	KU_{bo} [$]
	85	0.9	9	10
Heat Pump	COP_{hp}	P_{hp}^{min} [MW]	P_{hp}^{max} [MW]	KU_{hp} [$]
	1.5	0.4	4	0.5
Diesel Generator	π_m [$/MWh]	P_m^{min} [MW]	P_m^{max} [MW]	KU_m [$]
	61	0.25	2	10
Wind Turbine	$P_{wt,r}$ [MW]	v_{cin} [m/s]	v_{cout} [m/s]	v_r [m/s]
	3.6	3	25	12
Battery	SOC_b^{min} [MWh]	SOC_b^{max} [MWh]	$P_b^{ch,max}$ [MW/h]	$P_b^{dis,max}$ [MW/h]
	0.2	2	1.2	1.2

A. Numerical Results

Table II shows the operating costs in scenarios and the anticipated costs in Cases 1 and 2. When considering the robustness restrictions of the model in the stochastic model (Case 2), the operating costs are reduced in high cost scenarios (for instance, 6, 7 and 8) and augmented in other scenarios. As can be seen, even though the likely cost of the robust model in Case 2 is augmented by 3.48% in relation with Case 1, risk of high cost scenarios is covered in the model.

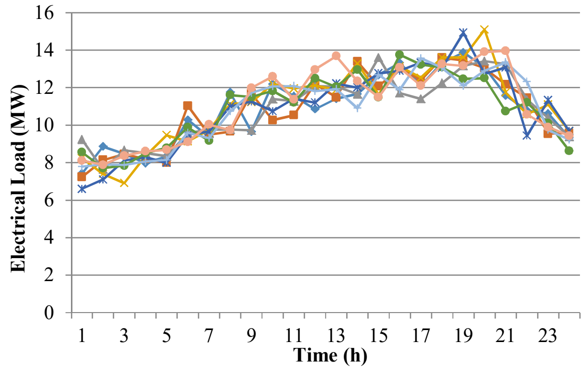
B. Sensitivity Analysis

As given in Figure 4, the anticipated energy cost is increased by increasing the model robustness parameter. It means that the model is more robust against all scenarios by utilizing more units and consequently more expected cost.

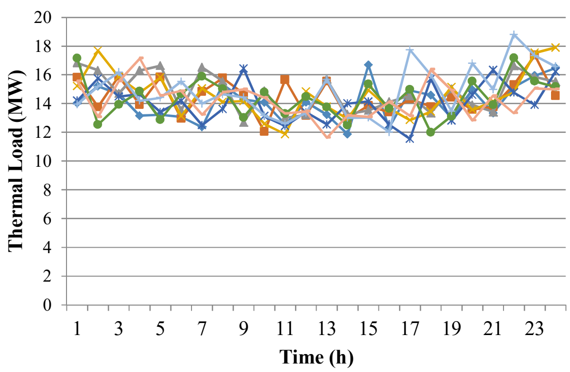
TABLE II
OPERATION COSTS IN SCENARIOS

Scenario	Case 1	Case 2	Change %	Probability
1	9648	10759	+11.51	0.147
2	10948	11371	+3.86	0.164
3	10683	11366	+6.39	0.190
4	11830	11956	+1.06	0.149
5	8721	10363	+18.8	0.071
6	12109	11884	**-1.8**	0.096
7	13392	12442	**-7.09**	0.069
8	12775	12266	**-3.98**	0.114
Expected Cost ($)	11097	11484	**+3.48**	-

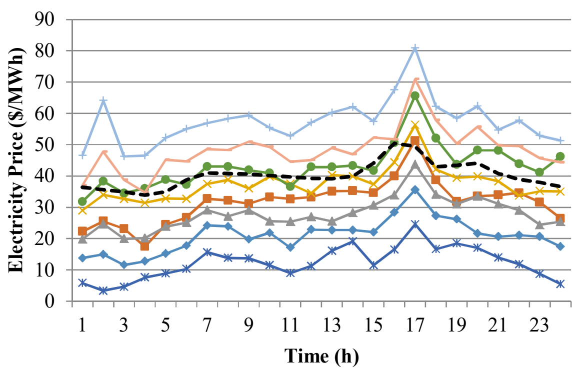
The procured electrical and thermal energy is shown in Fig. 5 and Fig. 6, respectively.



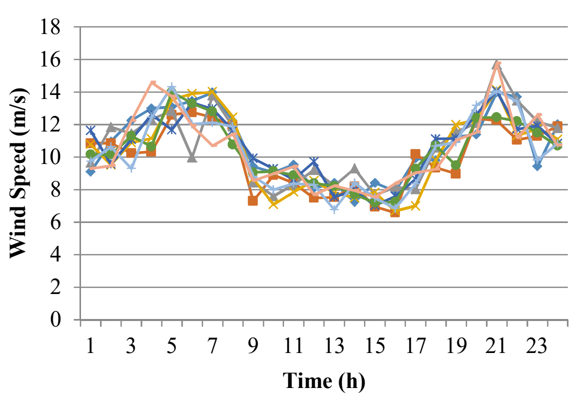
(a)



(b)



(c)



(d)

Fig. 3. Scenarios of a: electrical demand, b: thermal demand, c: real-time electricity prices, and d: wind speed

As shown in Fig. 5, the procured real-time electricity is decreased by improving the robustness of the model. On the other hand, the day ahead electricity procurement is increased by increasing the model robustness because of its less uncertainty. Other resources are dispatched based on their availability and their operation costs.

Fig. 6 demonstrates the utilization of thermal resources by varying the robustness parameter. As shown in this figure, increasing the model's robustness results in increasing the procurement of the thermal energy from the heat pump instead of the boiler.

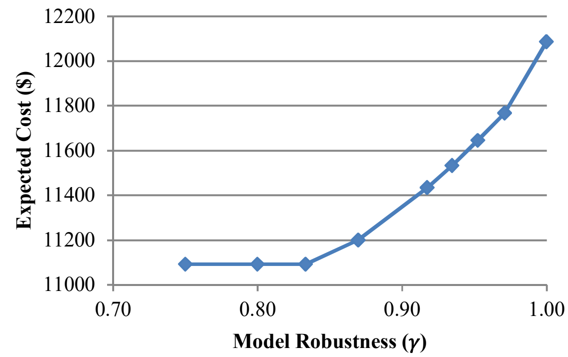


Fig. 4. Expected cost versus model robustness

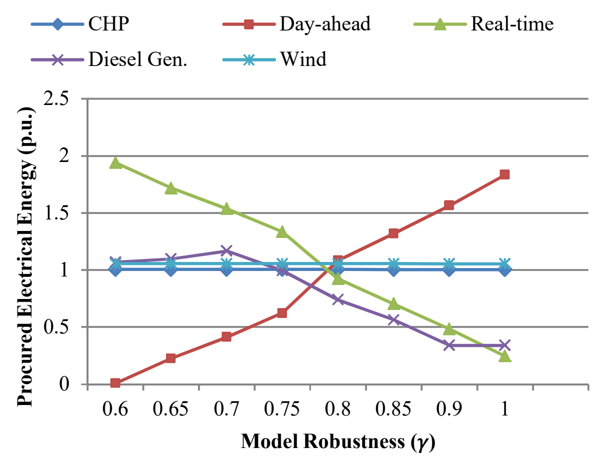


Fig. 5. Procured electrical energy by variation of model robustness

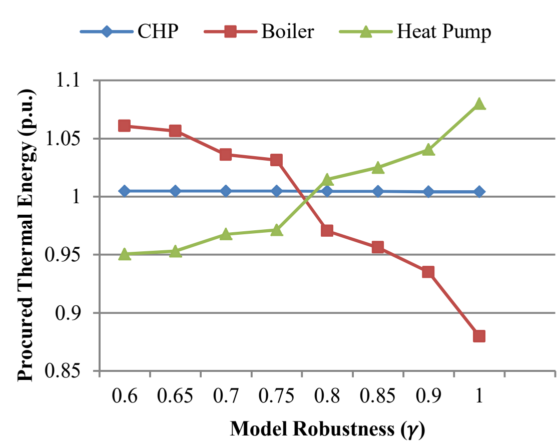


Fig. 6. Procured thermal energy by variation of model robustness

V. CONCLUSION

The last decade has witnessed several innovations in the field of operation scheduling in multi-carrier energy systems. To overcome the drawbacks of previous methods, this paper proposed a novel scenario-based robust approach to deal with the operation scheduling problem of energy hubs. The model was applied to an energy hub with uncertainties of loads, prices, and wind speeds. Results demonstrate that the model is immunized against all scenarios. It was shown that the commitment and the dispatch of unites are changed by varying the robustness level of the model.

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