

Chapter 5

Optimal Operation of Multi-carrier Energy Networks Considering Demand Response Programs



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5.1 Introduction

The smart energy hub (SEH) concept is widely used in power system literature based on the fact that the smart grid (SG) infrastructure utilizes multi-carrier distributed energy resources (DERs) that are controlled in a decentralized manner [1]. The SEH can generate, store, and convert electrical, heating, and cooling energy and utilizes a different form of energy conversion technologies [2].

The main facilities of SEHs are combined cool, heat, and power (CCHP), boilers, absorption chiller (ACH), compression chiller (CCH), electrical storage system (ESS), cooling energy storage system (CSS), and thermal energy storage system (TSS) [1]. Further, the demand response programs (DRPs), plug-in hybrid electric vehicles (PHEVs), and intermittent electricity generation facilities such as wind turbines (WTs) and photovoltaic arrays (PVAs) can be utilized in a smart distribution system. These energy resources have stochastic behavior and the integration of these resources into the smart distribution system may complicate the operational paradigms [3].

An active multi-carrier energy distribution system (AEDS) may utilize SEH facilities, WT, PVA, and PHEV parking lots as DERs and supply its electrical, heating, and cooling loads through the multi-carrier energy transmission networks.

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The optimal day-ahead operational planning (ODAOP) consists of the commitment of distributed energy resource facilities considering uncertainties of variables, security criteria, economic evaluations, and environmental aspects.

The ODAOP problem has been explored over recent years and multiple types of research were carried out to assess different aspects of this complicated problem.

Reference [1] introduced a two-level optimization framework for DA scheduling of distribution system that transacted electricity with energy hubs. The energy hubs proposed their contribution bids and the distribution system explored the optimality of submitted bids. The algorithm adopted linear optimization process and the 33-bus IEEE test system was utilized to assess the method. The operational costs of the system were reduced by 82% with respect to the base case. Reference [2] introduced an energy flow model to determine the capacity of energy-generating units. The TSS and CSS were modeled and the environmental, energetic, and economic variables were presented in the formulation. The particle swarm optimization (PSO) algorithm was utilized and the cost of system, environmental emission, and energy consumption were reduced by 11.2%, 25.9%, and 12.2%, respectively. Reference [3] proposed the optimal scheduling of energy centers, gas network, and electric system. Emission, voltage deviations, energy loss, operation costs, and pressure deviation of natural gas were considered and the analytic hierarchy process was utilized. The proposed method reduced the operating costs and energy consumptions by 21.77% and 39.12%, respectively. Reference [4] introduced the optimal scheduling of intelligent park MicroGrid (MG) in China and the genetic algorithm was utilized to optimize the problem. The proposed method reduced operation costs by 1.68%. Reference [5] proposed a stochastic optimization algorithm for energy hub DA scheduling that utilized conditional value-at-risk method. The risk mitigation method was used and operation cost was reduced by 1.37%. Reference [6] presented an energy hub model for optimal scheduling of DERs and mixed-integer linear programming (MILP) approach was utilized to minimize the operation costs. The results showed that the optimization algorithm reduced the operation costs by about 23%. Reference [7] introduced an iterative two-stage framework for optimization of interactions of the electric distribution system and SEHs. The stochastic optimization process was utilized to model the uncertainties of the wind electricity generations. Reference [8] proposed a mixed-integer nonlinear programming (MINLP) approach to scheduling of CCHP-based systems. The energy and cost-saving ratios were utilized to model the problem and the results compared the conventional systems with the CCHP-based systems. Reference [9] described the integrated model of CCHP-based energy hub wherein the emission pollution and operation costs were minimized. The algorithm successfully reduced emission pollution and operation costs by 2.3% and 4%, respectively. Reference [10] utilized an MINLP algorithm to schedule an energy hub. The efficiencies of electrical system for a cold day and hot day were improved by 59% and 47%, respectively. Further, the efficiencies of the heating load system for a cold day and hot day were improved by 15% and 29%, respectively. Reference [11] introduced an energy consumption model for a decentralized energy system that reduces energy consumption and peak load. The algorithm reduced the emission pollutant by about 46% that utilized DERs for

energy generation. Reference [12] utilized a two-stage framework that carried out the stochastic optimization for scheduling of energy and reserve. The method considered intermittent electricity generation and heating loads. The DRP procedure was utilized to minimize the operation costs and the results showed that the method reduced the system costs by about 15%. Reference [13] explored the effectiveness of DRP alternatives for modifying the heating and electrical loads. The model minimized the procurement costs; meanwhile, it maximized the system's profits. The consumption cost of the multi-carrier energy system was reduced and the peak load of energy carriers was modified. Reference [14] introduced a framework for energy management of multi-energy hubs and the model considered power quality, regulation costs, and voltage deviation variables in the goal programming. Reference [15] presented an algorithm for minimizing operation costs and emission pollution of energy hubs and modeled the PHEVs, DRPs, and ESSs as control variables. The procedure considered the revenue of energy sold to the upward network and the process increased the energy hub revenue by about 105% with respect to the base case. Reference [16] introduced a two-stage optimization algorithm for the DA and RT operation horizons. The optimization process was performed for electrical and thermal systems and results showed that the algorithm successfully reduced the system costs. Reference [17] proposed a multi-objective optimization process that considered the emission pollution, energy consumption, and system costs. The introduced method reduced operation costs by 24%. Reference [18] modeled an energy hub that utilized CCHP facilities and DRP alternatives. The operation costs of the energy hub and distribution system were reduced by 14% and 10%, respectively. Reference [19] introduced the responsive load model applications in a multi-carrier energy system and the procedure modeled different alternatives for responsive loads. The case study was carried out for a home and its costs were reduced by 4%. Reference [20] introduced a six-level optimization algorithm for optimal operation of a distribution system in DA and RT horizons considering risk-averse strategy. The DRP alternatives were utilized by the system. The 123-bus IEEE test system was utilized to assess the proposed method and the results showed that the revenue of the system was increased by 324% risk-averse conditions with respect to the base case. Reference [21] utilized an information-gap decision theory to model the stochastic behavior of the electricity and natural gas networks. The model minimized total costs of operation and encountered the uncertainties of electrical load, wind electricity generation, and gas load demands. Reference [22] presented a hydrogen-based smart micro-energy hub model that considered demand response alternatives and fuel cell-based hydrogen storage systems. The proposed model minimized the DA operational costs using the robust optimization process. Reference [23] introduced a two-stage unit commitment process for optimal operation of gas and electricity networks considering DRPs. The optimization procedure utilized ϵ -constraint technique to find the best solutions. Reference [24] proposed a two-stage stochastic network-constrained unit commitment for coordinated power and gas networks considering air energy storage and wind turbines. The effect of the participation of gas-fueled power plant in the energy and reserve markets has been investigated. Reference [25] introduced a value-at-risk-based stochastic model to

determine the optimal DA scheduling of energy hubs. The model considered the power-to-gas storage and compressed air energy storage systems. The model utilized the load shifting procedure for multiple electrical loads and reduced the operational costs by 4.5%.

The described references do not consider the locational marginal price (LMP) optimization on their operational scheduling optimization. Further, the introduced algorithm simultaneously optimizes DA and RT energy transactions in different multi-carrier energy resources.

5.2 Problem Modeling and Formulation

The AEDS operator (AEDSO) transacts energy with the upward electricity market and supplies the electrical, heating, and cooling load of downward customers. The AEDSO can sell active and reactive power to the upward electricity market. Further, it can transact electricity with PHEV parking lots. As shown in Fig. 5.1, the AEDS is equipped with the CCHPs, PVAs, SWTs, gas-fueled distributed generation (DGs),

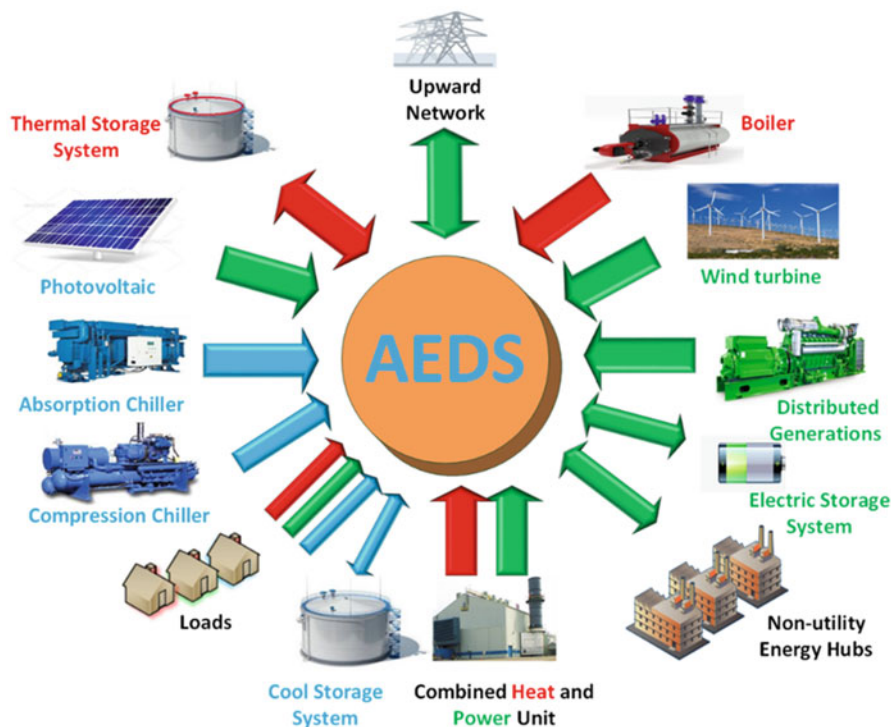


Fig. 5.1 The schematic diagram of AEDS energy interactions

TSSs, CSSs, and ESSs. The customers may have different energy generation, storage, and conversion facilities that can be modeled as energy hubs [26–28].

The AEDSO utilizes the DRP alternatives that consist of direct load control (DLC), time of use (TOU), and involuntary load shedding (ILS) alternatives and it schedules the distributed energy resources to maximize its revenues. The energy hub of customer that is named as the nonutility energy hub (NUEH) can sell its surplus active and reactive electrical energy to the upward system and participate in DRPs in DA and RT markets.

The optimization process of AEDSO has two-time horizons: DA market and RT market. Thus, the objective functions of ODAOP can be decomposed into DA and RT market horizons.

For the DA horizon, the AEDSO should optimize the scheduling of its distributed energy resources in DA horizon considering the uncertainties. The uncertainties of the problem in DA horizon are upward electricity market price, multi-carrier energy demands, intermittent DERs, PHEV contribution scenarios, and NUEH commitment strategies.

The AEDSO distributed energy resources are CCHPs, TSSs, CSSs, intermittent power generations (IPGs), and ESSs. Further, the PHEVs, NUEHs, and DRPs can be utilized as energy resources.

Thus, the objective function of optimal scheduling of system resource problem for the DA horizon can be proposed as Eq. (5.1):

$$\text{Min } \mathcal{A} = \sum_{\text{NWMS}} \text{prob.} \left(\begin{array}{l} W_1 (C_{\text{AEDSO}}^{\text{DA}} \cdot \psi_{\text{AEDSO}}^{\text{DA}} + \sum_{\text{NPHEVS}} \text{prob.} \cdot C_{\text{PHEV}}^{\text{DA}} \cdot \psi_{\text{PHEV}}^{\text{DA}}) \\ + C_{\text{Purchase}}^{\text{DA}} + \sum_{\text{NDRPS}} \text{prob.} \cdot C_{\text{DRP}}^{\text{DA}} + \\ \sum_{\text{NIPGS}} \text{prob.} \cdot C_{\text{IPG}}^{\text{DA}} + \sum_{\text{NNUEHS}} \text{prob.} \cdot C_{\text{NUEH}}^{\text{DA}} \\ - \text{revenue}^{\text{DA}}) + W_2 (\sum \text{LMP}) \end{array} \right) \quad (5.1)$$

The objective function is decomposed into eight groups: (1) the commitment costs of DERs that consist of CCHPs, PVAs, SWTs, gas-fueled DGs, TSSs, CSSs, and ESSs; (2) the energy purchased from the PHEVs costs; (3) the energy purchased from wholesale market costs; (4) the DRP costs; (5) the IPG costs; (6) the energy purchased from NUEH costs; (7) the revenue of AEDSO; and (8) the sum of LMPs.

The AEDSO can sell active, reactive, and spinning reserve to the upward wholesale market. Thus, the revenue of AEDSO can be written as Eq. (5.2):

$$\text{revenue}^{\text{DA}} = \sum_{\text{NWMS}} \text{prob.} \left(\sum \alpha_{\text{active}}^{\text{DA}} \cdot P_{\text{active}}^{\text{DA_upward}} + \sum \beta_{\text{active}}^{\text{DA}} \cdot Q_{\text{active}}^{\text{DA_upward}} \right. \\ \left. + \sum \gamma_{\text{spinning}}^{\text{DA}} \cdot R_{\text{spinning}}^{\text{DA_upward}} \right) \quad (5.2)$$

The revenue of AEDSO consists of three terms: (1) the revenue of active energy, (2) the revenue of reactive energy, and (3) the revenue of spinning reserve.

Equation (5.1) has the following groups of constraints of which some are not presented due to the lack of space:

1. The maximum discharge and charge constraints of ESS, TSS, and CSS [29].
2. The maximum discharge and charge constraints of PHEVs [1].
3. The energy storage facilities cannot discharge and charge at the same time constraints [29].
4. The DRP constraints [1].
5. The AEDS device loading constraints, electrical load flow constraints, and mass balance equations.

For the RT horizon, the AEDSO should minimize the deviations of its scheduling from the optimal values of DA horizon. Thus, the objective function of optimal scheduling of system resource problem for the RT horizon can be proposed as Eq. (5.3):

$$\text{Min } \mathfrak{M} = W_1(\Delta C_{\text{AEDSO}}^{\text{RT}} + \Delta C_{\text{PHEV}}^{\text{RT}} + \Delta C_{\text{Purchase}}^{\text{RT}} + \Delta C_{\text{DRP}}^{\text{RT}} + \Delta C_{\text{IPG}}^{\text{RT}} + \Delta C_{\text{NUEH}}^{\text{RT}} - \Delta \text{revenue}^{\text{RT}}) + W_1\left(\sum \text{LMP}\right) \quad (5.3)$$

The objective function is decomposed into eight groups: (1) the mismatch values of commitment costs of DERs; (2) the mismatch values of energy purchased from the PHEV costs; (3) the mismatch values of energy purchased from wholesale market costs; (4) the mismatch values of DRP costs; (5) the mismatch values of IPG costs; (6) the mismatch values of energy purchased from NUEH costs; (7) the mismatch values of revenue of AEDSO; and (8) the sum of LMPs.

The mismatch values of revenue of AEDSO in RT horizon can be written as Eq. (5.4):

$$\Delta \text{revenue}^{\text{RT}} = \left(\sum \alpha_{\text{active}}^{\text{RT}} \cdot \Delta P_{\text{active}}^{\text{RT-upward}} + \sum \beta_{\text{active}}^{\text{RT}} \cdot \Delta Q_{\text{active}}^{\text{RT-upward}} \right) \quad (5.4)$$

The revenue of AEDSO in RT horizon consists of two terms: (1) the mismatch values of revenue of active energy and (2) the mismatch values of revenue of reactive energy.

Equation (5.3) has the same constraints as in Eq. (5.1) in the RT scheduling horizon.

5.3 Solution Algorithm

For the optimization algorithm, the following assumptions are considered:

1. The alternating current (AC) load flow is linearized [1].

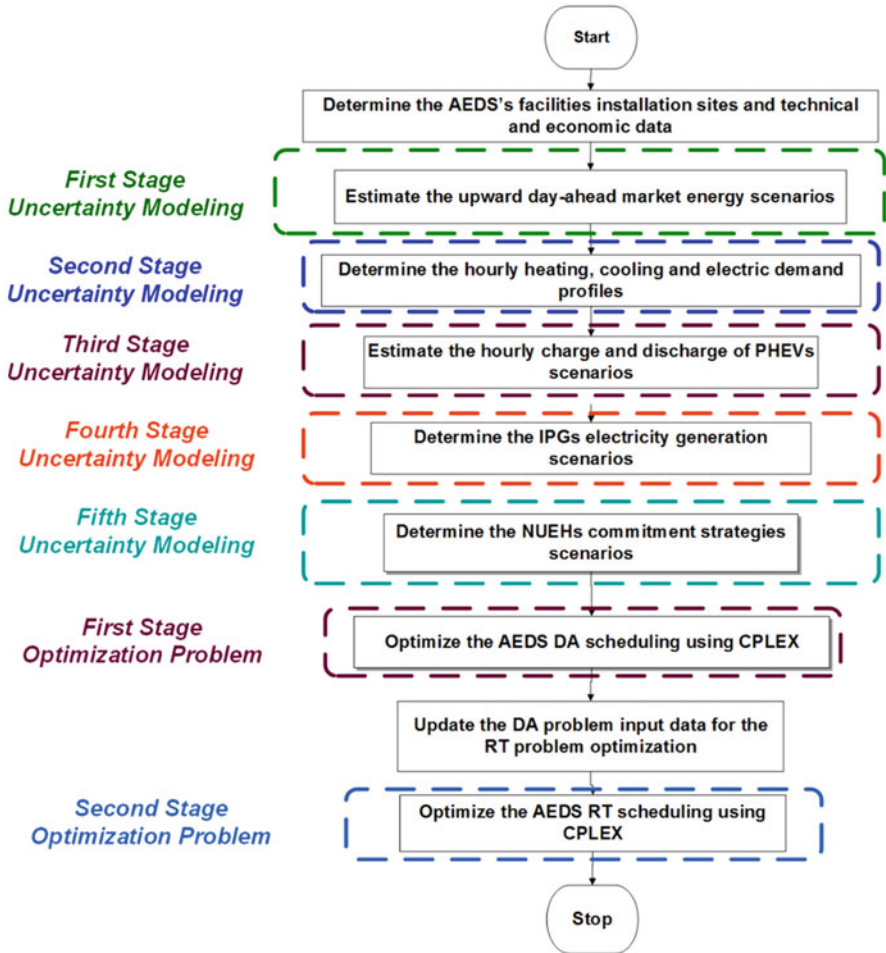


Fig. 5.2 Flowchart of the proposed algorithm

2. Scenario generation and reduction procedures are performed for modeling of uncertainties using the proposed procedure in [1].
3. All of the bids/offers of the distribution system are accepted by the wholesale market operator.
4. The DA load and price forecasting procedures are performed using the introduced method in [30].
5. The LMPs are calculated based on the introduced models of References [31–33].

The linear optimization of the two-staged problem was carried out using the CPLEX solver of GAMS. The flowchart of the algorithm is presented in Fig. 5.2.

5.4 Simulation Results

An industrial district 125-bus test system was used to assess the proposed algorithm. The NUEHs are presented in Fig. 5.3. Tables 5.1 and 5.2 present the optimization input data for the 125-bus system and NUEHs, respectively. The 125-bus industrial district system consists of multiple NUEHs, parking LOTs (PLOTs), CCHs, ACHs, CHPs, DGs, TSSs, CSSs, ESSs, and IPGs.

Figure 5.4 presents the wholesale electricity market price for three reduced scenarios. Figure 5.5 shows the hourly cooling, heating, and electrical load of the NUEHs for one of the reduced scenarios. Figure 5.6 presents the PVA and SWT electricity generation for energy hub for one of the reduced scenarios. Multiple scenario generation and reduction procedures were carried out.

The two-staged optimization procedure was carried out for DA and RT operational horizons. Figure 5.7 presents the estimated stacked column PLOT electricity generation/consumption for DA horizon. The estimated net transacted energy of PLOTs for DA was about 1233.40 kWh and its mean value was about 2.447 kWh. The estimated maximum values of DA PLOTs' charge and discharge were 20.7895 kWh and 11.1845 kWh, respectively. The optimization procedure updated the input data using the described process and the estimated PLOT electricity generation/consumption for RT horizon was determined.

Figure 5.8 shows the estimated stacked column PLOT electricity generation/consumption for RT horizon. The estimated net transacted energy of PLOTs for RT was about 1326.69 kWh and its mean value was about 2.632 kWh. The estimated maximum values of RT PLOTs' charge and discharge were 23.5473 kWh and 10.8208 kWh, respectively.

Figure 5.9 depicts the estimated CCH and ACH cooling energy generation, CSS cooling energy charge and discharge, and cooling energy loss for DA horizon. The aggregated cooling energy generations of CCHs and ACHs in DA horizon were about 81.111 MWh and 23.371 MWh, respectively. Further, the mean values of cooling energy generations of CCHs and ACHs in DA horizon were about 3.379 MWh and 0.973 MWh, respectively.

Figure 5.10 shows the estimated CCH and ACH cooling energy generation, CSS cooling energy charge and discharge, and cooling energy loss for RT horizon. The aggregated cooling energy generations of CCHs and ACHs in RT horizon were about 59.843 MWh and 18.112 MWh, respectively. Further, the mean values of cooling energy generation of CCHs and ACHs in RT horizon were about 2.493 MWh and 0.754 MWh, respectively.

Figure 5.11 presents the estimated stacked column NUEH electricity generation/consumption for DA horizon. The estimated net transacted energy of NUEHs for DA was about 24.229 MWh and its mean value was about 72.11 kWh. The estimated maximum values of DA NUEHs' electricity consumptions/generations were 2357.33 kWh and 2538.12 kWh, respectively.

Figure 5.12 depicts the estimated stacked column of NUEH electricity generation/consumption for RT horizon. The estimated net transacted energy of NUEHs for RT

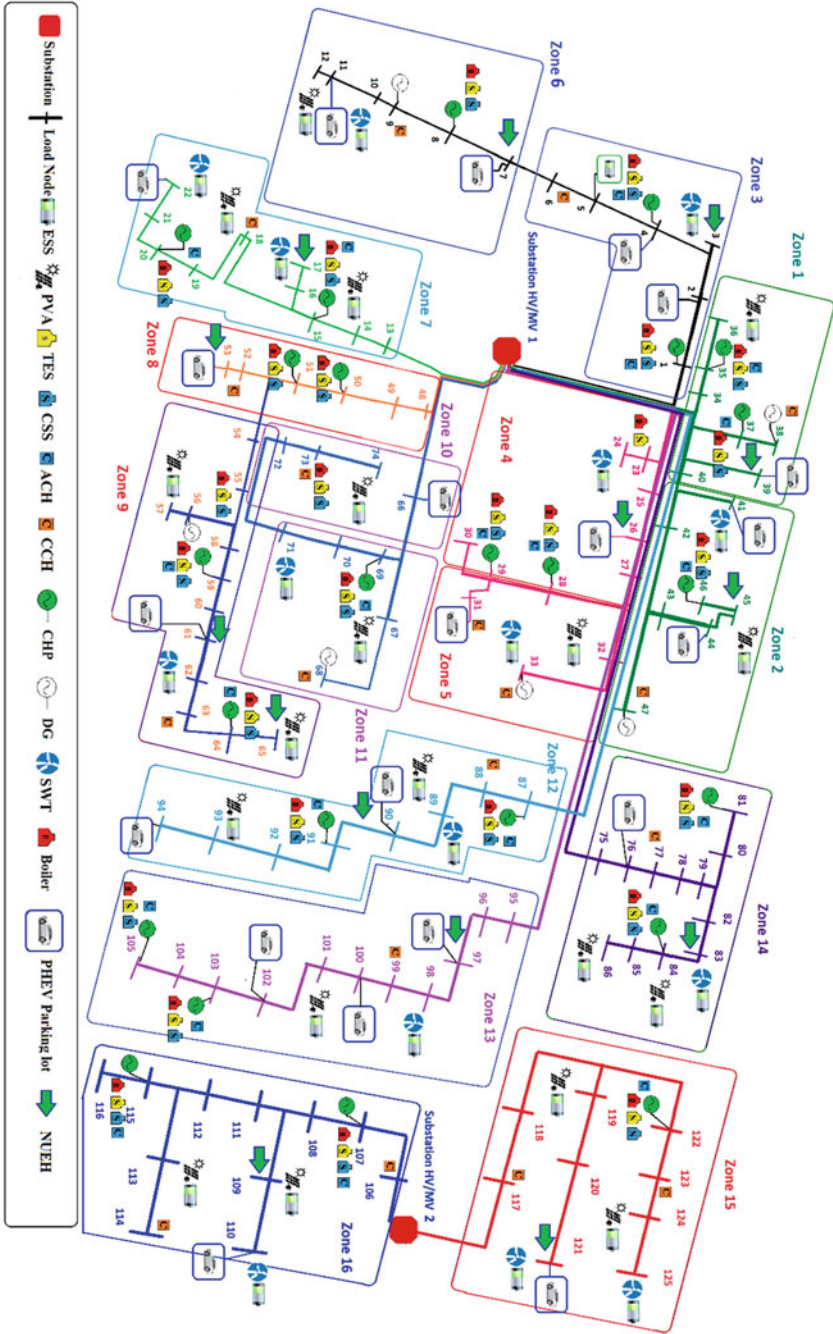


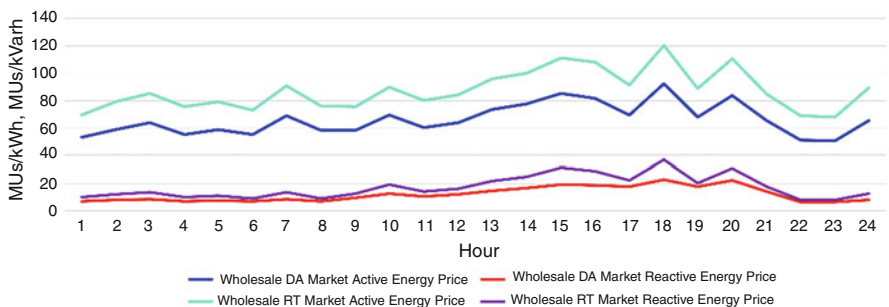
Fig. 5.3 The 125-bus industrial district distribution system

Table 5.1 The optimization input data for the 125-bus system

Distribution system parameters	Value
Number of solar irradiation scenarios	5000
Number of SWT power generation scenarios	5000
Number of upward market price scenarios	150
Number of PHEV contribution scenarios	5000
Number of DRP commitment scenarios	3000
Number of solar irradiation reduced scenarios	20
Number of SWT power generation reduced scenarios	20
Number of upward market price reduced scenarios	3
Number of PHEV contribution reduced scenarios	20
Number of DRP commitment reduced scenarios	20

Table 5.2 The optimization input data for the NUEHs

NUEH parameters	Value
Number of solar irradiation scenarios	5000
Number of SWT power generation scenarios	5000
Number of proposed DSO TOU price and DLC fee scenarios	15
Number of PHEV contribution scenarios	1000
Number of solar irradiation reduced scenarios	5
Number of SWT power generation reduced scenarios	5
Number of TOU price and DLC fee reduced scenarios	3
Number of PHEV contribution reduced scenarios	4

**Fig. 5.4** The wholesale electricity market price for three reduced scenarios

was about 20.206 MWh and its mean value was about 60.13 kWh. The estimated maximum values of RT NUEHs' electricity consumptions/generations were 1497.23 kWh and 1381.83 kWh, respectively.

Figure 5.13 shows the estimated NUEH electricity generation/consumption, IPG electricity generation, CHP and DG electricity generation, and import/export of electricity for the DA horizon. The aggregated electricity generation of IPGs and CHPs and DGs were about 117.848 MWh and 123.432 MWh, respectively.

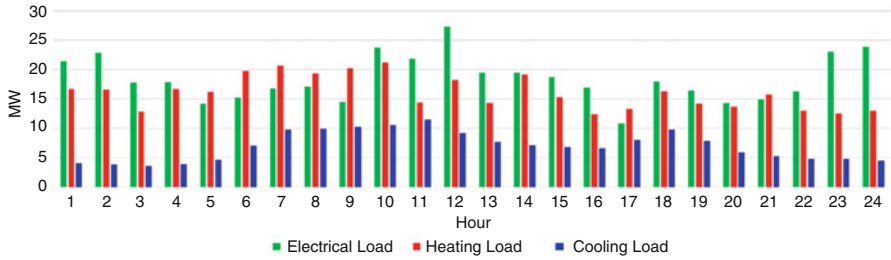


Fig. 5.5 Hourly cooling, heating, and electrical load of the energy hubs

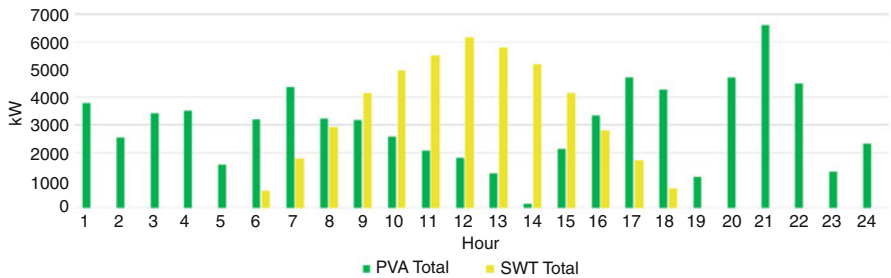


Fig. 5.6 The PVA and SWT electricity generation for energy hub for one of the reduced scenarios

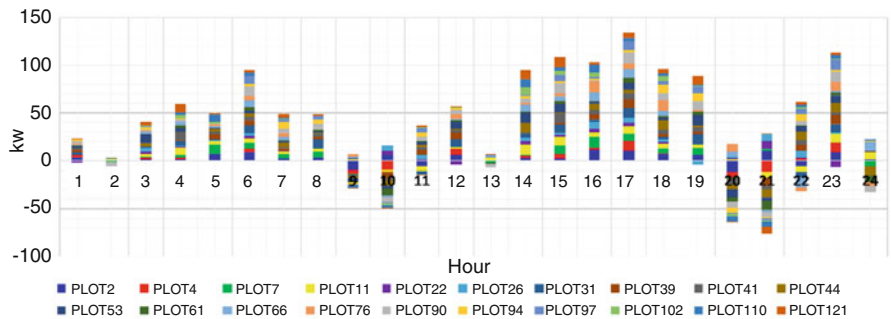


Fig. 5.7 The stacked column of PLOT electricity generation/consumption for DA horizon

The net transacted energy of the system with the upward market was about 228.447 MWh for the DA horizon.

Figure 5.14 presents the estimated NUEH electricity generation/consumption, IPG electricity generation, CHP and DG electricity generation, and import/export of electricity for RT horizon. The aggregated electricity generation of IPGs and CHPs and DGs were about 140.132 MWh and 136.187 MWh, respectively.

The net transacted energy of the system with the upward market was about 189.349 MWh for the RT horizon.

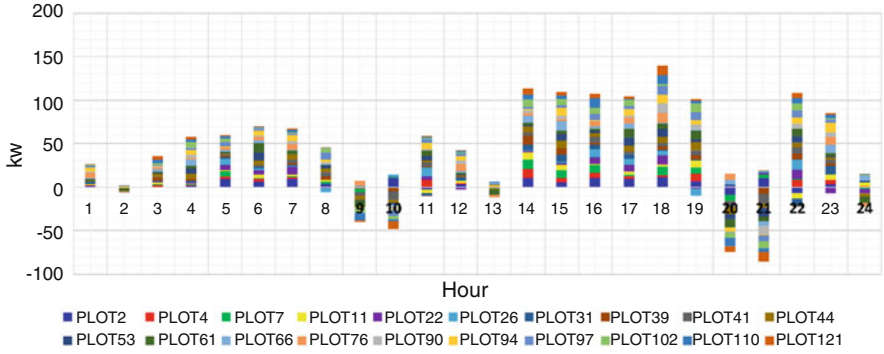


Fig. 5.8 The stacked column of PLOT electricity generation/consumption for RT horizon

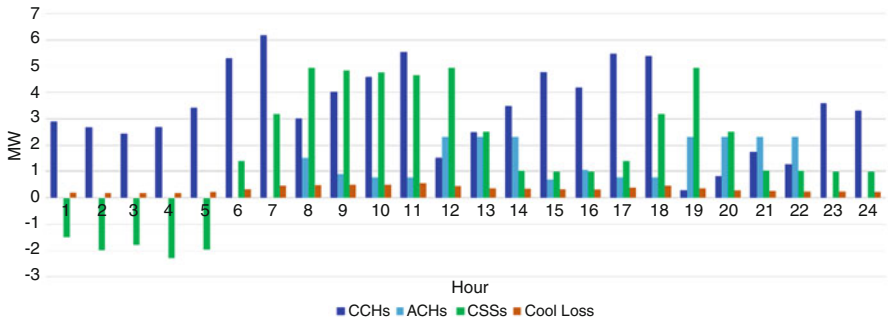


Fig. 5.9 The estimated CCH and ACH cooling energy generation, CSS cooling energy charge and discharge, and cooling energy loss for DA horizon

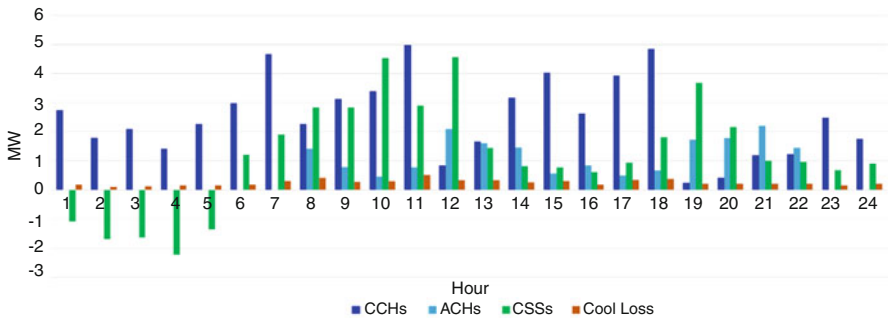


Fig. 5.10 The estimated CCH and ACH cooling energy generation, CSS cooling energy charge and discharge, and cooling energy loss for RT horizon

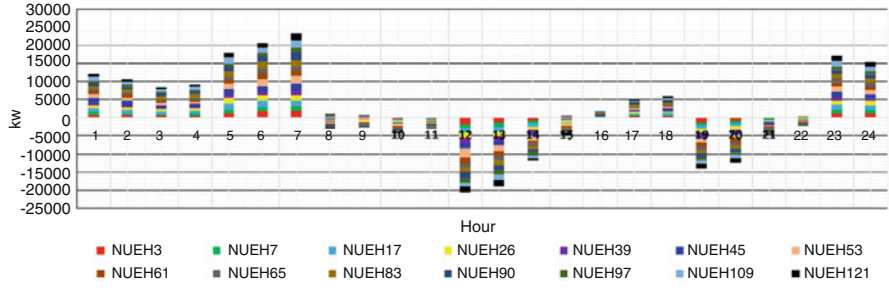


Fig. 5.11 The estimated stacked column of NUEH electricity generation/consumption for DA horizon

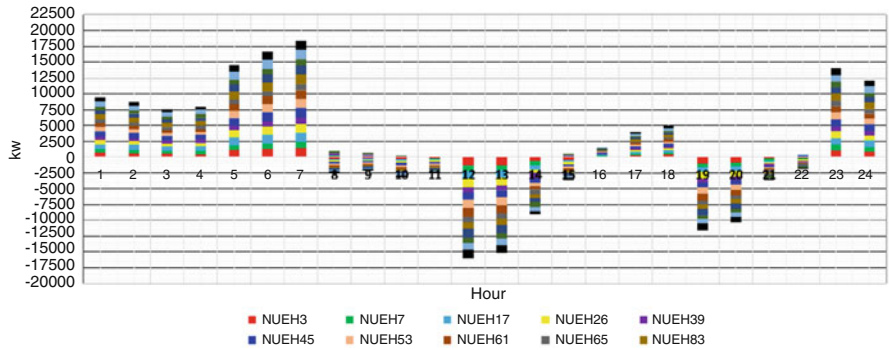


Fig. 5.12 The estimated stacked column of NUEH electricity generation/consumption for RT horizon

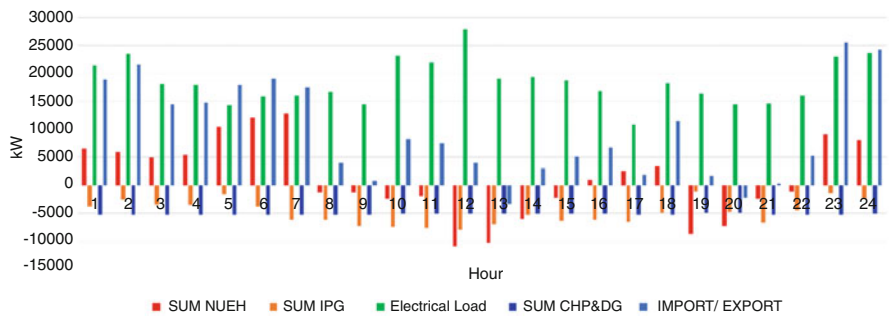


Fig. 5.13 The estimated NUEH electricity generation/consumption, IPG electricity generation, CHP and DG electricity generation, and import/export of electricity for DA horizon

Figure 5.15 depicts the estimated CHP and boiler heating energy generation, TSS heating energy charge and discharge, and heating energy loss for DA horizon.

The aggregated heating energy generation of CHPs and boilers in DA horizon were about 178.358 MWh and 183.102 MWh, respectively. Further, the mean values

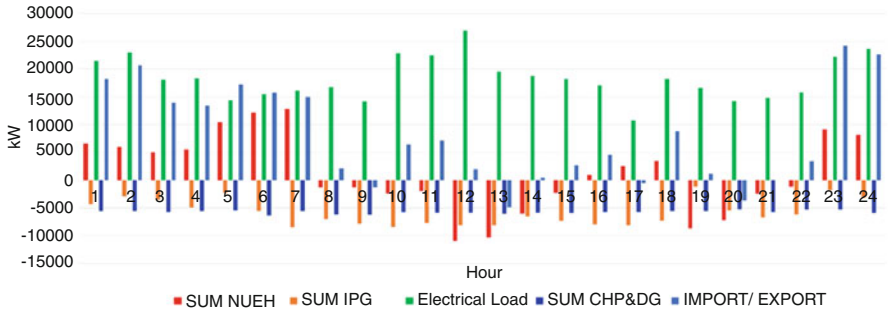


Fig. 5.14 The estimated NUEH electricity generation/consumption, IPG electricity generation, CHP and DG electricity generation, and import/export of electricity for RT horizon

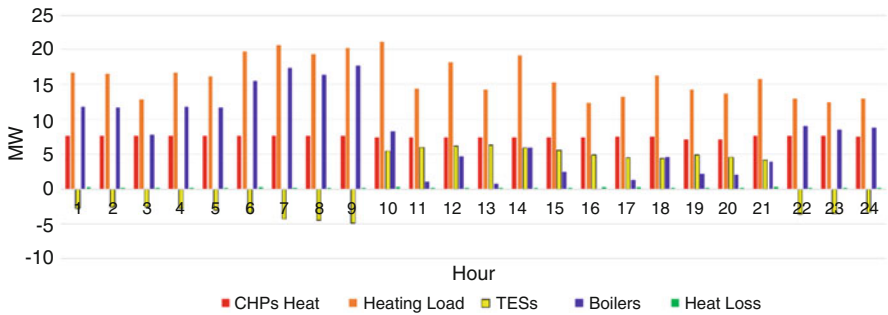


Fig. 5.15 The estimated CHP and boiler heating energy generation, TSS heating energy charge and discharge, and heating energy loss for DA horizon

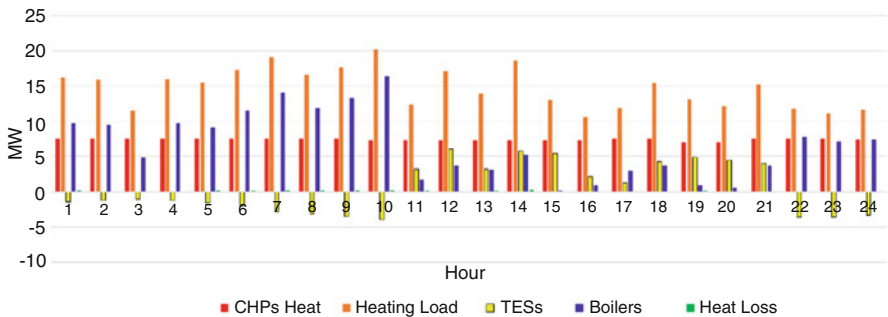


Fig. 5.16 The estimated CHP and boiler heating energy generation, TSS heating energy charge and discharge, and heating energy loss for RT horizon

of heating energy generation of CHPs and boilers in DA horizon were about 7.431 MWh and 7.629 MWh, respectively.

Figure 5.16 shows the estimated CHP and boiler heating energy generation, TSS heating energy charge and discharge, and heating energy loss for RT horizon.

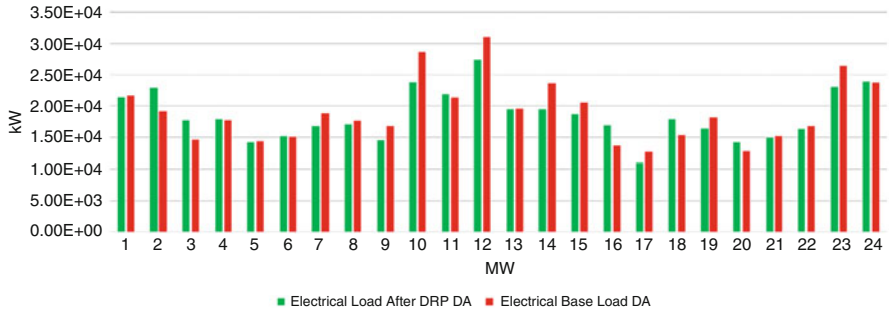


Fig. 5.17 The estimated electrical load after DRP and the base electrical load for DA horizon

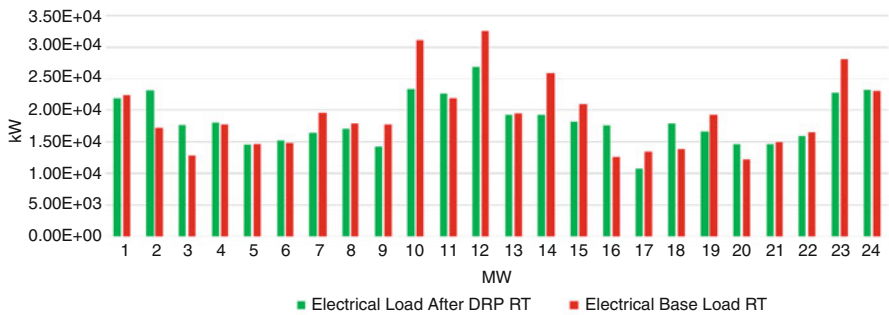


Fig. 5.18 The estimated electrical load after DRP and the base electrical load for RT horizon

The aggregated heating energy generation of CHPs and boilers in RT horizon were about 178.698 MWh and 183.732 MWh, respectively. Further, the mean values of heating energy generation of CHPs and boilers in RT horizon were about 7.659 MWh and 7.425 MWh, respectively.

Figure 5.17 presents the estimated electrical load after DRP and the base electrical load for DA horizon. The aggregated electrical energy consumptions before and after DRP implementation in DA horizon were about 443 MWh and 455 MWh, respectively. Further, the mean values of electrical energy consumptions before and after DRP implementation in DA horizon were about 18.52 MWh and 19.01 MWh, respectively.

Figure 5.18 shows the estimated electrical load after DRP and the base electrical load for RT horizon. The aggregated electrical energy consumptions before and after DRP implementation in RT horizon were about 461 MWh and 442 MWh, respectively. Further, the mean values of electrical energy consumptions before and after DRP implementation in RT horizon were about 19.21 MWh and 18.40 MWh, respectively.

Figure 5.19 depicts the estimated cost/benefit of NUEHs and distribution system for DA horizon. The estimated aggregated revenues of NUEHs for purchasing of active and reactive power to the distribution system in DA horizon were about

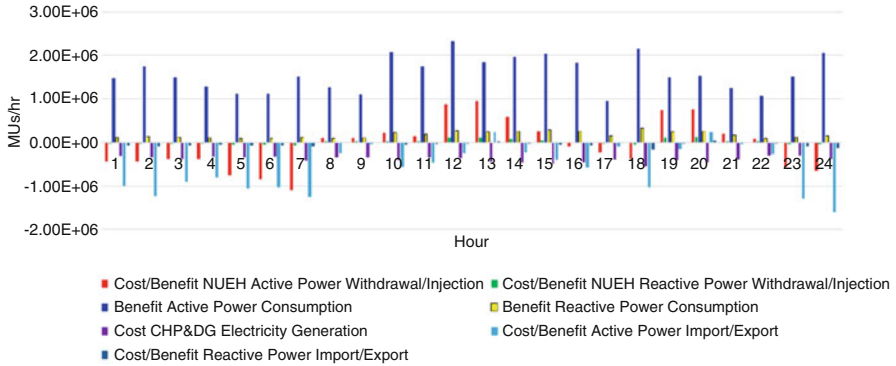


Fig. 5.19 The estimated cost/benefit of NUEHs and distribution system for DA horizon

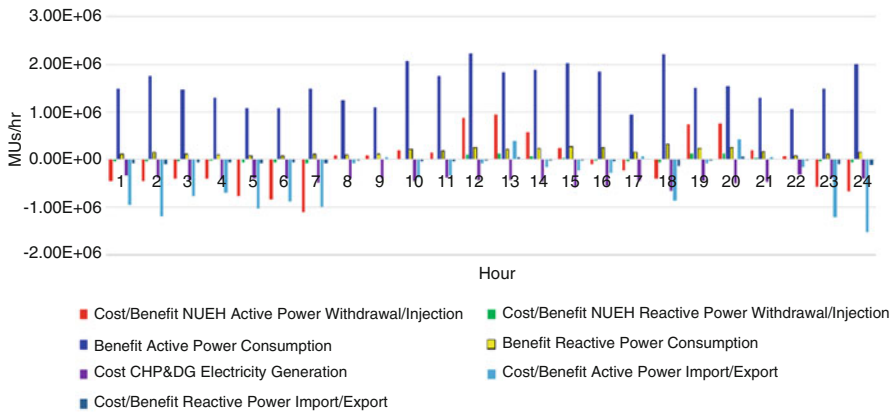


Fig. 5.20 The estimated cost/benefit of NUEHs and distribution system for RT horizon

1.37 MMU and 0.116 MMU, respectively. The aggregated revenues of AEDSO for purchasing of active and reactive power to its customers in DA horizon were about 37.8 MMU and 4.15 MMU, respectively. The aggregated cost of electricity generation of CHPs and DGs was about 9.37 MMUs. Finally, the aggregated costs of active and reactive energy purchased from DA upward market were about 14.1 MMU and 1.28 MMU, respectively.

Figure 5.20 shows the estimated cost/benefit of NUEHs and distribution system for RT horizon. The aggregated revenues of NUEHs for purchasing of active and reactive power to the distribution system in RT horizon were about 1.3664 MMU and 0.11559 MMU, respectively. The aggregated revenues of AEDSO for purchasing of active and reactive power to its customers in RT horizon were about 37.73 MMU and 4.1492 MMU, respectively. The aggregated cost of electricity generation of CHPs and DGs was about 10.29 MMUs. Finally, the aggregated costs of active and reactive energy purchased from RT upward market were about 10.76 MMU and 0.9037 MMU, respectively.

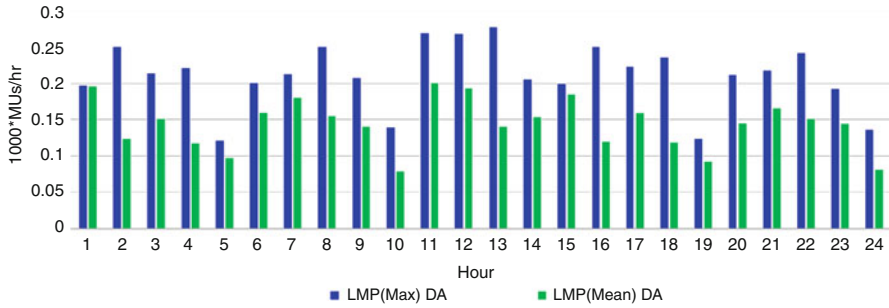


Fig. 5.21 The estimated maximum and mean values of LMPs for DA horizon

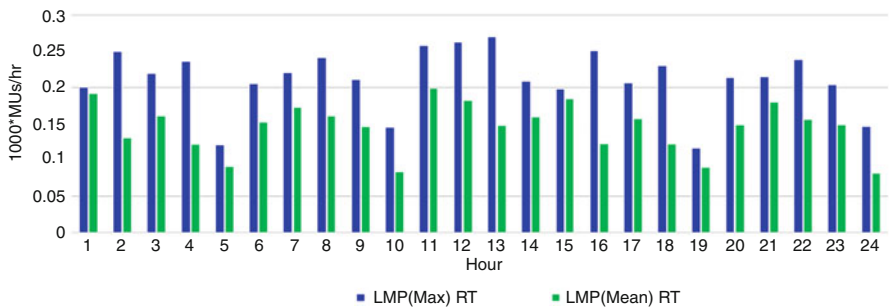


Fig. 5.22 The estimated maximum and mean values of LMPs for RT horizon

Figure 5.21 presents the estimated maximum and mean values of LMPs for DA horizon. The maximum values of LMP_{max} and LMP_{mean} were about 276.8 MU/h and 200.94 MU/h, respectively. Further, the average values of LMP_{max} and LMP_{mean} were about 210.7 MU/h and 143.61 MU/h, respectively

Figure 5.22 shows the estimated maximum and mean values of LMPs for RT horizon. The maximum values of LMP_{max} and LMP_{mean} were about 269.08 MU/h and 198.32 MU/h, respectively. The average values of LMP_{max} and LMP_{mean} were about 210.26 MU/h and 144.71 MU/h, respectively

The proposed algorithm successfully reduced the maximum values of LMP_{max} and LMP_{mean} .

5.5 Conclusion

This chapter presented an optimal operational scheduling algorithm for active distribution system that utilized multiple-energy resources to supply the electrical, cooling, and heating loads. The nonutility energy hubs transacted with the system and participated in the demand response programs. Further, the absorption chillers, compression chillers, boilers, thermal and cooling energy storages, electrical storage

systems, plug-in hybrid vehicle parking lots, and intermittent energy generation facilities were considered in the model and optimization process. The introduced algorithm optimized the multi-carrier energy system operational scheduling in day-ahead and real-time horizons.

The costs of operation and energy purchased from active and reactive upward markets were considered in the optimization process. Further, the locational marginal prices of system buses were formulated in the introduced optimization procedure. The objective functions and constraints were linearized and the CPLEX solver was utilized to optimize the problem.

An industrial district multiple-energy carrier system was used to assess the introduced method. The optimization process was carried out and the operational scheduling of system in day-head and real-time horizons was determined. The optimization algorithm successfully minimized the operational costs and locational marginal prices of the system and encountered the nonutility energy hub contributions in the operational scheduling of multi-carrier energy system. The optimization procedure successfully reduced the locational marginal prices by about 2.78%.

Nomenclature

Abbreviations

AC	Alternating current
AEDS	Active multi-carrier energy distribution system
AEDSO	AEDS operator
ACH	Absorption chiller
CCH	Compression chiller
CCHP	Combined cool, heat, and power
CSS	Cooling energy storage system
DA	Day-ahead
DER	Distributed energy resource
DLC	Direct load control
DRP	Demand response program
ESS	Electrical storage system
ILS	Involuntary load shedding
LMP	Locational marginal price
MG	Microgrid
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
NUEH	Nonutility energy hub
ODAOP	Optimal day-ahead operational planning
PHEV	Plug-in hybrid electric vehicle
PLOT	Parking LOT
PSO	Particle swarm optimization
PVA	Photovoltaic arrays
SEH	Smart energy hub
SG	Smart grid
TSS	Thermal energy storage system
TOU	Time of use
WT	Wind turbine

Variables

C_{AEDSO}^{DA}	The day-ahead cost of operation of AEDSO
C_{PHEV}^{DA}	The day-ahead cost of operation of PHEV
$C_{Purchase}^{DA}$	The day-ahead cost of electricity purchased from upward market
C_{DRP}^{DA}	The day-ahead cost of DRP
C_{IPG}^{DA}	The day-ahead cost of IPG
C_{NUEH}^{DA}	The day-ahead cost of electricity purchased from NUEHs
ψ	The binary decision variable of resource commitment
revenue ^{DA}	The revenue of active and reactive sold to the DA upward market
Prob	Probability of scenario
W	Weighting factor
α_{active}^{DA}	The price of active energy sold to DA electricity market
β_{active}^{DA}	The price of reactive energy sold to DA electricity market
NWMS	Number of wholesale market price scenarios
ΔC_{AEDSO}^{RT}	The mismatch of real-time cost of operation of AEDSO
ΔC_{PHEV}^{RT}	The mismatch of real-time cost of operation of PHEV
$\Delta C_{Purchase}^{RT}$	The mismatch of real-time cost of electricity purchased from upward market
ΔC_{DRP}^{RT}	The mismatch of real-time cost of DRP
ΔC_{IPG}^{RT}	The mismatch of real-time cost of IPG
ΔC_{NUEH}^{RT}	The mismatch of real-time cost of electricity purchased from NUEHs
$\Delta revenue^{RT}$	The mismatch of revenue of active and reactive sold to the RT upward market

References

1. Bostan A, Setayesh Nazar M, Shafie-khah M, Catalão JPS (2020) Optimal scheduling of distribution systems considering multiple downward energy hubs and demand response programs. *Energy* 190:116349
2. Wang J, Zhai Z, Jing Y, Zhang C (2010) Particle swarm optimization for redundant building cooling heating and power system. *Appl Therm Eng* 87:3668–3679
3. Lin W, Jin X, Mu Y, Jia H, Xub X, Yu X, Zhao B (2018) A two-stage multi-objective scheduling method for integrated community energy system. *Appl Energy* 216:428–441
4. Wang Y, Huang Y, Wang Y, Zeng M, Li F, Wang Y, Zhang Y (2018) Energy management of smart micro-grid with response loads and distributed generation considering demand response. *J Clean Prod* 197:1069–1083
5. Dolatabadi A, Mohammadi-Ivatloo B (2017) Stochastic risk-constrained scheduling of smart energy hub in the presence of wind power and demand response. *Appl Therm Eng* 123:40–49
6. Ma T, Wu J, Hao L (2017) Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub. *Energy Convers Manag* 133:292–306
7. Davatgaran V, Saniei M, Mortazavi S (2019) Smart distribution system management considering electrical and thermal demand response of energy hubs. *Energy* 169:38–49
8. Wu J, Wang J, Li S (2012) Multi-objective optimal operation strategy study of micro-CCHP system. *Energy* 48:472–483
9. Saberi K, Pashaee-Didani H, Nourollahi R, Zare K, Nojavan S (2019) Optimal performance of CCHP based microgrid considering environmental issue in the presence of real time demand response. *Sustain Cities Soc* 45:596–606
10. Gerami Moghaddam I, Saniei M, Mashhour E (2016) A comprehensive model for self-scheduling an energy hub to supply cooling, heating and electrical demands of a building. *Energy* 94:157–170

11. Orehounig K, Evins R, Dorer V (2015) Integration of decentralized energy systems in neighbourhoods using the energy hub approach. *Appl Energy* 154:277–289
12. Shams M, Shahabi M, Khodayar M (2018) Stochastic day-ahead scheduling of multiple energy carrier microgrids with demand response. *Energy* 155:326–338
13. Sheikhi A, Bahrami S, Ranjbar A (2015) An autonomous demand response program for electricity and natural gas networks in smart energy hubs. *Energy* 89:490–499
14. La Scala M, Vaccaro A, Zobaa A (2014) A goal programming methodology for multiobjective optimization of distributed energy hubs operation. *Appl Therm Eng* 71:658–665
15. Brahman F, Honarmand M, Jadid S (2015) Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. *Energ Buildings* 90:65–75
16. Ramírez-Elizondo LM, Paap GC (2015) Scheduling and control framework for distribution-level systems containing multiple energy carrier systems: theoretical approach and illustrative example. *Int J Electr Power Energy Syst* 66:194–215
17. Fang F, Wang Q, Shi Y (2011) A novel optimal operational strategy for the CCHP system based on two operating modes. *IEEE Trans Power Syst* 27:1032–1041
18. Rastegar M, Fotuhi-Firuzabad M, Lehtonen M (2015) Home load management in a residential energy hub. *Electr Power Syst Res* 119:322–328
19. Maleh M, Akbarimajid A, Valipour K, Dejamkhooy A (2018) Generalized modeling and optimal management of energy hub based electricity, heat and cooling demands. *Energy* 159:669–685
20. Bostan A, Setayesh Nazar M, Shafie-khah M, Catalão JPS (2020) An integrated optimization framework for combined heat and power units, distributed generation and plug-in electric vehicles. *Energy* 202:117789
21. Mirzaei MA, Nazari-Heris M, Mohammadi-Ivatloo B, Zare K, Marzband M, Anvari-Moghaddam A (2020) A novel hybrid framework for co-optimization of power and natural gas networks integrated with emerging technologies. *IEEE Syst J*:1–11
22. Saatloo AM, Agabalaye-Rahvar M, Mirzaei MA, Mohammadi-Ivatloo B, Abapour M, Zare K (2020) Robust scheduling of hydrogen based smart micro energy hub with integrated demand response. *J Clean Prod* 267:122041
23. Nazari-Heris M, Mirzaei MA, Mohammadi-Ivatloo B, Marzband M, Asadi S (2020) Economic-environmental effect of power to gas technology in coupled electricity and gas systems with price-responsive shiftable loads. *J Clean Prod* 244:118769
24. Mirzaei A, Sadeghi Yazdankhah A, Mohammadi-Ivatloo A, Marzband M, Shafie-khah M, Catalao JPS (2019) Stochastic network-constrained co-optimization of energy and reserve products in renewable energy integrated power and gas networks with energy storage system. *J Clean Prod* 223:747–758
25. Mirzaei MA, Zare Oskouei M, Mohammadi-Ivatloo B, Loni A, Zare, Marzband M, ; Shafiee M (2020) Integrated energy hub system based on power-to-gas and compressed air energy storage technologies in the presence of multiple shiftable load. *IET Gener Transm Distrib*, 14: 2510–2519
26. Nazari-Heris M, Mohammadi-Ivatloo B, Asadi S (2020) Optimal operation of multi-carrier energy networks with gas, power, heating, and water energy sources considering different energy storage technologies. *J Energy Storage* 31:101574
27. Nazari-Heris M, Mohammadi-Ivatloo B, Asadi S (2020) Optimal operation of multi-carrier energy networks considering uncertain parameters and thermal energy storage. *Sustainability* 12:5158
28. Mirzaei MA, Nazari-Heris M, , Mohammadi-Ivatloo B, Zare K, Marzband M, Anvari-Moghaddam (2019) Hourly price-based demand response for optimal scheduling of integrated gas and power networks considering compressed air energy storage. *Demand response applications in smart grid*. Springer: 55–74

29. Varasteh F, Setayesh Nazar M, Heidari A, Shafie-khah M, Catalão JPS (2019) Distributed energy resource and network expansion planning of a CCHP based active microgrid considering demand response programs. *Energy* 172:79–105
30. Setayesh Nazar M, Eslami Fard A, Heidari A, Shafie-khah M, Catalão JPS (2018) Hybrid model using three-stage algorithm for simultaneous load and price forecasting. *Electr Power Syst Res* 165:214–228
31. Salarkheili S, Setayesh Nazar M (2017) Capacity withholding assessment in the presence of integrated generation and transmission maintenance scheduling. *IET Gener Transm Distrib* 11:3903–3911
32. Salarkheili S, Setayesh Nazar M (2016) Capacity withholding analysis in transmission-constrained electricity markets. *IET Gener Transm Distrib* 10:487–495
33. Salarkheili S, Setayesh Nazar M (2015) New indices of capacity withholding in power markets. *Int Trans Electr Energy Syst* 25:180–196