Optimal Scheduling of Distribution Systems considering Multiple Downward Energy Hubs and Demand Response Programs

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Abstract

This paper presents a two-level optimization problem for optimal day-ahead scheduling of an active distribution system that utilizes renewable energy sources, distributed generation units, electric vehicles, and energy storage units and sells its surplus electricity to the upward electricity market. The active distribution system transacts electricity with multiple downward energy hubs that are equipped with combined cooling, heating, and power facilities. Each energy hub operator optimizes its day-ahead scheduling problem and submits its bid/offer to the upward distribution system operator. Afterwards, the distribution system operator explores the energy hub's bids/offers and optimizes the scheduling of its system energy resources for the day-ahead market. Further, he/she utilizes a demand response program alternative such as time-of-use and direct load control programs for downward energy hubs. In order to demonstrate the preference of the proposed method, the standard IEEE 33-bus test system is used to model the distribution system, and multiple energy hubs are used to model the energy hubs system. The proposed method increases the energy hubs electricity selling benefit about 185% with respect to the base case value; meanwhile, it reduces the distribution system operational costs about 82.2% with respect to the corresponding base case value.

Keywords: Combined Cooling, Heating, and Power (CCHP), Mixed Integer Linear Programming (MILP), Active distribution system, Demand response program, Energy hub.

NOMENCLATURE

Abbreviation

AC	Alternative Current.
ACH	Absorption Chiller.
ADS	Active Distribution System.
CCH	Compression Chiller.
CES	Cooling Energy Storage.
CHP	Combined Heating and Power.
CCHP	Combined Cool and Heat and Power.
CO_2	Carbon dioxide.
DA	Day-Ahead.
DER	Distributed Energy Resource.
DLC	Direct Load Control.
DSO	Distribution System Operator.
DG	Distributed Generation.
DLC	Direct Load Control.
DRP	Demand Response Program.
DSO	Distribution System Operator.
EHO	Energy Hub Operator.
ESS	Electrical Storage System.
EH	Energy Hub.
ESS	Energy Storage System.
MILP	Mix Integer Linear Programming.
MILP	Mixed Integer Linear Programming.
MINLP	Mixed Integer Non-Linear Programming.
MUs	Monetary Units.
MMUs	Million MUs.
ODAS	Optimal Day-Ahead Scheduling.
PGU	Power Generation Unit.
PHEV	Plug-in Hybrid Electric Vehicle.
PVA	Solar Photovoltaic Array.
PU	Per-unit
RES	Renewable Energy Resources.
RL	Responsive Load.
SWT	Small Wind Turbine.
TES	Thermal Energy Storage.
TOU	Time of Use.

Index Sets

t	Time index.

Parameters

B_{EH}^{Sell}	Energy sold benefit of EH (MUs)
B_{EH}^{DRP}	DRP Benefit of EH (MUs)
C_{ADS}^{DG}	Total operational and emission costs of ADS DG (MUs).
C_{ADS}^{ESS}	Total operational costs of ADS ESS commitment (MUs).
C_{ADS}^{PHEV}	Total operational costs of ADS PHEVs commitment (MUs).
$C_{ADS}^{Purchase}$	Energy purchased costs of ADS (MUs).
C_{ADS}^{DRP}	DRP costs of ADS (MUs).
C_{ADS}^{PVA}	Operational costs of ADS PVA (MUs).
C_{ADS}^{SWT}	Operational costs of ADS SWT (MUs).
C_{op}	Operational cost of ADS facilities (MUs/MWh).
C_{EH}^{CHP}	Total operational and emission costs of EH CHP (MUs).
C_{EH}^{Boiler}	Operational costs of EH boiler (MUs).
C_{EH}^{ACH}	Operational costs of EH ACH (MUs).
C_{EH}^{CCH}	Operational costs of EH CCH (MUs).
C_{EH}^{ESS}	Operational costs of EH ESS (MUs).
C_{EH}^{CES}	Operational costs of EH CES (MUs).
C_{EH}^{PHEV}	Operational costs of EH PHEV (MUs).
C_{EH}^{TES}	Operational costs of EH TES (MUs).
$C_{EH}^{Purchase}$	Energy purchased costs of EH (MUs).
Cap	Capacity of ADS energy storage facilities (kW).
COP_{EH}^{ACH}	Coefficient of performance of EH absorption chiller.
COP_{EH}^{CCH}	Coefficient of performance of EH compression chiller.
I	Solar irradiation of ADS PVA (kW/m).
$NEMS$	Total number of upward electricity market scenarios.
$NEHS$	Total number of EH operation scenarios.
$NPSWTGS$	Total number of SWT generation scenarios.
$NPVAGS$	Total number of PVA generation scenarios.
$NDRPS$	Total number of DRP scenarios.
$NPHEVS$	Total number of PHEV contribution scenarios.
Y	Admittance.
t_0	Outside air temperature (°C).
λ	Active or reactive power price of upward wholesale market (MU/kWh) ,
ψ	Binary decision variable of ADS facilities commitment (equals to 1 if device is
τ	Duration of device operation.
η	Active or reactive power price sold to the downward energy hubs (MU/kWh) ,
ϖ_{PHEV}^{Charge}	Charge limitation ratio.
$\varpi_{PHEV}^{Discharge}$	Discharge limitation ratio.
$\kappa_{Purchased}^{Elect}$	EH electricity purchasing price that is purchased from ADS (MUs/kWh).
κ_{DLC}^{Elect}	Energy cost of DLC program (MUs/kWh).
κ_{Sell}^{Elect}	EH electricity selling price that is sold to ADS (MUs/kWh).
g	Maximum discharge coefficient of ADS energy storage.
$a_{CHP}^{th}, b_{CHP}^{th}, c'^{th}_{CHP}$	Coefficient of heat-power feasible region for EH CHP unit.

ξ	ADS photovoltaic array conversion efficiency.
v_c^{Wind}	ADS small wind turbine cut-in wind velocity.
v_f^{Wind}	ADS small wind turbine cut-off wind speed.
Δt	Time interval.

Variables

A	Binary variable of ADS energy storage discharge; equals 1 if energy storage is discharged.
B	Binary variable of ADS energy storage charge; equals 1 if energy storage is
$ENPHEV$	State of charge of PHEV
PCH	Power charge of ADS or EH energy storage or PHEV (kW).
$PDCH$	Power discharge of ADS or EH energy storage or PHEV (kW).
P	Active power (kW).
P_{ADS}^{DG}	DG active power of ADS (kW).
P_{ADS}^{EH}	Active power transaction of EH with ADS (kW).
P_{ADS}^{Load}	Active load of ADS (kW).
P_{ADS}^{ESS}	ESS active power of ADS (kW).
P_{ADS}^{PHEV}	PHEV active power of ADS (kW).
P_{ADS}^{SWT}	SWT active power of ADS (kW).
P_{ADS}^{PVA}	PVA active power of ADS (kW).
P_{ADS}^{DRP}	DRP active power of ADS (kW).
P_{EH}^{Load}	Active load of EH (kW).
P_{EH}^{PVA}	PVA active power of EH (kW).
P_{EH}^{ESS}	ESS active power of EH (kW).
P_{EH}^{SWT}	SWT active power of EH (kW).
P_{EH}^{CHP}	CHP active power of EH (kW).
P_{EH}^{ACH}	ACH active power of EH (kW).
P_{EH}^{CCH}	CCH active power of EH (kW).
P_{EH}^{DRP}	DRP active power of EH (kW).
P_{EH}^{PHEV}	PHEV active power of EH (kW).
$P_{DA\_upward}^{active}$	ADS active power purchased from upward wholesale market (kW)
$P_{DA\_downward}^{active}$	ADS active power sold to downward EHs and custom loads (kW)
P^{Loss}	Active power loss (kW).
P^{PVA}	Electric power generated by ADS PVA (kW).
P^{ESS}	Electric power delivered by electricity storage (kW).
$P_{Critical}^{Load}$	Critical electrical load (kW).
$P_{Controllable}^{Load}$	Controllable electrical load (kW).
ΔP^{TOU}	Change in load based on TOU program (kW).
$P_{Deferrable}^{Load}$	Deferrable electrical load (kW).
ΔP^{DLC}	Electric power withdrawal changed for DLC program (kW).
P^{SWT}	Electric power generated by ADS SWT (kW).
Q	Reactive power (kVAR).
Q_{ADS}^{DG}	DG reactive power of ADS (kW).

Q_{ADS}^{EH}	Reactive power transaction of EH with ADS (kW).
Q_{ADS}^{DRP}	DRP reactive power of ADS (kW).
$Q_{DA\_upward}^{reactive}$	ADS reactive power purchased from upward wholesale market (kVAR)
$Q_{DA\_downward}^{reactive}$	ADS reactive power sold to downward EHs and custom loads (kVAR)
Q^{EH}	Reactive power of EH (kW).
Q_{EH}^{Load}	Load reactive power of EH (kW).
Q_{EH}^{ACH}	ACH reactive power of EH (kW).
Q_{EH}^{CCH}	CCH reactive power of EH (kW).
Q_{EH}^{DRP}	DRP reactive power of EH (kW).
Q^{Loss}	Reactive power loss (kW).
Q'^{Load}_{EH}	Thermal load of EH (kW_{th}).
Q'^{B}_{EH}	Boiler thermal power output of EH (kW_{th}).
Q'^{ACH}_{EH}	ACH thermal power output of EH (kW_{th}).
Q'^{CHP}_{EH}	CHP thermal power output of EH (kW_{th}).
Q'^{Loss}_{EH}	Thermal loss of EH (kW_{th}).
R_{EH}^{Load}	EH cooling load (kW_c).
R_{EH}^{CCH}	Cooling power generated by EH compression chiller (kW_c).
R_{EH}^{ACH}	Cooling power generated by EH absorption chiller (kW_c).
R_{EH}^{Loss}	Loss of cooling power in EH (kW_c).
R_{EH}^{CES}	Cooling power delivered by EH cooling storage (kW_c).
V	Voltage of ADS bus (kV).
δ	Voltage angle of ADS bus (rad).
θ	Angle difference of two ADS voltage buses (rad).

1. Introduction

Recently, Energy Hubs (EHs) concept have been widely used in power systems planning and operations literature based on the fact that the Distributed Energy Resources (DERs)-based systems are mainly EHs [1].

An EH can be introduced as a system, which includes DERs such as Combined Heat and Power (CHP), Solar Photovoltaic Array (PVA), Small Wind Turbine (SWT), Electrical Storage System (ESS), Thermal Energy Storage system (TES) and Responsive Load (RL) [2]. Thus, an energy hub can play an important role in energy production, storage and conversion [3].

However, due to the stochastic nature of the Renewable Energy Resources (RESs), the large-scale integration of these facilities into power systems has a large impact on the operational and planning paradigms of the electric distribution system [4].

Further, as shown in Fig. 1 an Active electric Distribution System (ADS) can transact electrical energy with the downward EHs and custom loads. The Optimal Day-Ahead Scheduling (ODAS) of ADS consists of determining the optimal coordination of the ADSs' DERs considering of the stochastic behavior of the wholesale market prices, ADS intermittent electricity generation, downward EHs power generation/consumption scenarios, Plug-in Hybrid Electric Vehicle (PHEV), Demand Response (DRP) contributions, and cost-benefit analysis [5].

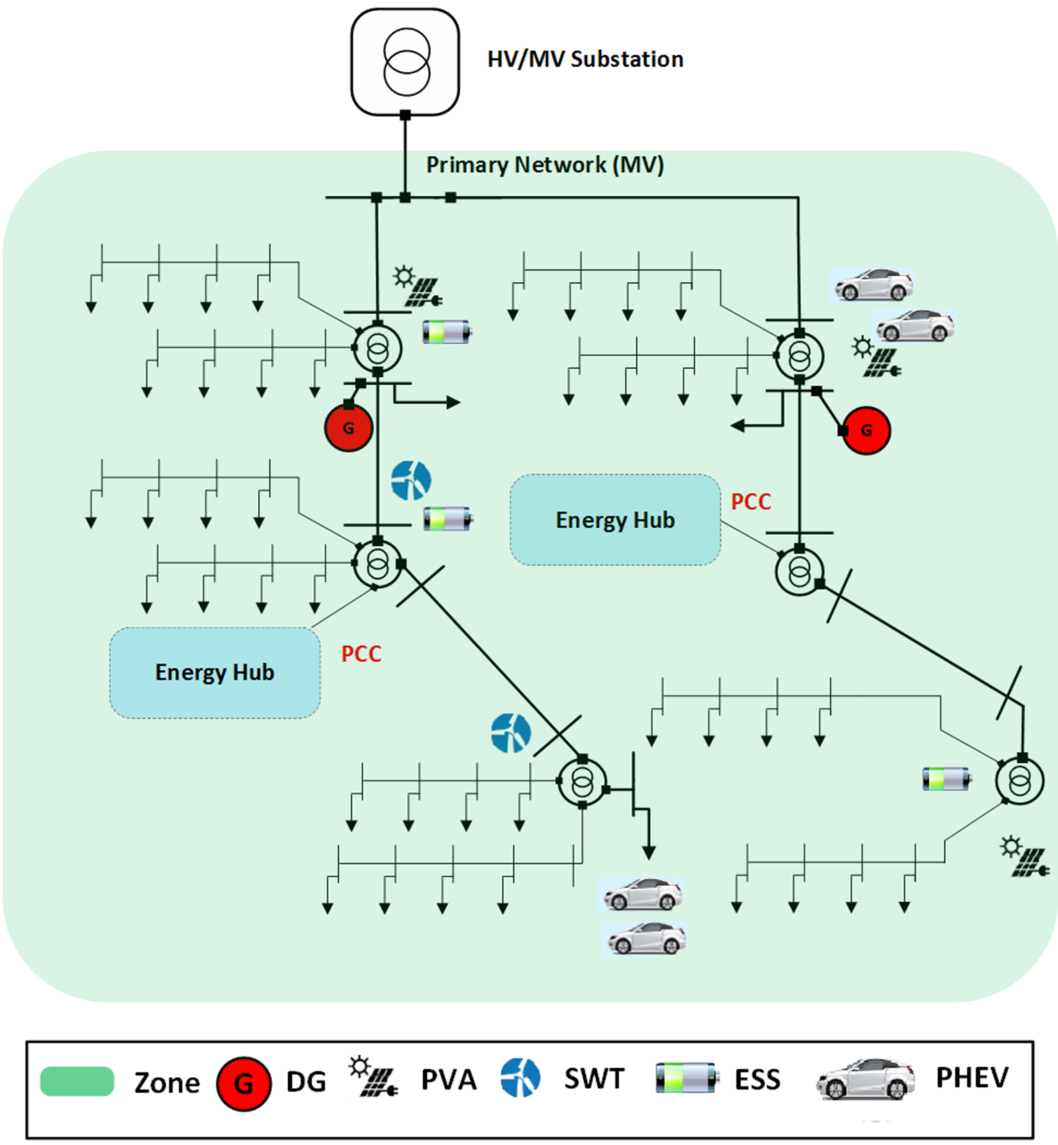


Fig. 1. Schematic diagram of ADS with its downward energy hubs.

Over recent years, different aspects of ODAS have been studied and the literature can be categorized into the following groups.

The first category developed models for device specification, static and dynamic methods of capacity expansion, long-term/short-term energy management and performance evaluation. The second category proposes solution techniques that determine the global optimum of the first category problems. The third category introduces new conceptual ideas in the ODAS paradigms.

Based on the above categorization and for the third category of ODAS paradigms, an integrated framework that considers the optimal bidding of EHs, DRP procedures and optimizes the day-ahead scheduling of ADS is less frequent in the literature.

Paudyal et al. [2] proposed a load management framework for energy hub management systems. The model considered the interactions of distribution companies for automated and optimal scheduling of their processes. Further, their developed model considered the detailed model of processes, process interdependencies, storage units, distribution system components, and various other operating requirements set by distribution system and industrial process operators. The case study was performed for industrial facilities in Southern Ontario, Canada; including an Ontario clean water agency water pumping facility and their results showed that the method reduced the total costs up to 38.1%.

Ma et al. [4] proposed a coordinated operation and optimal dispatch strategies for multiple energy systems. Based on a generic model of an energy hub, a framework for minimization of daily operation cost was introduced. The model used mixed-integer linear programming optimization procedure and results indicated that the method was effective over the scheduling horizon and reduced the operational costs up to 22.89% with respect to the base case costs.

Lin et al. [5] presented a two-stage multi-objective scheduling method that considered an electric distribution network, natural gas network, and the energy centers. Five indices were considered to characterize the operation cost, total emission, power loss, the sum of voltage deviation of the network, and the sum of pressure deviation of the natural gas network. The analytic hierarchy process method was used and numerical studies showed that effectiveness of the algorithm. Their method proposed that the optimal solution had 268.7041 $ and 52.1608 kW for operational cost and loss, respectively; based on the fact that the base case solution proposed 210.1872 $ and 85.6906 kW for operational cost and loss, respectively.

Dolatabadi et al. [6] presented a stochastic optimization model for solving the energy hub-scheduling problem. The stochastic method was used to model the uncertainties of wind power and load forecasting. The conditional value-at-risk method was used to mitigate the risk of the expected cost of uncertainties. Their proposed method reduced the operational cost up to 1.37% with respect to the base case value.

Sabari et al. [7] proposed an improved model of an energy hub in the micro energy grid. The model integrated Combined Power, Cooling and Heating (CCHP) system in the introduced framework, and the amount of operation cost and CO_2 emission was investigated. Two cases were analyzed and the comparison of results showed that the demand response programs reduced operation costs 3.97% and CO_2 emission 2.26%.

Wang et al. [8] developed the model of intelligent park micro-grid consisting of DERs and DRP to study the optimal scheduling of microgrid. The optimization problem was solved by the genetic algorithm and a microgrid project in China was used to carry out optimization simulation. Results showed that the optimization algorithm reduced the operation costs between 1.38% ~ 1.68% after demand response procedures.

Davatgaran et al. [9] proposed a recursive two-level optimization structure to model the interactions between the Distribution System Operator (DSO) and energy hubs. Stochastic optimization was used to handle the uncertainty of intermittent energies. The strategy was implemented in a 6-bus and 18-bus test systems and the results showed that peak loads of energy hub and distribution grid are reduced by 29% and 14% in the 6-bus test system, respectively.

Salehi Maleh et al. [10] introduced an algorithm for scheduling of CCHP-based energy hubs and DRPs. The energy loss and depreciation cost of energy storages were modeled. The results showed that the demand curve flattened with lower operating costs and the operational costs of the distribution system and EH reduced by 10% and 14%, respectively.

Shams et al. [11] proposed a two-stage stochastic optimization problem to determine the scheduled energy and reserve capacity. The uncertainties of wind and solar photovoltaic generation and electrical and thermal demands were modeled by scenarios. Further, the effectiveness of DRPs to reduce the operation costs were investigated and the system costs were reduced up to 15% by the proposed method.

Gerami Moghaddam et al. [12] introduced a mixed-integer nonlinear programming model to maximize the profit of the energy hub for short term scheduling. The results showed that average electrical and thermal efficiencies for the cold day were 59.3% and 15.4%, respectively. Further, these values for the hot day were 47.1% and 28.9%, respectively.

Najafi et al. [13] proposed an energy management framework for intermittent power generation in energy hubs to minimize the total cost using stochastic programming and conditional value at risk method. The results showed that the minimum cost was obtained by the best decisions involving the electricity market and purchasing natural gas. The optimal solution reduced the system cost up to 5.94%.

Ramirez-Elizondo et al. [14] proposed a two-level control strategy framework for 24 hour and real-time optimization intervals. Electricity and gas were considered as input, electricity, and heat as the output and a multi-carrier unit commitment framework was presented.

Roustai et al. [15] introduced a model to minimize energy bill and emissions that considered conditional value at risk method to control the operational risk. Results showed that the daily energy cost was reduced by 43.03% by using the proposed method.

Fang et al. [16] proposed an integrated performance criterion that simultaneously optimized the primary energy consumption, the operational cost, and carbon dioxide emissions. Results showed that the proposed strategy was better than that with the traditional strategy. The operational costs reduced 24.17% with respect to the base case value.

Rastegar et al. [17] introduced an energy hub framework to determine a modeling procedure for multi-carrier energy systems. The algorithm considered different operational constraints of responsive residential loads. The method was applied to home to study the different aspects of the problem and the method reduced the payment cost up to 4%.

Orehounig et al. [18] proposed a method to integrate decentralized energy systems. The method optimized the energy consumption of these systems and reduced the peak energy demand. Results showed that 46% lower emissions than for a scenario with DER systems.

La Scala et al. [19] introduced optimal energy flow management in multicarrier energy networks for interconnected energy hubs that were solved by a goal attainment based methodology. Simulation results showed that the algorithm voltage deviations, regulating costs, power quality indexes were adequately considered. The operational cost reduced about 6.8%.

Evins et al. [20] proposed a mixed-integer linear programming problem to balance energy demand and supply between multiple energy. The problem minimized operational costs and emissions and considered the minimum time of systems operation. Results showed a 22% CO_2 emissions reduction.

Sheikhi et al. [21] developed DRP models to modify electricity and natural gas consumption on the customer side. Their model maximized the natural gas and electricity utility companies' profit and minimized the customers' consumption cost. The results showed that the electricity and gas consumption cost were reduced; meanwhile, at the supplier side, the peak load demand in the electricity and natural gas load profiles were reduced.

Parisio et al. [22] used a robust optimization algorithm to minimize cost functions of energy hubs. An energy hub structure designed in Waterloo, Canada was considered for the case study and the results showed that the robust schedules of input power flows that were significantly less sensitive to uncertain converter efficiencies than the nominal schedules. The operational cost increased up to 11.4% for the worst-case scenario operation paradigm.

Wang et al. [23] presented the energy flow analysis of the conventional separation production system and four decision variables were considered as objective functions. The capacity of Power Generation Unit (PGU), the capacity of the heat storage tank, the on–off coefficient of PGU and the ratio of electric cooling to cool load were optimized. The energetic, economic and environmental benefits were formulated as objective functions and were maximized. Particle swarm optimization algorithm was employed and a case study was performed to ascertain the feasibility and validity of the optimization method. Their method saved 12.2% energy and 11.2% cost and reduced 25.9% CO_2 emission than the conventional system.

Wu et al. [24] presented an MINLP algorithm for optimal operation of micro-CCHP systems. Energy- saving ratio and cost-saving ratio were used as the objectives and results showed that the optimal operation strategy changed with load conditions for energy-saving optimization. The results showed that the CCHP system was superior to the conventional system when the dimensionless energy price ratio was less than 0.45.

Tan et al. [25] proposed a model of DRP for plug-in electric vehicles and renewable distributed generators. A distributed optimization algorithm based on the alternating direction method of multipliers was developed. Numerical examples showed that the demand curve was flattened after the optimization, even though there were uncertainties in the model, thus the method reduced the cost paid by the utility company and the energy costs were reduced about 25.41%.

Brahman et al. [26] proposed an optimization algorithm for residential energy hub that considered electric vehicles, DRPs, and energy storage devices. A cost and emission minimization were presented and results showed that the introduced method reduced the total cost of operation. The energy hub revenue of energy purchased to the network was increased up to 105% by the proposed method.

The described researches do not consider the effect of DRPs on the EHs operational scheduling optimization. Further, the ODAS algorithm that simultaneously optimizes energy transactions between ADS, upward wholesale market and downward EHs and considers SWTs, PVAs, ESSs, DRPs, and PHEVs uncertainties, and EHs bid/offer scenarios is less frequent in the previous researches. Table 1 shows the comparison of the proposed ODAS model with the other researches. The present research introduces an ODAS algorithm that uses the MILP model.

The main contributions of this paper can be summarized as:

- The proposed two-level MILP algorithm considers power transactions between the downward EHs and ADSs' loads based on the smart grid conceptual model.
- The proposed stochastic algorithm models five sources of uncertainty: upward electricity market price, EHs bids/offers, ADS intermittent power generation, PHEV contribution, and DRP commitment.
- The proposed framework simultaneously optimizes the DSO and EHO objective functions and considers the dynamic interaction of the ADS and EH systems.

The paper is organized as follows: The formulation of the problem is introduced in Section II. In Section III, the solution algorithm is presented. In section IV, the case study is presented. Finally, the conclusions are included in Section V.

2. Problem Modeling and Formulation

As shown in Fig.2, the Distribution System Operator (DSO) utilizes Distributed Generations (DGs), PVAs, SWTs to supply its electrical loads and downward EHs [27]. The DSO can utilize ESSs and PHEVs to optimize its operational parameters and it can transact electricity with the upward wholesale market; meanwhile, it can electricity with the downward EHs. Thus, the distribution system behaves as ADS. EHs can submit their bid/offer and the DSO can consider the EHs optimal operation scheduling in its optimization procedure.

Table 1: Comparison of proposed ODAS with other researches.

References		Paudyal [2]	Dolatabadi [6]	Saberi [7]	Wang [8]	Davatgaran [9]	Salehi Maleh [10]	Shams [11]	Gerami [12]	Najafi [13]	Ramirez [14]	Roustai [15]	Ma [4]	Lin [5]	Fang [16]	Rastegar [17]	Orehounig [18]	La Scala [19]	Evins [20]	Sheikhi [21]	Parisio [22]	Wang [23]	Wu [24]	Tan [25]	Brahman [26]	Proposed Approach
Method	MILP	×	✓	✓	×	✓	×	×	×	×	×	✓	✓	×	×	✓	✓	×	✓	×	×	×	×	×	×	✓
	MINLP	✓	×	×	×	×	✓	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×
	Heuristic	×	×	×	✓	×	×	×	×	✓	✓	×	×	✓	✓	×	×	✓	×	✓	✓	✓	×	✓	✓	×
Model	Deterministic	✓	×	×	✓	×	✓	×	✓	×	✓	×	✓	✓	✓	✓	✓	✓	✓	×	×	✓	✓	✓	✓	✓
	Stochastic	×	✓	✓	×	✓	×	✓	×	✓	×	✓	×	×	×	×	×	×	×	×	✓	×	×	×	×	×
Objective Function	Revenue	×	✓	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	×	×	✓
	Gen. Cost	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	ESS Cost	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓
	PEV	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	✓	✓
	DRP	×	✓	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	✓	✓	✓
	SWT	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓
	PVA	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	×	✓	×	×	×	×	×	×	✓
	Emission	×	×	×	×	×	✓	×	×	✓	×	×	✓	×	✓	×	✓	×	×	×	×	✓	×	×	×	✓
CHP Nonlinearity		×	×	✓	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓
Single level or Bi-level optimization	DSO optimization	×	×	×	✓	✓	×	✓	×	×	✓	×	×	✓	×	×	×	×	×	✓	×	×	×	×	×	✓
	EH scheduling optimization	✓	✓	✓	×	✓	✓	×	✓	✓	×	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Uncertainty Model	PEV	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	✓
	DERs	×	✓	✓	×	×	×	✓	×	✓	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	✓
	DA Market	×	✓	✓	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	✓
	Loads	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	✓
Storage System	ESS	×	✓	×	×	✓	✓	×	✓	×	✓	✓	✓	×	×	×	✓	×	✓	×	✓	✓	×	×	×	✓
	HES	×	✓	×	×	×	✓	✓	✓	×	✓	✓	✓	×	×	×	✓	×	×	×	✓	✓	×	×	✓	✓
	CES	×	×	×	×	×	✓	×	×	×	×	✓	✓	×	×	×	×	×	×	×	×	✓	×	×	×	✓
AC model		×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	✓	×	×	×	×	×	✓	×	×	✓

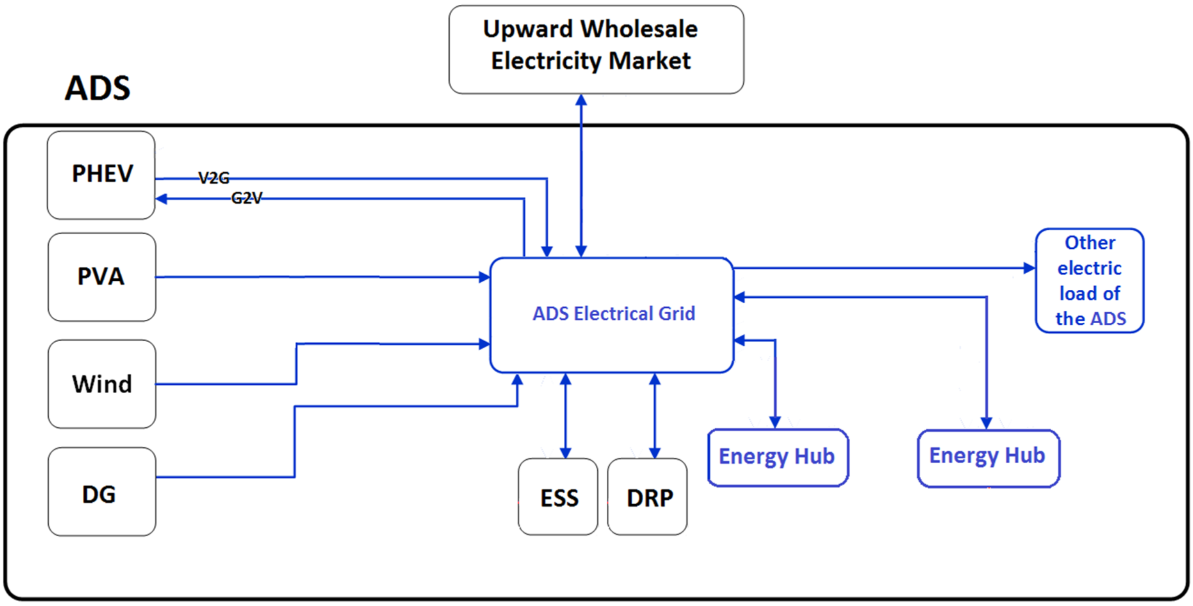


Fig. 2. The ADS energy resources and storages.

Each energy hub can utilize CCHP, PVA, SWT, PHEV, TES, ESS and CES to supply its cooling, heating and electrical loads. Further, the EHO can participate in the ADS DRPs and maximizes its benefits. The ADS DRPs consist of Time of Use (TOU) programs and Direct Load Control (DLC). The EHO optimizes its day-ahead scheduling problem and submits its bids/offers to DSO. Next, the DSO explores the EHO's bids and it optimizes the scheduling of its energy resources in day-ahead markets. Fig. 3 depicts the EH facilities and its interactions with the DSO. The ODAS algorithm must simultaneously optimize the ADS and EHs day-ahead scheduling and consider their operational interactions and coupling constraints.

The model has five sources of uncertainty: upward electricity market price, EHs bids/offers, intermittent power generation, PHEV contribution, and DRP commitment that are modeled in the following subsections.

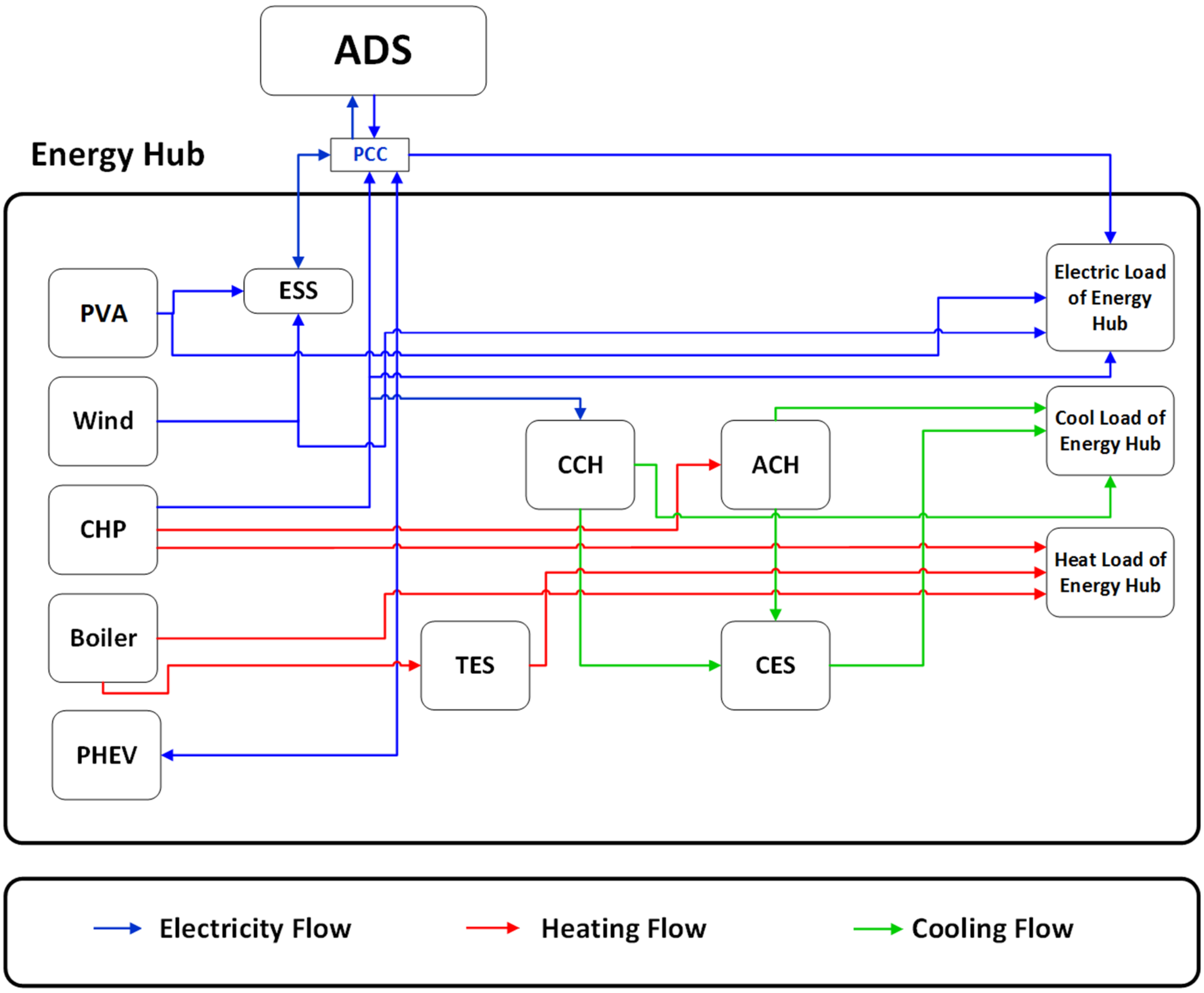


Fig. 3 The EH facilities and its interactions with the DSO.

2.1. Distribution System Operator Optimization Problem Formulation

An optimal ODAS must minimize the total operating costs of ADS. The objective function of the ODAS problem can be proposed as (1):

$$Min\ \mathbf{Z} = \sum_{NEMS} prob\ . \begin{pmatrix} (C_{ADS}^{DG}\ .\psi^{DG} + C_{ADS}^{ESS}.\psi^{ESS} + \sum_{NPHEVS} prob.C_{ADS}^{PHEV}\ .\psi^{PHEV}) \\ +C_{ADS}^{Purchase} + \sum_{NDRPS} prob.C_{ADS}^{DRP} + \sum_{NPVAGS} prob.C_{ADS}^{PVA} + \\ \sum_{NPSWTGS} prob.C_{ADS}^{SWT} + \sum Penalty\ - revenue \end{pmatrix} \tag{1}$$

The objective function can be decomposed into five groups: 1) the commitment costs of DGs, ESSs, and PHEVs; 2) the energy purchased from wholesale market costs; 3) the costs of DRPs; 4) the penalty of deviation in the wholesale market, and; 5) the revenue of ADS.

The ADS costs can be presented as:

$$C_{ADS}^{X} = \sum_{NOSS} prob \times \sum_{T_x} \tau \times (C_{Op}^{X}) \quad \forall\ X \in \{DG,\ ESS,\ PHEV\} \tag{2}$$

The ADS can sell its surplus electricity to the upward wholesale market. Further, the ADS transacts electricity with its downward EHs. Thus, the revenue of ADS can be written as:

$$revenue = \begin{pmatrix} \sum_{NEMS} prob \times (\sum \lambda^{active} \times P_{DA\_upward}^{active} + \sum \lambda^{reactive} \times Q_{DA\_upward}^{reactive}) + \\ \sum_{NEHS} prob \times (\sum \eta_{DA\_downward}^{active} \times P_{DA\_downward}^{active} + \sum \eta_{DA\_downward}^{reactive} \times Q_{DA\_downward}^{reactive}) \end{pmatrix} \tag{3}$$

The revenue of ADS consists of four terms: 1) the revenue of energy that is sold to upward electricity market; 2) the revenue of reactive power that is sold to upward electricity market; 3) the revenue of energy that is sold to downward loads and EHs; 4) the revenue of reactive power that is sold to downward loads and EHs.

If the ADS energy consumption is less than 0.95 of its day-ahead bidding volume, then ADS will be penalized an additional fee. The penalty is modelled as Eq. (4):

$$Penalty = k.Q^{\text{Reactive}} \quad \text{if } |\text{Cos } \varphi_{ADS}| \ \leq\ \text{Cos } \varphi_{ADS}^{\min} \quad \text{else } =0 \tag{4}$$

$$\text{Cos } \varphi_{ADS} = \frac{P_{DA\_upward}^{active}}{\sqrt{{P_{DA\_upward}^{active}}^{2} + {Q_{DA\_upward}^{active}}^{2}}} \tag{5}$$

Where, k is the penalty coefficient; and $P_{DA\_upward}^{active}$, $Q_{DA\_upward}^{reactive}$ are active and reactive power that are purchased from the upward wholesale market, respectively, ADS bidding quantity to the upward wholesale active and reactive power markets.

A. ESS, CES, TES and PHEV constraints:

The ADSs' ESS, CES, TES and PHEV constraints can be categorized as:

Maximum discharge and charge constraints [28]:

$$PDCH_{ADS}^{Y'} \leq (g \times Cap^{Y'}) \times A^{Y'} \qquad A^{Y'} \in \{0,1\}\ ,\ \forall\ Y' \in \{ESS,\ CES,\ TES, PHEV\} \tag{6}$$

$$PCH_{ADS}^{Y'} \leq Cap^{Y'} \times B^{Y'} \qquad B^{Y'} \in \{0,1\}\ ,\ \forall\ Y' \in \{ESS,\ CES,\ TES, PHEV\} \tag{7}$$

Storages cannot discharge and charge at the same time:

$$A^{Y'}(t)+B^{Y'}(t)\leq 1 \quad \forall\, t\ ,\ A^{Y'}\ and\ B^{Y'}\in\{0,1\}\ ,\forall\, Y'\in\{ESS,\ TES,\ CES, PHEV\} \tag{8}$$

B. SWT and PVA constraints:

The SWT electricity generation equation can be written [28]:

$$P^{SWT}=\begin{cases} 0 & if\ v^{Wind}\leq v_c^{Wind}\ or\ v^{Wind}\geq v_f^{Wind} \\ P_r^{Wind}.\dfrac{(v^{Wind}-v_c^{Wind})}{(v_r^{Wind}-v_c^{Wind})} & if\ v_c^{wind}\leq v^{Wind}\leq v_r^{wind} \\ P_r^{Wind} & otherwise \end{cases} \tag{9}$$

The maximum electricity output of PVA can be written as [28]:

$$\mathrm{P}^{\mathrm{PV}}=S^{PVA}\times\zeta\times I\times(1-0.005\times(t_0-25)) \tag{10}$$

C. DRP constraints:

The ADS loads consist of critical, deferrable and controllable loads. Thus, energy hub and other ADS deferrable loads can participate in the ADS load-shifting procedure for their deferrable loads based on TOU programs. Further, the DSO can contract with the energy hub and other ADS curtailable loads to perform DLC procedure by paying a predefined fee. Hence, the DRP constraints for each bus of the system can be written as [28]:

$$P_{ADS}^{Load}=P_{ADS\ Critical}^{Load}+P_{ADS\ Deferrable}^{Load}+P_{ADS\ Controllable}^{Load} \tag{11}$$

$$\Delta P_{ADS}^{TOU}=P_{ADS\ Deferrable}^{Load} \tag{12}$$

$$\sum_{t=1}^{Period}\Delta P_{ADS}^{TOU}=0 \tag{13}$$

$$\Delta P_{ADS\ Min}^{TOU}\leq\Delta P_{ADS}^{TOU}\leq\Delta P_{ADS\ Max}^{TOU} \tag{14}$$

$$\Delta P_{ADS\ Min}^{DLC}\leq\Delta P_{ADS}^{DLC}\leq\Delta P_{ADS\ Max}^{DLC}\ ,\Delta P_{ADS\ Max}^{DLC}=P_{ADS\ Controllable}^{Load} \tag{15}$$

$$P_{ADS}^{DRP}=\Delta P_{ADS}^{DLC}+\Delta P_{ADS}^{TOU} \tag{16}$$

The ΔP_{ADS}^{TOU} is the sum of the load shifting of energy hubs and other ADS deferrable loads. Further, the ΔP_{ADS}^{DLC} is the sum of the direct load control of energy hubs and other ADS controllable loads.

D. ADS Electric network constraints:

The ADS electric network constraints consist of electric device loading constraints and load flow constraints.

1) Supply-demand balancing constraints:

The active and reactive power balance equations can be written as (17), (18), respectively. The ESS, PHEV, SWT and PVA reactive powers are assumed constant.

$$\begin{aligned}&\sum P_{ADS}^{DG} \mp \sum P_{ADS}^{EH} - \sum P_{ADS}^{Loss} - \sum P_{ADS}^{Load}\\ &\mp \sum P_{ADS}^{ESS} \mp \sum P_{ADS}^{PHEV} + \sum P_{ADS}^{SWT} + \sum P_{ADS}^{PVA} \mp \sum P_{ADS}^{DRP} = 0\end{aligned} \tag{17}$$

$$\sum Q_{ADS}^{DG} + \sum Q_{ADS}^{EH} - \sum Q_{ADS}^{Loss} \pm \sum Q_{ADS}^{DRP} = 0 \tag{18}$$

2) Steady-state security constraints:

The apparent power flow limit of ADS lines and voltage limit of buses can be written as:

$$\sqrt{{P_{nm}}^2(V,\delta) + {Q_{nm}}^2(V,\delta)} \le F_{nm} \tag{19}$$

$$V_n^{\min} \le |V_n| \le V_n^{\max} \tag{20}$$

3) Maximum apparent power for exchanging with the upstream network:

The apparent power rating of the interconnection, the transformer capacity, or the contracted capacity for exchanging power between ADS and the upstream high voltage grid, is considered as below:

$$\sqrt{P_{jt}^2 + Q_{jt}^2} \le F_j^{\max-upstream} \quad \forall j,\ \forall t \tag{21}$$

2.2. Energy Hub Optimization Problem Formulation

The second stage problem, each EHO maximizes its benefit; meanwhile, minimizes its operating costs based on the following formulation:

$$Min\ \mathbf{R} = \sum_{NEHS} prob \times \begin{pmatrix} C_{EH}^{CHP} + C_{EH}^{Boiler} + C_{EH}^{ACH} + C_{EH}^{CCH} + C_{EH}^{ESS} \\ + C_{EH}^{CES} + C_{EH}^{PHEV} + C_{EH}^{TES} + C_{EH}^{Purchase} - B_{EH}^{Sell} - B_{EH}^{DRP} \end{pmatrix} \tag{22}$$

The EHO utilizes its DERs to supply its cooling, heating and electrical loads; meanwhile, it participates in the DSO DRPs and bids/offers to the upward DSO. The EHO determines its bid/offer parameters from Eq. (22) and the DSO explores the optimality of EHs' bids and offers and declares the accepted ones.

Electric power balance constraint of energy hub can be written as (23):

$$P^{EH} = (-\sum P_{EH}^{Load} + \sum P_{EH}^{PVA} + \sum P_{EH}^{ESS} + \sum P_{EH}^{SWT} + \sum P_{EH}^{CHP} - \sum P_{EH}^{ACH} - \sum P_{EH}^{CCH} + \sum P_{EH}^{DRP} + \sum P_{EH}^{PHEV} - P^{Loss}) \quad (23)$$

$$Q^{EH} = (-\sum Q_{EH}^{Load} - \sum Q_{EH}^{ACH} - \sum Q_{EH}^{CCH} + \sum Q_{EH}^{DRP} - Q^{Loss}) \quad (24)$$

The heating and cooling power balance constraint at the simulation interval can be written as (25) and (26), respectively:

$$-\sum Q'^{Load}_{EH} + \sum Q'^{B}_{EH} - \sum Q'^{ACH}_{EH} + \sum Q'^{CHP}_{EH} - Q'^{Loss}_{EH} = 0 \quad (25)$$

$$-\sum R_{EH}^{Load} + \sum R_{EH}^{CCH} + \sum R_{EH}^{ACH} - R_{EH}^{Loss} + \sum R_{EH}^{CES} = 0 \quad (26)$$

$$P_{EH}^{CCH} = \frac{R_{EH}^{CCH}}{COP_{EH}^{CCH}} \quad (27)$$

$$Q'^{ACH}_{EH} = \frac{R_{EH}^{ACH}}{COP_{EH}^{ACH}} \quad (28)$$

$$\frac{R_{EH}^{ACH}}{COP_{EH}^{ACH}} \leq Q'^{CHP}_{EH} \quad (29)$$

A. CHP constraints:

Nonlinear feasible operating region for CHP units:

$$a_{CHP}^{th} \times P_{EH}^{CHP} + b_{CHP}^{th} \times Q'^{CHP}_{EH} \geq c'^{th}_{CHP} \quad (30)$$

$$P_{EH\ Min}^{CHP} \leq P_{EH}^{CHP} \leq P_{EH\ Max}^{CHP} \quad (31)$$

$$Q'^{CHP}_{EH\ Min} \le Q'^{CHP}_{EH} \le Q'^{CHP}_{EH\ Max} \tag{32}$$

B. Boiler constraints:

Heat output limit for ADS and EH boilers:

$$Q'^{B}_{Min} \le Q'^{B} \le Q'^{B}_{Max} \tag{33}$$

$$Q'^{B}_{EH\ Min} \le Q'^{B}_{EH} \le Q'^{B}_{EH\ Max} \tag{34}$$

C. EH's TES, CES and ESS constraints:

The EH's TES, CES and ESS constraints are maximum capacity and charge and discharge constraints.

Energy storage maximum discharge and charge constraints:

$$PDCH^{Y"}_{EH} \le (g \times Cap^{Y"}) \times A^{Y"} \qquad A^{Y"} \in \{0,1\} \ , \ \forall \ Y" \in \{ESS,\ TES,\ CES\} \tag{35}$$

$$PCH^{Y"}_{EH} \le Cap^{Y"} \times B^{Y"} \qquad B^{Y"} \in \{0,1\} \ , \forall \ Y" \in \{ESS,\ TES,\ CES\} \tag{36}$$

D. ACH and CCH constraints:

Feasible operating region for EH's ACH and CCH units [29]:

$$R^{X}_{EH\ Min} \le R^{X}_{EH} \le R^{X}_{EH\ Max} \quad \forall X \in CCH, ACH \tag{37}$$

$$Q'^{X}_{EH\ Min} \le Q'^{X}_{EH} \le Q'^{X}_{EH\ Max} \quad \forall X \in CCH, ACH \tag{38}$$

E. DRP constraints:

The EH loads consist of critical, deferrable and controllable loads. Thus, the DRP constraints for each EH can be written as [28]:

$$P^{Load}_{EH} = P^{Load}_{EH\ Critical} + P^{Load}_{EH\ Deferrable} + P^{Load}_{EH\ Controllable} \tag{39}$$

$$\Delta P^{TOU}_{EH} = P^{Load}_{EH\ Deferrable} \tag{40}$$

$$\sum_{t=1}^{Period} \Delta P_{EH}^{TOU} = 0 \tag{41}$$

$$\Delta P_{EH\ Min}^{TOU} \leq \Delta P_{EH}^{TOU} \leq \Delta P_{EH\ Max}^{TOU} \tag{42}$$

$$\Delta P_{EH\ Min}^{DLC} \leq \Delta P_{EH}^{DLC} \leq \Delta P_{EH\ Max}^{DLC}\ ,\ \Delta P_{EH\ Max}^{DLC} = P_{EH\ Controllable}^{Load} \tag{43}$$

$$P_{EH}^{DRP} = \Delta P_{EH}^{DLC} + \Delta P_{EH}^{TOU} \tag{44}$$

The energy purchased costs and energy sold benefits can be written as (45) and (46), respectively:

$$If\ \ P^{EH} > 0\ \ Then\ \ B_{Sell}^{EH} = P^{EH}\ .\ \kappa_{Sell}^{Elect} else\ \ C_{Purchase}^{EH} = P^{EH}\ .\ \kappa_{Purchased}^{Elect} \tag{45}$$

$$B_{DRP}^{EH} = \Delta P_{EH}^{TOU}\ .\kappa_{Purchased}^{Elect} + \Delta P_{EH}^{DLC}\ .\ \kappa_{DLC}^{Elect} \tag{46}$$

F. PHEV model and constraints:

The charge/discharge behaviour of each PHEV is determined by the behaviours of the vehicle owners that can be modelled as stochastic parameters. However, in a specific area with a large number of ADS-connected PHEVs and EH-connected PHEVs, the random behaviour of PHEVs can be modelled by probability distributions. In order to model the behaviour of PHEVs correctly, the following assumptions are considered [30]:

1. All ADS-connected PHEVs and EH-connected PHEVs have the same batteries and can contribute to two smart charge/discharge modes.
2. PHEVs are independent of each other.

According to the above assumptions, historical data can be used to compute the probability density function [30].

The energy balance of PHEV battery and the PHEV's battery energy limits can be formulated as (47) and (48), respectively:

$$\begin{aligned} ENPHEV(t) = {} & ENPHEV(t-1) + \varpi_{PHEV}^{Charge} \times PCH^{PHEV}(t) \times \Delta t \\ & - \frac{1}{\varpi_{PHEV}^{Discharge}} \times PDCH^{PHEV} \times \Delta t \end{aligned} \tag{47}$$

$$ENPHEV^{min} \le ENPHEV \le ENPHEV^{max} \tag{48}$$

$$0 \le PCH^{PHEV} \le PCH^{PHEV,Max} \tag{49}$$
$$0 \le PDCH^{PHEV} \le PDCH^{PHEV,Max}$$

$$ENPHEV(t) = \sigma \times ENPHEV^{max} \qquad \forall\ t = t_{Departure} \tag{50}$$

The charge and discharge rates of PHEV battery are formulated as Eq. (49). The desired PHEV state of charge at the leaving time is formulated as (50) and σ is the expected coefficient.

3. Solution Algorithm

3.1. Distribution System Operator Optimization Problem Algorithm

For the DSO optimization problem algorithm, the following assumptions are considered:

1. The control variables of the ADS system are assumed as continuous variables.
2. A linearized Alternating Current (AC) load flow is performed [31].
3. Numerous scenarios for upward electricity market price, ADS intermittent power generation, PHEV contribution, and DRP commitment must be generated. The EHO operation scenarios are received from the energy hub optimization problem. However, from a computational burden, a scenario reduction procedure must be performed. The forward selection algorithm is implemented to reduce the generated scenarios [32].
4. It is assumed that the ADS submits its bids/offers to the upward electricity market and all of its submitted values will be accepted.

For the DSO optimization problem algorithm, a CPLEX solver of GAMS is used.

3.2. Energy Hub Optimization Problem Algorithm

At the energy hub optimization problem, the following assumptions are considered:

1. All of the control variables of EH systems are assumed as continuous variables.
2. The AC load flow algorithm is utilized [31].

3. The EHO generates scenarios for its intermittent power generation, PHEV commitment, and DSO’s TOU prices and DLC fees. The scenario reduction procedure is performed [32].

For the EH optimization problem algorithm, a CPLEX solver of GAMS is used.

The proposed model of ODAS has a large state space that involves non-convex, non-linear discrete and continuous variables. A linearization technique is used to linear the non-linear equations and the presented method is modeled as a MILP model. An iterative two-level MILP optimization algorithm is proposed and Fig. 4 depicts the flowchart of the proposed optimization algorithm. The flowchart blocks are presented in the following paragraphs.

At the first step, the initial value of energy hub bids/offers are generated and then the DSO optimization is performed. The output of the DSO optimization problem is delivered to the EH optimization problem. The initial values of energy hubs bids/offers are updated based on the EH optimization problem and the values of TOU prices and DLC fees are linearly changed and the procedure is repeated. The procedure will be stopped if no more improvement is achieved.

4. Simulation Results

The 33-bus test system is used to assess the proposed algorithm and it is considered as ADS. Three energy hubs are connected to the 33-bus system. The 33-bus test system data is presented at [33]. Fig. 5 shows the 33-bus system topology. The energy hub data are available at [4].

Table. 2 presents the optimization input data for the 33-bus test system. Table. 3 presents the optimization input data for the EH systems. Fig.6 depicts the reduced wholesale market prices scenarios. Fig. 7 presents the EHs’ cooling, heating and electrical loads. The PHEV data are available at [30]. Fig.8 shows the PVA and SWT electricity generation for energy hub for one of the reduced scenarios.

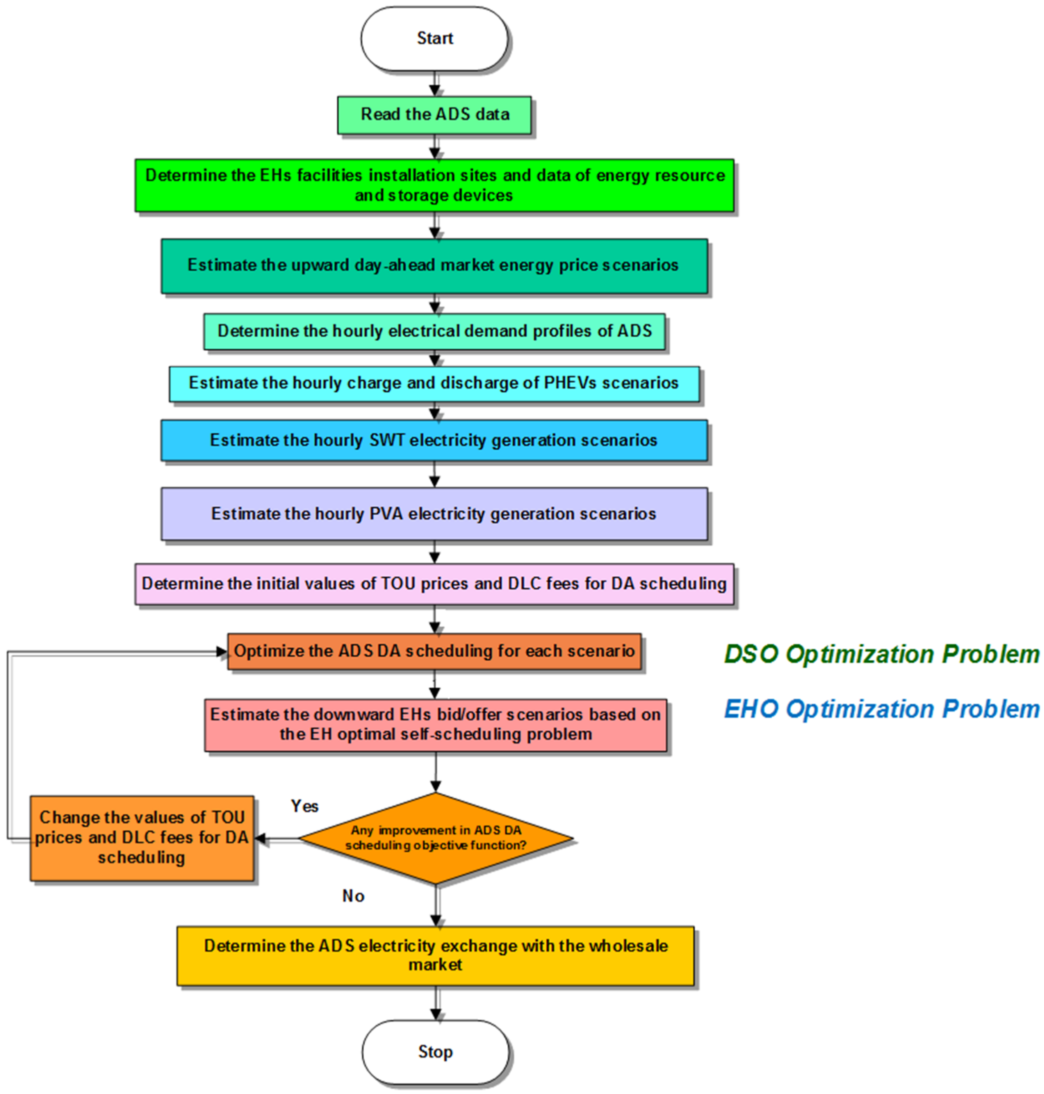


Fig. 4. Flowchart of the proposed ODAS algorithm.

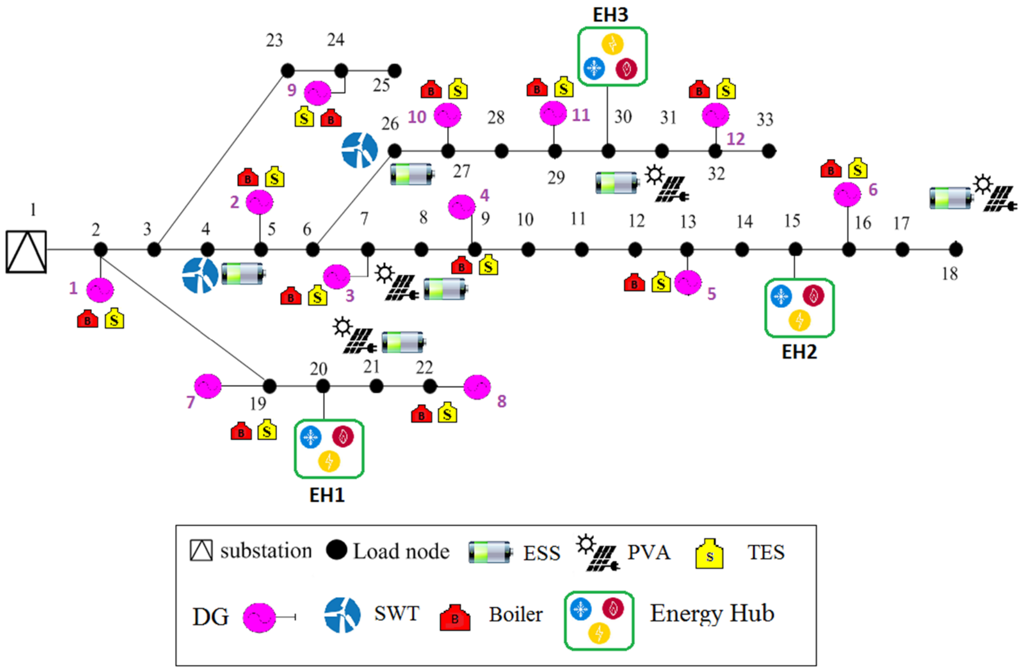


Fig. 5. The 33-bus ADS.

Table 2. The optimization input data for the 33-bus system.

ADS system parameter	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 3. The optimization input data for the EHs.

EH system parameter	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

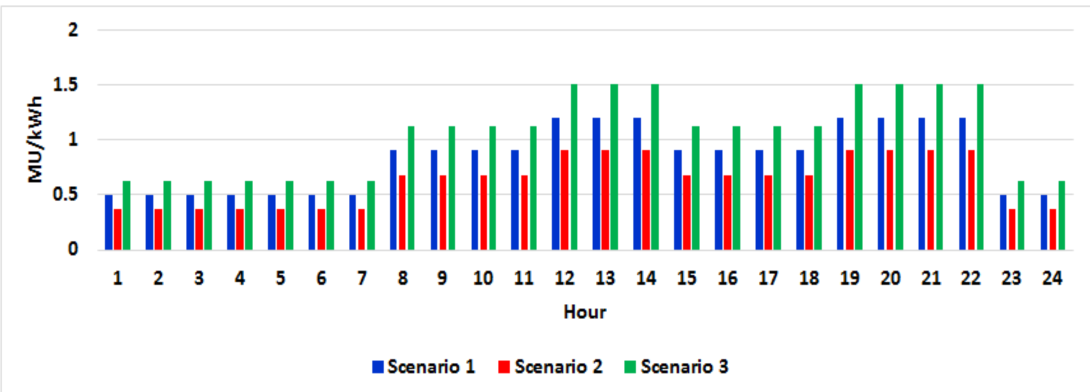


Fig. 6. Wholesale electricity market price in three scenarios.

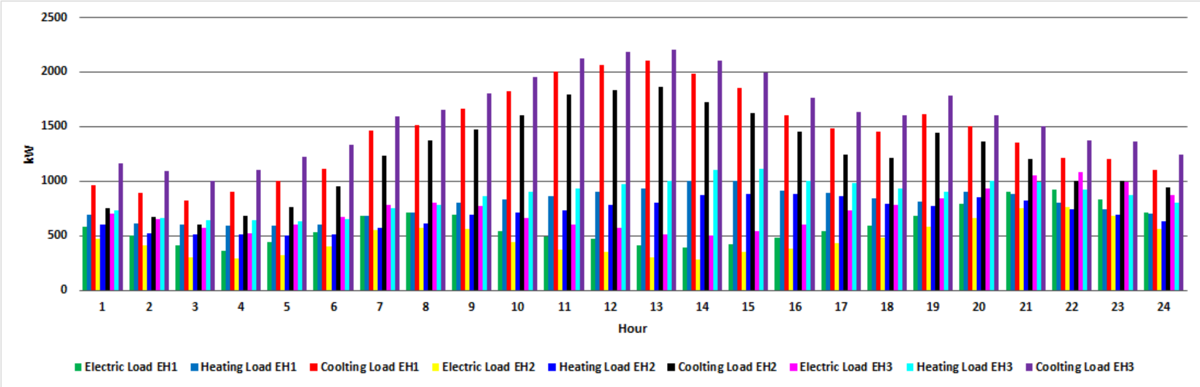


Fig.7. Hourly cooling, heating, and electrical load of the energy hubs.

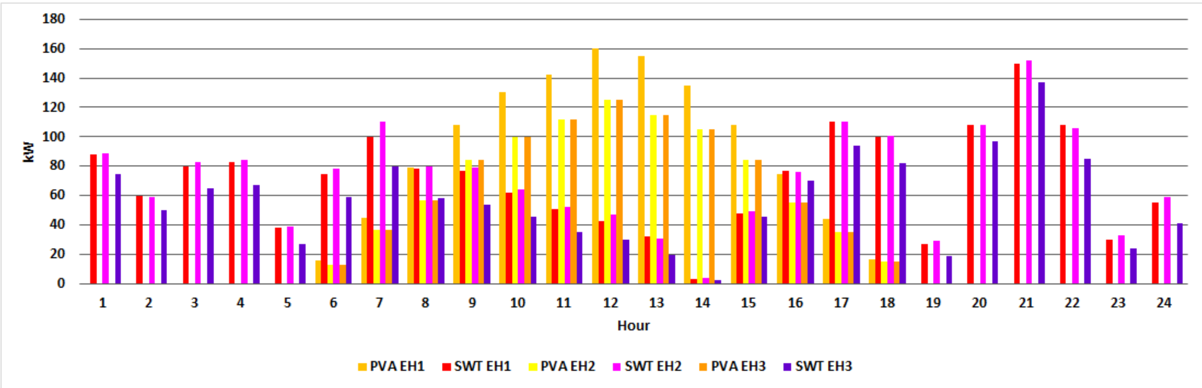


Fig 8. The PVA and SWT electricity generation for energy hub for one of the reduced scenarios.

Two cases are considered to assess the proposed algorithm. The first case optimizes the ODAS without considering DRP alternatives. The second case considers DRP scenarios in the ODAS procedure. For both cases, a scenario generation and reduction procedure were performed. The scenario reduction method reduced the wholesale market prices, SWT electricity generation, PVA electricity generation, PHEV contribution and DRP commitment scenarios for the second case. The forward selection algorithm is used to reduce the generated scenarios [34].

The first case did not encounter DRP commitment scenarios.

Case 1: Without considering demand response scenarios

For the first case, the 33-bus distribution system did not utilize demand response procedures. The energy hubs transacted energy with the 33-bus system and proposed their bids/offers to the distribution system.

Fig. 9 presents the columns of bids/offers of energy hubs that EH L, EH M and EH H present the minimum, mean and maximum value of energy hubs bids/offers, respectively. Fig. 10 depicts the heat generation of energy hubs. The energy hubs' combined heat and power units were committed at full load for and the boiler was tracking the heating load. Fig. 11 depicts the energy hubs thermal energy storage charge and discharge. The energy hubs' thermal energy storages were heavily used for 08:00 AM to 24:00 PM based on the fact that the thermal energy storages improved the flexibility of energy hubs to handle the heating energy supply. Fig. 12 depicts the energy hubs cooling power generation and charge and discharge of cooling energy storages. Energy hubs mostly utilized compression chillers to supply their cooling loads and the absorption chillers and cooling storages were committed when the energy hubs cooling loads were exceeded the compression chillers cooling capacity. Fig. 13 depicts the energy hubs electricity generation and electrical energy storages charge and discharge. The combined heat and power units were committed for 08:00 AM to 24:00 AM and energy hubs imported electricity from distribution system for 24:00 AM to 07:00 PM.

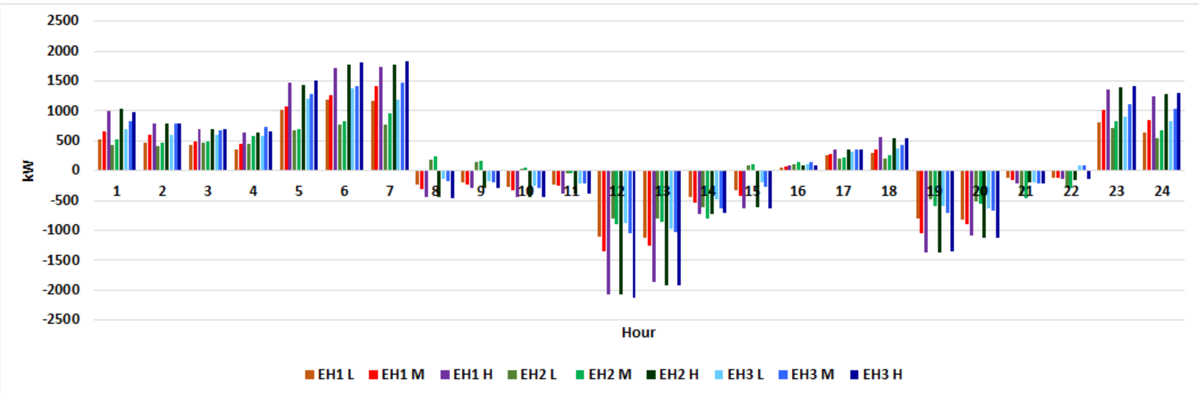


Fig.9. The energy hubs bid/offer columns for the first case.

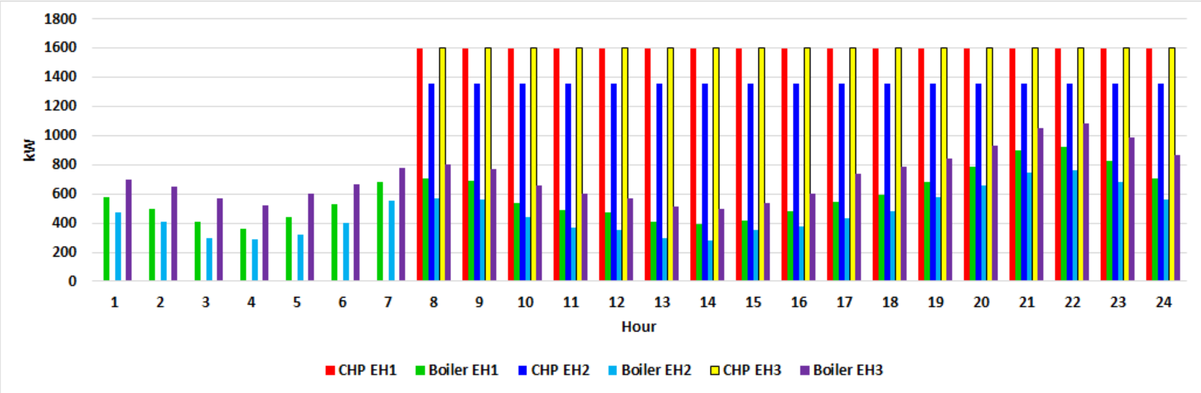


Fig. 10. The energy hubs combined heat and power units and boiler heat generation.

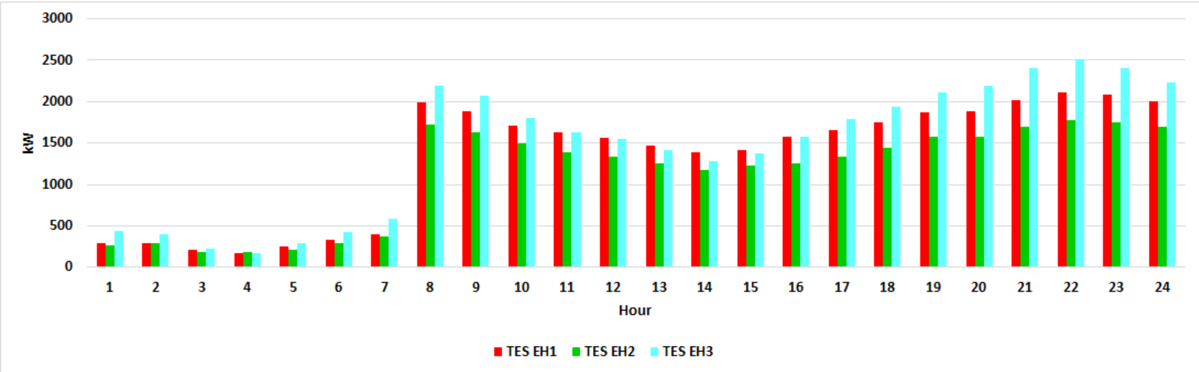


Fig. 11. Energy hub charge and discharge of thermal energy storage.

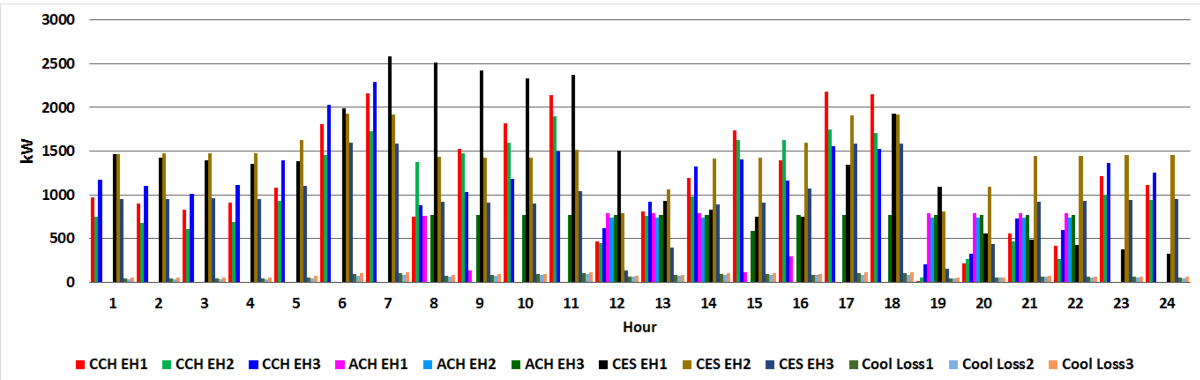


Fig. 12. The cooling power generation of cooling energy generation facilities, charge, and discharge of cooling energy storage of energy hubs.

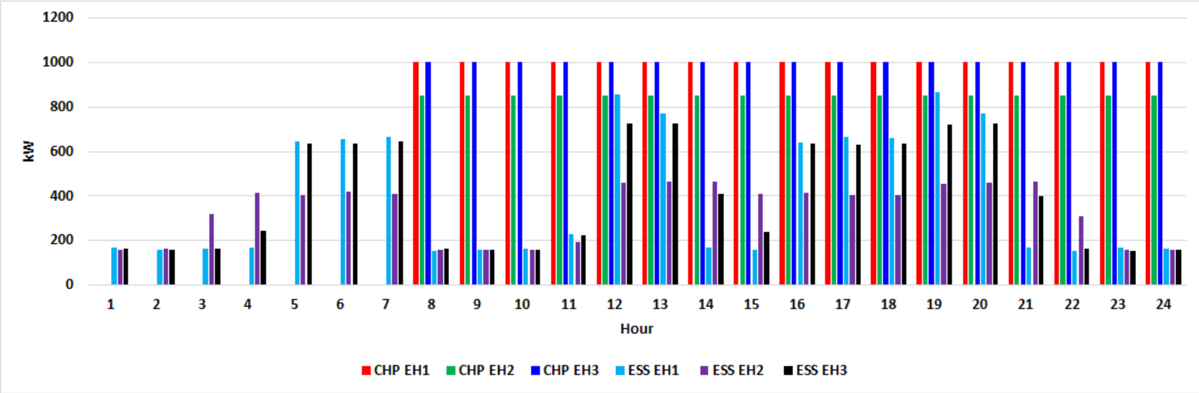


Fig. 13. The energy hubs CHP electricity generation and electrical energy storage charge and discharge.

Fig. 14 shows the EH2 commitment of six plug-in electric vehicles that were utilized by the second energy hub. The EH2 has 1500 electric vehicles and their commitment has a stochastic behaviour based on their initial state of charge and the availability of the electric vehicles.

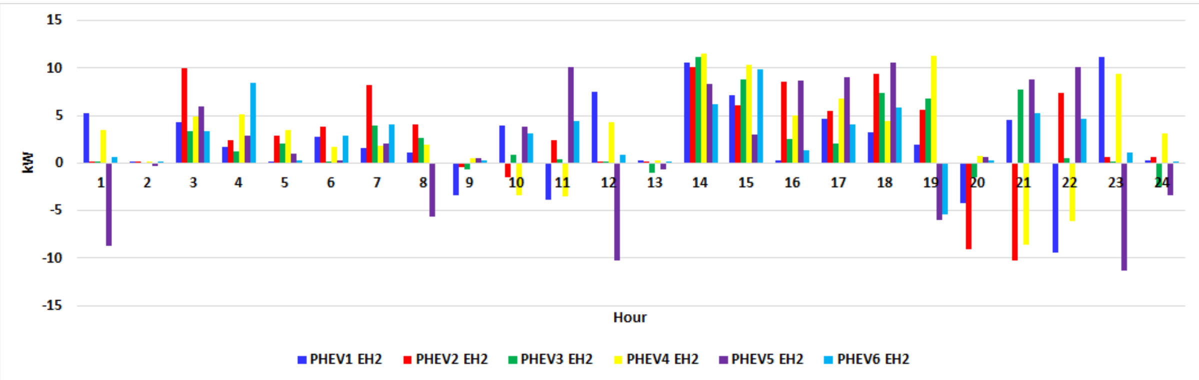


Fig. 14. The EH2 commitment of six plug-in electric vehicles that were utilized by the second energy hub.

Fig. 15 depicts the electricity transactions of energy hubs with the 33-bus distribution system where a power withdrawal of energy hub has minus value.

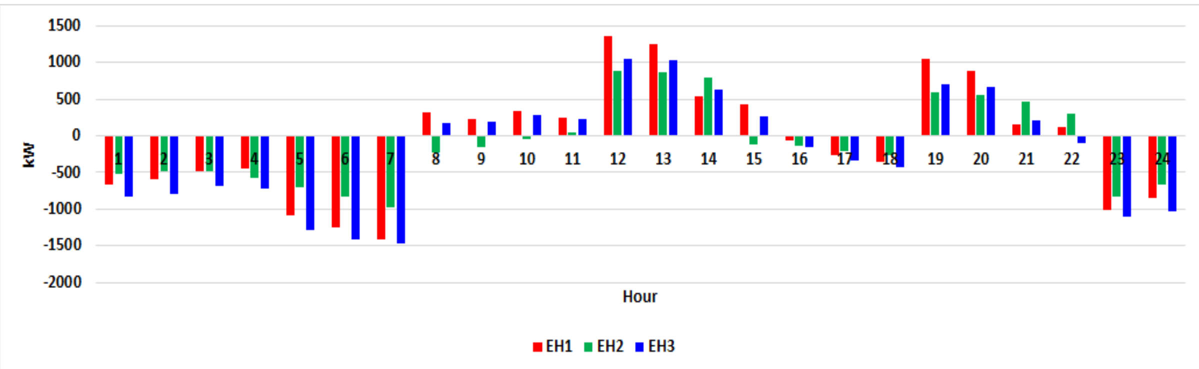


Fig. 15. The electricity transactions of energy hubs with the 33-bus system.

The EH1 and EH3 proposed electricity injection for 08:00 PM to 15:00 PM and 19:00 PM to 21:00 PM. The energy hubs proposed electricity withdrawal for 01:00 AM to 07:00 AM and 23:00 PM to 24:00 PM. Further, based on the distributed energy resources electricity generation and energy hubs bids/offers, the distribution system submits different values of electricity generation or consumption to the upward wholesale electricity market.

Case 2: With considering demand response scenarios

At the second case, the 33-bus distribution system implemented demand response procedures that consisted of time-of-use and direct load control procedures. As shown in Fig. 16, different demand response price scenarios are considered in the optimization procedure. Fig. 17 presents the demand response constraints for different scenarios.

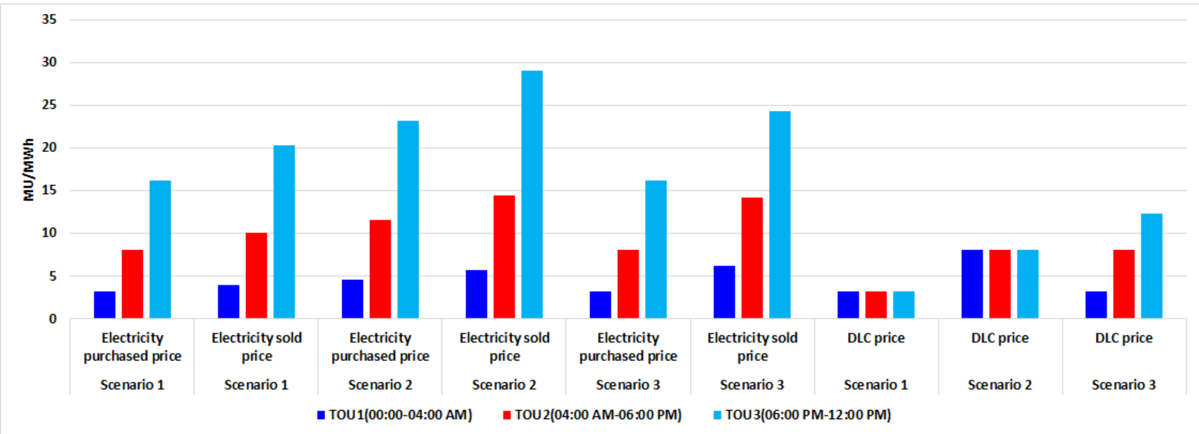


Fig. 16. The electricity price for different scenarios.

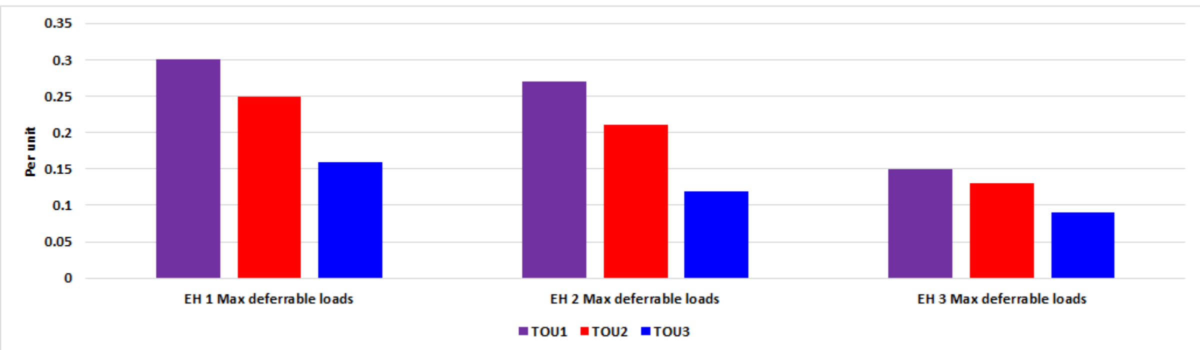


Fig. 17. The maximum deferrable load of energy hubs.

Based on the proposed flowchart, the distribution system examined different demand response price scenarios and it iteratively proceeded the optimization procedure. Finally, the optimal values of demand response fees were determined and proposed the optimal pricing scenarios to energy hubs. Based on the defined procedure, the distribution system selected the second demand response pricing scenarios as the optimal demand response scenario.

Fig. 18 presents the energy hubs bid/offer columns for the optimal values of demand response prices and fees. Fig. 19 depicts the heat generation of energy hubs. The EH3's combined heat and power unit was additionally committed for 01:00 AM to 02:00 AM and 07:00 AM with respect to the first case. However, the EH2's combined heat and power unit was off for 08:00 AM and 09:00 AM with respect to the first case. Fig. 20 depicts the energy hubs thermal energy storage charge and discharge. The energy hubs' thermal energy storages were heavily used for 10:00 AM to 24:00 PM. Further, the thermal energy storage of EH3 was fully utilized for 01:00 AM to 02:00 AM and 07:00 AM to 09:00 AM to store the surplus heating energy of EH3's combined heat and power unit.

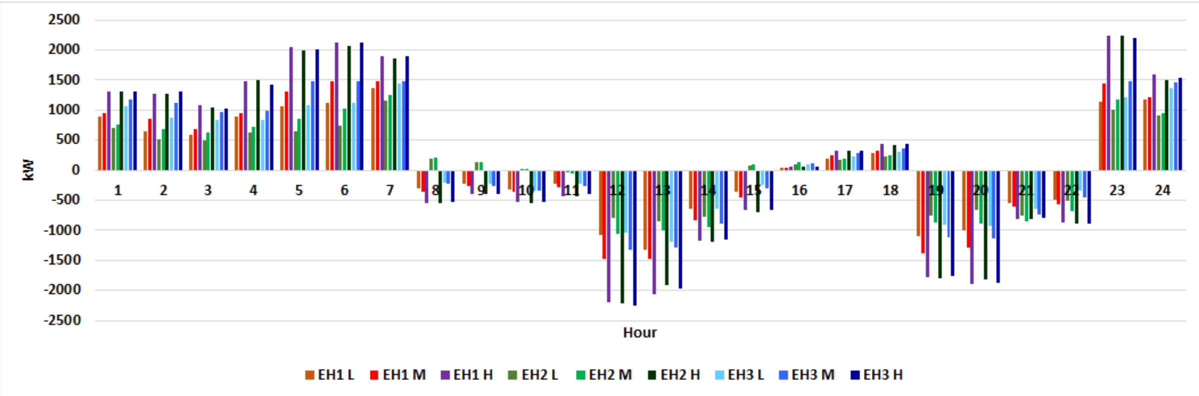


Fig. 18. The energy hubs bid/offer columns for the optimal values of demand response prices.

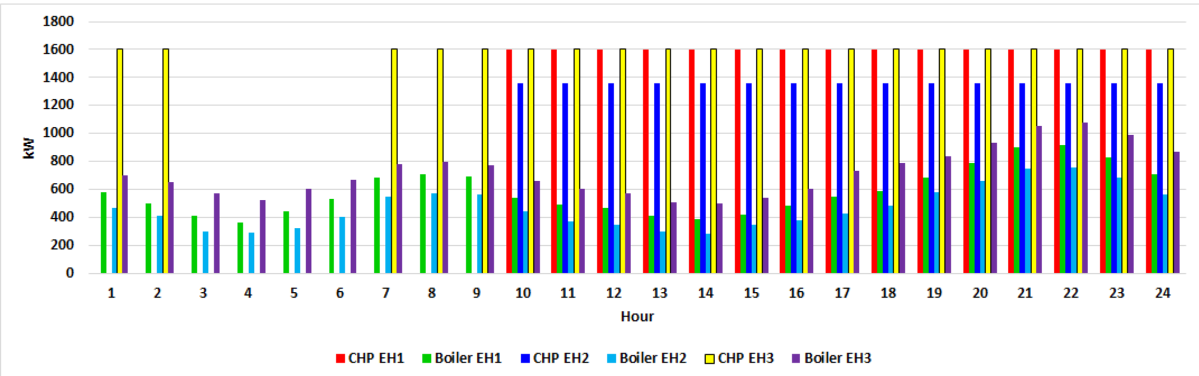


Fig. 19. The energy hubs combined heat and power units and boiler heat generation.

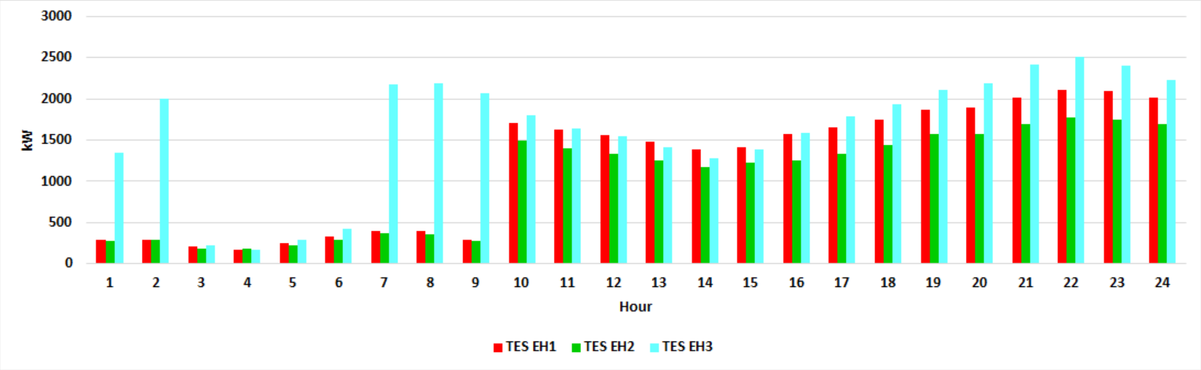


Fig. 20. Charge and discharge of thermal energy storage of energy hubs.

Fig. 21 depicts the cooling power generation of energy hubs. Same as the first case, the energy hubs mostly utilized compression chillers and the absorption chillers and cooling energy storages were committed when the energy hubs cooling loads were exceeded the compression chillers cooling capacity.

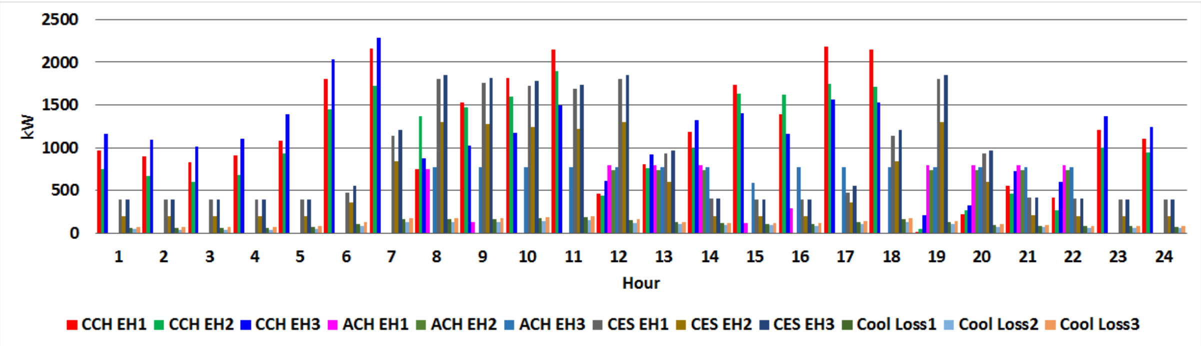


Fig. 21. The cooling power generation of cooling energy generation facilities and charge and discharge of CES of energy hubs.

Fig. 22 depicts the energy hubs combined heat and power electricity generation unit and electrical energy storage charge and discharge. The combined heat and power units were committed for 10:00 AM to 24:00 AM. However, the EH3 committed its combined heat and power units from 01:00 AM to 02:00 AM and 07:00 AM to 09:00 AM. Fig. 23 shows the EH2 commitment of six plug-in electric vehicles that were utilized by the second energy hub.

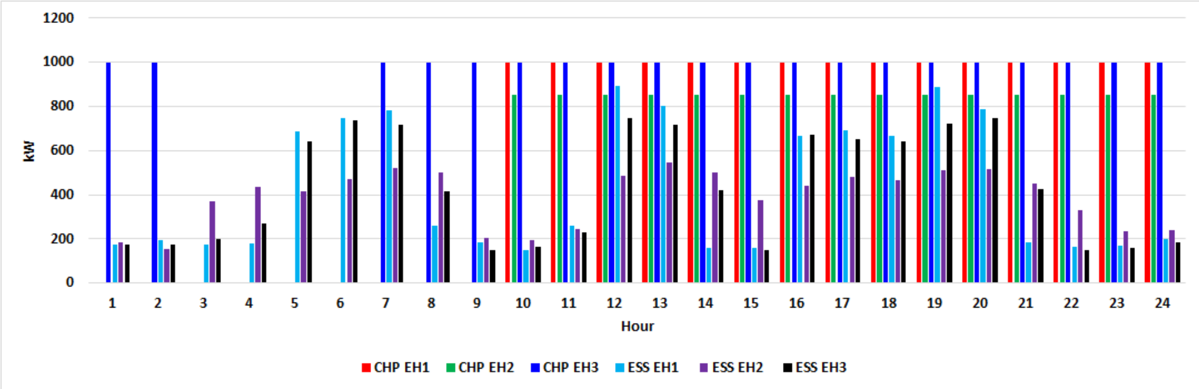


Fig. 22. The energy hubs electricity generation and electrical energy storage charge and discharge.

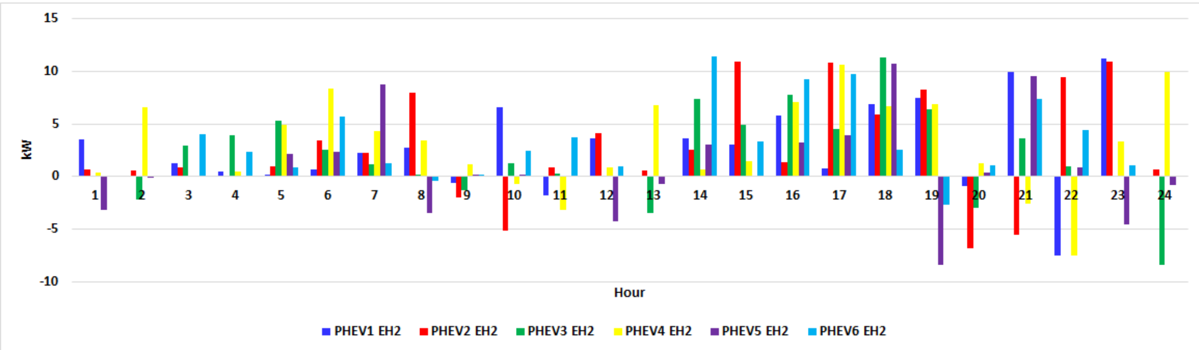


Fig. 23. The EH2 commitment of six electric vehicles that were utilized by the second energy hub.

Fig. 24 presents the energy hubs electricity transactions with the distribution system. It can be concluded that the total transacted energy between energy hubs and distribution system are 42297.34 kWh and 56366.57 kWh for the first and second case, respectively. Thus, the demand response procedure has improved the energy hubs contribution in distribution system operational scheduling. Fig. 25 depicts the optimal scheduled electricity generation, the sum of energy hubs electricity generation/consumption and net distribution system electricity injection/withdrawal for the 1st scenario. Fig. 26 (a), (b), (c) depict the estimated energy hubs contribution costs, emission costs, distribution system operational costs and cost/benefit of the distribution system for electricity transaction with the upward market for the first, second and third scenario of the second case, respectively.

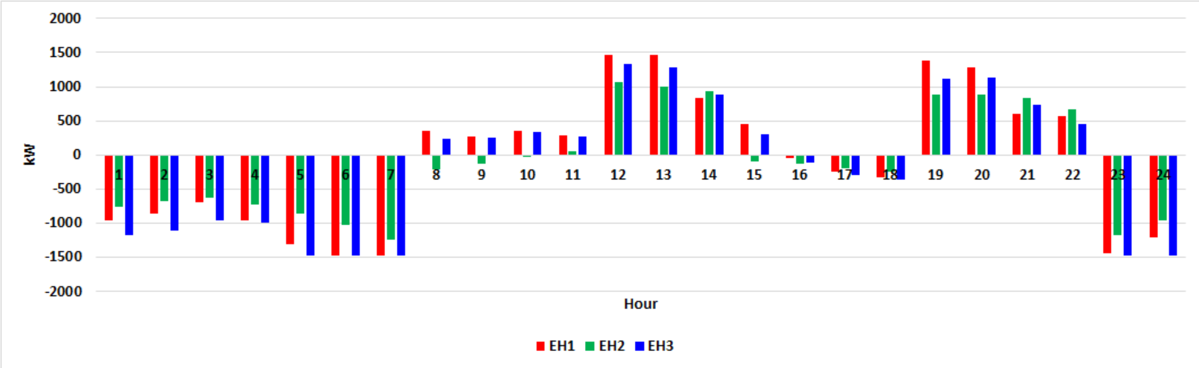


Fig. 24. The electricity transactions of energy hubs with the 33-bus distribution system.

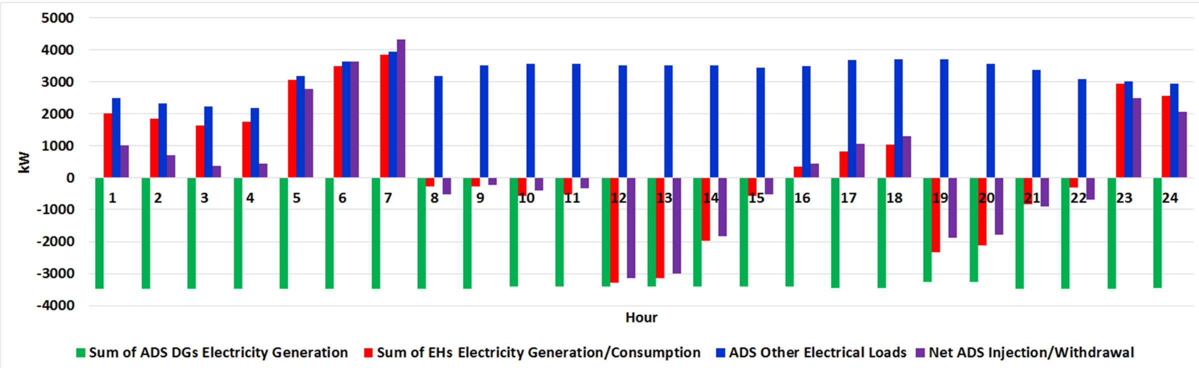
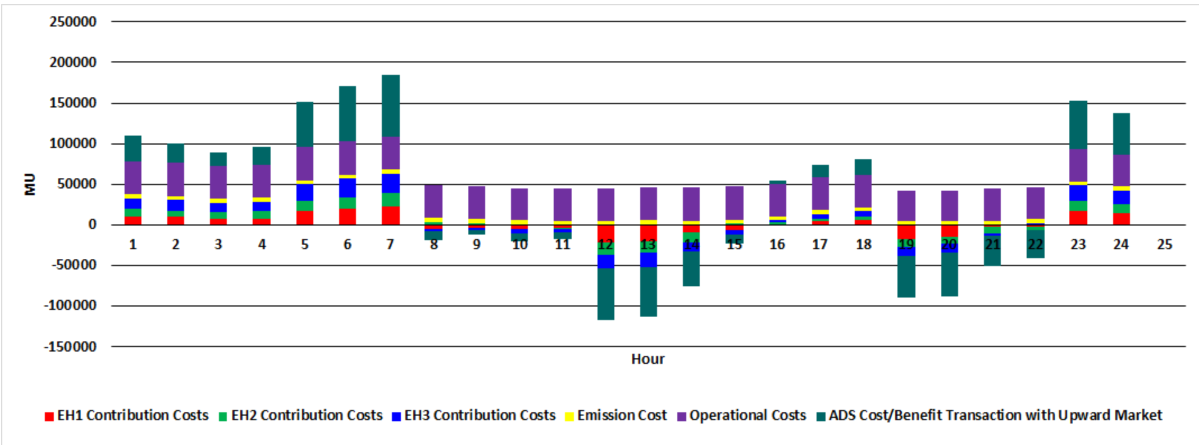
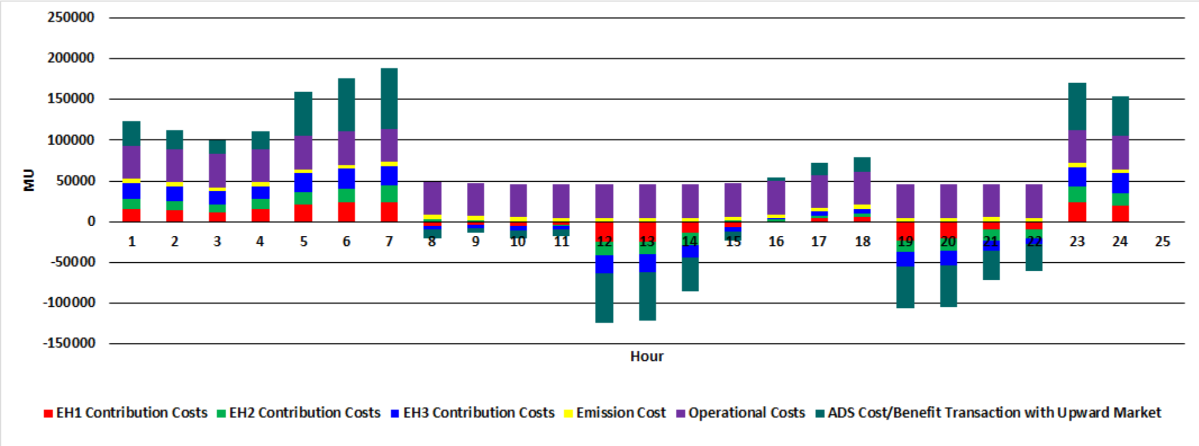


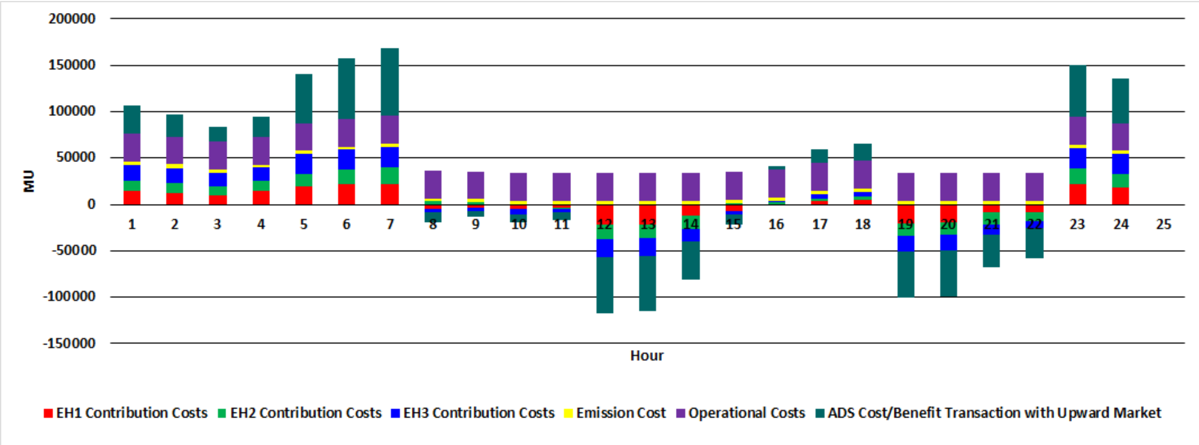
Fig. 25. The optimal scheduled distribution system electricity generation, sum of energy hubs electricity generation/consumption and net electricity injection/withdrawal for the first scenario.



(a)



(b)



(c)

Fig. 26. The estimated energy hubs contribution costs, emission costs, operational costs and cost/benefit of distribution system for electricity transaction with upward market for the (a) first, (b) second and (c) third scenario of the second case.

Fig. 27 shows the final costs and benefits of the distribution system and energy hubs for different cases and scenarios. As shown in Fig. 27, for the third scenario of the second case, the energy hubs electricity selling benefit is increased to 71894.1073 MU that is about 185% of its corresponding value of the first case. The distribution system costs are 51364.40588 MU that is the lowest value of the cases and scenarios and is about 82.2% of its corresponding value of the first case.

Thus, the third scenario of the second case is the optimal day-ahead scheduling and Fig. 28 presents the estimated corresponding values of electricity generation, energy hubs accepted bid/offers (electricity consumption/generation), and net electricity sold to/purchased from the upward electricity market. According to Fig. 28, the ODAS reduces the operational costs of the distribution system and increases the energy hubs benefits for the third scenario of the second case about 82.2% and 185% with respect to their corresponding first case parameters, respectively. It means that the distribution system can reduce its operational costs; meanwhile, the downward energy hubs maximize their benefits. A zero-carbon-emission micro energy internet concept that uses demand response procedures to coordinate the downward energy hubs bids/offers with the active distribution system is considered as future work [35].

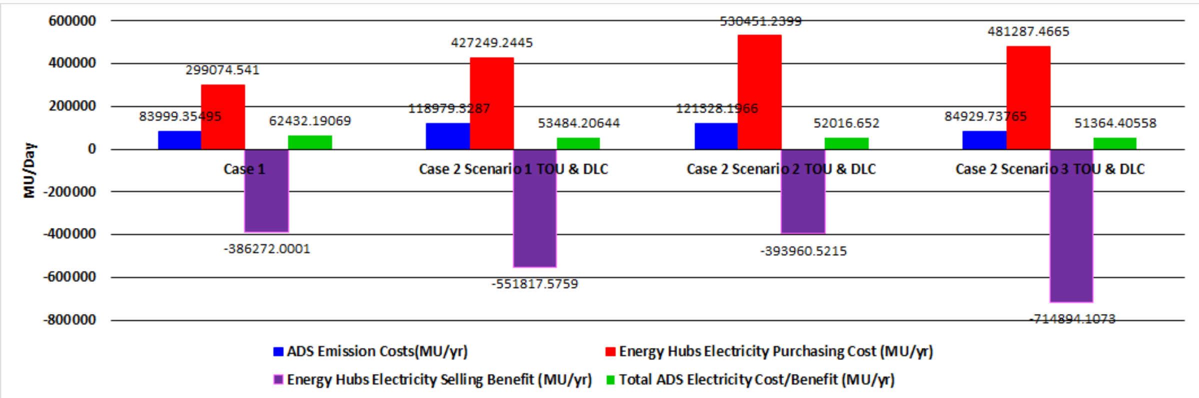


Fig. 27. The final costs and benefits of distribution system and energy hubs for different cases and scenarios.

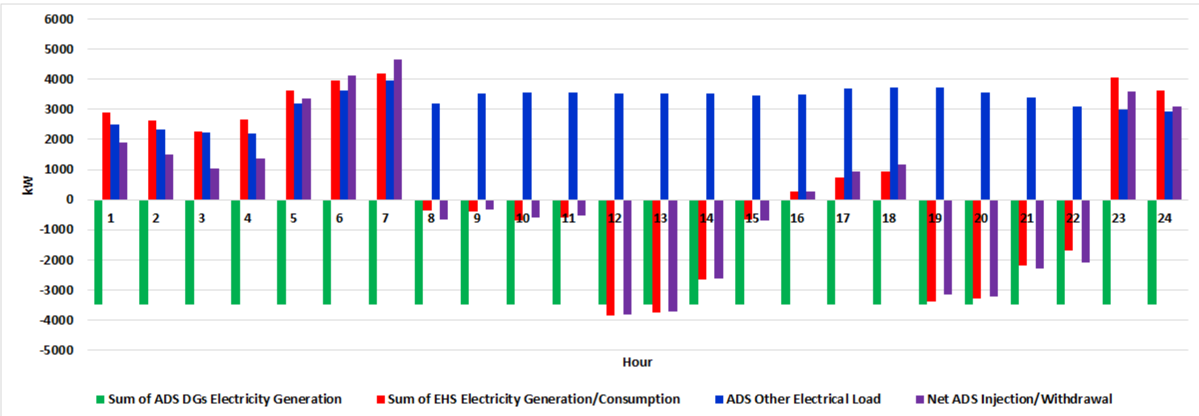


Fig. 28. Estimated distribution system electricity generation, energy hubs accepted bid/offers (electricity consumption/generation), and net electricity sold to/bought from the upward electricity market.

5. Conclusion

This paper presented an operational scheduling framework for ADS having renewable energy sources, distributed generation units, electric vehicles, and energy storage units. The distribution system DRPs considered were TOU and DLC programs. Five different sources of uncertainties were modelled and a two-level optimization algorithm was presented. At the first stage, the ADS minimized the operational cost of its system for different scenarios. At the second stage, the ADS estimates the EHs operational scheduling. Two cases were considered for the 33-bus test system. For one of the worst-case scenarios, the EHs electricity selling benefit was increased to 71894.1073 MU, which was about 185% of its corresponding value of the first case. Further, the ADS costs were 51364.40588 MU that was the lowest value of cases and scenarios and was about 82.2% of its corresponding value of the first case. Thus, the TOU and DLC demand response procedures improved the energy hubs contribution in the ADS operational scheduling and the total transacted energy between energy hubs and distribution system were increased. The proposed ODAS algorithm reduces the ADS operational costs; meanwhile, it maximizes the downward EHs benefits. In conclusion, the adoption of the proposed ODAS allowed increasing the ADS and EHs benefits. The authors are investigating the use of other DRP methods for the ODAS procedure of zero-carbon-emission micro energy internet as future work.

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