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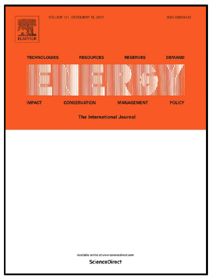

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Optimal bidding strategy for an energy hub in energy market

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Abstract

An energy hub, as an active element in smart distribution grid, can participate in the day-ahead market via submitting bids to maximize its profit. The multi-input and multi-output energy vectors make energy hub different from other active elements. In this paper, a comprehensive optimal bidding strategy for an energy hub is modeled. The proposed model enables the energy hub to benefit from day-ahead and real-time markets. Stochastic optimization is proposed in this strategy to handle several market uncertainties consisting of day-ahead market prices, real-time market prices, and wind generation. The model takes advantages of multi-inputs vector of energy hub to submit the optimal bids including electricity selling/buying and optimizes the cost. Moreover, it handles the coupling between different types of loads. The problem is modeled as a mixed integer linear program. Numerical simulations evaluate the proposed model.

Keywords: energy hub, bidding strategy, stochastic optimization, prosumer

Nomenclature	
t	Time-interval
i,j,m	Indices for input energy, output energy, and energy storage system respectively
s	Indices for scenarios
N_{ess}	number of energy storage systems
N_s	number of scenarios
N_i,N_o	number of input/output energies
δ^{ch}_m,δ^{dis}_m	Binary variables; 1 if energy storage system *m* is charging/discharging
I_{ik}	Binary variable; 1 if convertor *ik* is on
L	Matrix of output energies
$L_j(t)$	Output energy *j* at time *t*
C	Conversion matrix
P	Matrix of input energies
$P_i(t)$	Input energy *i* at time *t*
P^{min}_i,P^{max}_i	Minimum/maximum capacity of input energy *i*
P^{min}_{ik},P^{max}_{ik}	Minimum/maximum capacity of input energy to convertor *ik*

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v_{ik}	Dispatch factor
E(t)	Matrix of energies stored in storage systems
$E_m(t)$	Level of energy stored in energy storage *m* at time *t*
E^{loss}	Matrix of energy loss of energy storages
Q^{ch},Q^{dis}	Charging/discharging matrix of energy storages
$Q_m^{ch,max}$,$Q_m^{dis,max}$	Maximum charging/discharging capacity of energy storage *m*
η_m^{ch},η_m^{dis}	Charging/discharging efficiencies of energy storage *m*
A^{ch},A^{dis}	Matrix of charging/discharging efficiencies
C_e^{DA}	Day-ahead prices of electricity
C_e^{RT}	Real-time prices of electricity
C_g	Natural-gas prices
P_e^{DA}	Power exchanged in day-ahead market
P_e^{DA}	Power exchanged in real-time market
P_g	Natural-gas consumption
P_w	Wind power generation
P_w^r	Rated power of wind unit
π_s	Probability of day-ahead scenarios

1. Introduction

An important part of energy consumption including electrical loads is used for heating and cooling [1]. On the other hand, extension of energy distribution systems and developments in CHP, fuel cell, and micro-turbine generators make it necessary to improve the efficiency via smart management of energy infrastructures. The use of multi energy systems is considered as a pioneer method for optimizing energy systems [2]. An energy hub is an infrastructure unit in which different types of energy carries as inputs are converted to the other types of energy and may be stored [3]. Therefore, it can play a promoting role in energy provision [4].

Multi-energy input increases degrees of freedom in the management of the energy hub. Therefore, flexibility of decision-making is increased. Since the main aim of energy hub is optimal operation, energy provision of different types of loads is improved both in economic and security points of view [5]. This advantage has many benefits for loads and distribution system such as peak shaving [6].

Energy hub has been introduced in “Vision of Future Energy Networks” project as a key approach to increase flexibility and efficiency of supplying [3]. Consequently, due to advantages of energy hub, it has been studied in several aspects. Totally, the most studies on energy hub may be categorized in modeling [4, 7-12], operation and energy management [13-22], planning [23], and security analysis [24] aspects.

Several papers have focused on modeling of energy hub. Ref. [7] proposed a matrix model for coupled power flow between various energy carriers. Ref. [8] employed energy hub concept to model a tri-generation system with matrix formulation using cooling system in coordination with other converters. Parisio et al. [9] presented a formulation for modeling the energy hub considering both electrical and thermal energy storage systems. In this model, efficiencies of convertors are supposed uncertain. Ref. [10] presented an energy hub structure equipped with solar and energy storage systems. Allegarini et al. [11] compared different approaches and tools used for simulation of distributed energy system. Ref. [12] focused on the flexibility of energy hub and its capability to provide ancillary services. Gerami et al. [4] used feasible operation region model of CHP in the format of energy hub to make a more accurate model. Moreover, by using energy flow method, the storage systems could be placed in both output and input.

Ref. [13] focused on modeling of residential equipment in the energy hub to form an autonomous energy management system. Moreover, it has classified energy hub as micro and macro energy hubs with a hierarchical control system to optimize the energy consumption. Refs. [14-16] presented a supervisory control layer, which determines the optimal set point of equipment for energy management system of an energy hub. Paudyal et al. [17] adopted energy hub concept for industrial loads to optimize energy cost by management of industrial process. Ref. [18] employed energy hub concept as a real-time supervisory controller to reduce demand and energy consumption in a greenhouse. Evins et al. [19] developed energy hub formulation to include emission constraints. They used a step-wise estimation to model the behavior of loads more accurately. Refs. [20, 21] integrated plug-in hybrid electric vehicles (PHEV) as a demand response source in residential energy hub. PHEV was used by Ref. [22] as a source to provide reserve as an output of the energy hub.

Due to the flexibility of energy hub, demand response programs can be applied optimally. Demand response can be integrated into energy management system of energy hub in order to minimize cost [25] or maximize profit [26]. Ref. [27] employed demand response in a dynamic pricing scheme for an energy hub with different types of loads in which operation of equipment depends on dynamic price signals. Ha et al. [28] presented a mathematical model for residential energy hub using different energy tariffs and capacity limitation. Najafi et al. [5] presented an optimal decision-making model for energy management system of energy hub in which profit of selling electricity and heat is maximized and cost of energy provision is minimized through a bi-level scheduling.

Based on the literature, energy hub is studied in different aspects such as the effect of energy hub in the market. Ref. [29] described advantages of energy hub and matrix modeling. Moreover, it discussed the role of energy hub in energy market considering its features and concluded that the synergy between energy carriers improved operation and loads management.

In the future smart distribution systems, the active customer such as active loads, prosumers, and microgrids are classified as proactive customers. They may improve the operation of distribution system through a distribution market [30, 31]. Due to flexibility of energy hub, it may play a proactive role in the market. Therefore, the energy management system of proactive customer needs to decide the optimal bid to take part in the market [32]. According to literature, focusing on optimal bidding strategy of an energy hub is needed, due to its specific features such as multi-energy input vector.

Optimal bidding strategy is an important prerequisite for participating in power market. Several works are carried out on optimal bidding problems. The major part of these works focused on generation side of power market to maximize the profit of generation companies (GENCOs) [33-35]. Moreover, optimal bidding strategies for demand side entities such as distribution companies and retailer enable them to participate in the deregulated market [36, 37]. By developing distributed energy resources (DERs), other entities such as virtual power plant and microgrid are introduced. These entities consist of distributed energy resources with the ability to buy energy from the grid or sell energy to it. Ref. [38] focused on the optimal bidding of the microgrid to maximize its profit via participating in the power market.

The main contribution of this paper is proposing a new stochastic model for energy hub bidding problem. Multi-input energy vector and complexity of energy flow in energy hub, which is due to coupling between energy carriers, makes it different from other proactive systems.

In this paper, a comprehensive energy hub model is considered to address the advantage of proposed bidding strategy. For this purpose, wind energy is integrated into energy hub model. Since the power production of wind energy is uncertain, a stochastic model is presented for wind energy that is compatible with optimal bidding problem of energy hub.

The proposed bidding strategy in this paper consists of sell/buy bid in the day-ahead market. Since the deviation of power should be compensated in the real-time market by real-time prices, the uncertainty of both day-ahead and real-time market prices are considered. Therefore, the problem is modeled as a stochastic MILP problem.

The rest of this paper is organized as follow. In Section 2, a generic model of an energy hub is described. The proposed bidding strategy and necessary modification to the energy hub model are presented in the Section 3. In Section 4, the proposed strategy is implemented on a test system and the results are discussed.

2. Energy hub modeling

Energy hub is a system that increases the flexibility of energy provision [3]. In order to meet different kind of demands, energy hub is equipped by energy convertors, generators, and energy storage systems [39]. Fig. 1 shows the schematic representation of an energy hub.

Based on the application, a generic model of energy hub may be equipped by combined heat and power system (CHP), electric heater (EH), electric heat pump (EHP), boiler and furnace, absorption chiller, electrical energy storage (EES), thermal energy storage (TES), electric transformer, and renewable power generation system such as wind turbines [4]. Each of this equipment has an input and one or two outputs. Thus, the energy management system and power flow between equipment depend on the structure of their connections. the energy flow in an energy hub is [8]:

$$L=C.P \tag{1}$$

Where $L=[L_1, \dots, L_{No}]'$ is output energy vector and matrix $P=[P_1, \dots, P_{Ni}]'$ stands for input energy vector. Matrix C is called convertor coupling matrix. The elements of C are efficiencies of convertors. For example, c_{ij} represents the efficiency of the converter for receiving energy carrier j at its input and produce energy type i. Moreover, $c_{ij}=0$ means no conversion between i and j carriers.

Since some converters and storages are supplied through a specific input energy carrier, dispatch factors (v) for each input energy carrier should be introduced. Dispatch factors represent the portion of each converters from input energy [29]. Clearly, the sum of dispatch factors for a specific input energy is equal to unity. In order to represent the consumption of each converter from an input energy by dispatch factors, (1) is modified and constraints (2) and (3) are added to the model.

$$0 \le v_{ik} \le 1 \tag{2}$$

$$\sum_k v_{ik} = 1 \quad , \quad k \in e_i = \{\text{converters supplying by input } i\} \tag{3}$$

In this paper, instead of using dispatch factor, another approach is innovated. Since each converter has its input capacity limit, their input energies are decomposed. Hence, each P_i in input vector is replaced by vector $Pi=[P_{i,1}, \dots, P_{i,Nei}]'$ where N_{ei} is the number of elements using energy input i. In addition, constraint (4) is added to the problem instead of (2) and (3). Applying this method, the capacity limit of each converter and total input limit are met as (5) and (6), respectively.

$$\sum_k P_{ik} = P_i \quad , \quad k \in s_i = \{\text{converters supplying by input } i\} \tag{4}$$

$$P_{ik}^{min} \le P_{ik} \le P_{ik}^{max} \tag{5}$$

$$P_i^{min} \le P_i \le P_i^{max} \tag{6}$$

In order to model a generic storage device, state of charge can be modeled in the discrete-time system as [9]:

$$E_m(t+1) = E_m(t) + \eta_m^{ch} Q_m^{ch}(t) - \eta_m^{dis} Q_m^{dis}(t) - E_m^{loss} \tag{7}$$

where, E_m(t) is the level of charge in time-interval t for the m*th* energy storage system. $Q_m^{ch}(t)$ and $Q_m^{dis}(t)$ are the power charging and discharging the m*th* storage, respectively. η_m^{ch} and η_m^{dis} are efficiencies of charging and discharging, respectively. Finally, E_m^{loss} is the loss of stored energy in interval t. Since an energy hub may have some storage devices, each of them is modeled by (7). In order to integrate the equations of storages in energy hub model, it is better to represent them in the matrix format. Diagonal matrices $A^{ch} = diag\left(\eta_1^{ch}, \ldots, \eta_{Ness}^{ch}\right)$ and $A^{dis} = diag\left(\eta_1^{dis}, \ldots, \eta_{Ness}^{dis}\right)$ represent charging and discharging efficiencies of storage devices, respectively. Consequently, storage equation may be rewritten as [9]:

$$E(t+1) = E(t) + A^{ch} Q^{ch}(t) - A^{dis} Q^{dis}(t) - E^{loss} \tag{8}$$

Note that, storage may not be charged and discharged simultaneously. Hence, two binary variables $\delta_m^{ch}(t)$ and $\delta_m^{dis}(t)$ are used to model the charging or discharging state of storage. Consequently, capacity limit of storage and charge/discharge transaction limits are considered by constraints (9)-(12).

$$E^{min} \le E(t) \le E^{max} \tag{9}$$

$$0 \le Q_m^{ch}(t) \le Q_m^{ch,max} \delta_m^{ch}(t) \tag{10}$$

$$0 \le Q_m^{dis}(t) \le Q_m^{dis,max} \delta_m^{dis}(t) \tag{11}$$

$$\delta_m^{ch}(t) + \delta_m^{dis}(t) \le 1 \tag{12}$$

Now, the power flow equation of energy hub (1) is modified as (13) to consider the effect of charging and discharging of energy storage systems on balances of different types of loads.

$$L(t) = C.P(t) - Q^{ch}(t) + Q^{dis}(t) \tag{13}$$

3. Bidding strategy of energy hub in market environment

This section describes an optimal bidding strategy for an energy hub in the day-ahead market in a stochastic circumstance. First, the market structure and factors affecting bidding strategy are discussed and then, based on the first part, the objective function and constraints of the bidding problem are derived.

An energy hub may exchange power with main grid. Therefore, it may play the role of a prosumer in the energy market by access to real-time signals [29]. However, energy hub may transact power and signals with smart distribution grid and be classified as a price-taker entity. Price-taker entities submit their bids to the day-ahead market. Their bids consist of hourly selling and buying electricity [32]. Distribution system operator (DSO) is an intermediate between proactive customer and energy market. DSO receives all bids, combines them, and participates in whole sale market [30]. This structure of distribution market is shown in Fig.2.

The bids submitted to the day-ahead market are based on the forecasted data [32]. After clearing the market by the market operator, the production and consumption may be different from the schedules especially due to intermittent nature of renewable energy. Therefore, the proactive customer should participate in the real-time market in order to supplement the deviations from the schedule. It has to be noted that, the prices in this secondary market differ from the day-ahead market [40].

The energy management system of energy hub performs an optimization to determine the optimal schedule based on forecasted data. Due to various uncertainties in the forecasted data and in the system, finding an optimal bidding approach is a challenging issue. The main resources of uncertainties are renewable generation, day-ahead prices, and real-time prices. Since three types of uncertainty are considered in the proposed problem, stochastic optimization [41] is applied to handle these uncertainties. Monte Carlo simulation is employed to generate scenarios for stochastic optimization. In this method, the increase in the number of generated scenarios leads to a more accurate solution. Consequently, the computational burden of the problem is increased. Therefore, a scenario reduction method is helpful to make a trade-off between computational burden and accuracy of the problem [42].

3.1 Objective function

In the assumed system, three resources of uncertainty are considered: day-ahead market prices, wind energy generation, and real-time market prices. The scenario tree of this problem is shown in Fig. 3. In the first stage, the energy hub submits day-ahead hourly biddings into the day-ahead market while all uncertain variables are unknown. After clearing day-ahead market, the energy hub optimizes the schedules according to determined day-ahead market. In the second stage (i.e. the moment of operation), in order to follow the accepted bids, the schedules is optimized based on the realization of wind energy which is intermittent. This stage happens right before clearing of the real-time market at each hour. Thus, the set points of generators, converters, and storage system are optimized. However, the deviation from the schedule is compensated by transaction with the real-time market in real-time operation.

Based on the above description of bidding problem, the objective function which is maximization of expected benefit or equivalently minimization of cost can be formulated as:

$$\min \sum_{sd=1}^{N_s} \pi_s \left[\sum_{t=1}^{24} C_e^{DA}(t,s).P_e^{DA}(t,s) + \sum_{t=1}^{24} C_g(t).P_g(t,s) + \sum_{t=1}^{24} C_e^{RT}(t,s).P_e^{RT}(t,s) \right] \tag{14}$$

where, positive values of P_e^{DA} show the electrical power has been bought from the grid and vice versa. In the above objective function, the first line aims to minimize the power bought bid and maximizes power sell bid. The second line minimizes the natural gas cost that is purchased from the natural gas distribution system. It is noteworthy that the price of natural gas is supposed to be certain for each hour which is practical (for example, see: [4]). The third line minimizes the power transacted with the grid in the real-time market.

3.2 constraints

In the following of this section, important constraints of optimization problem are described. Obviously, the most important constraint of the optimization for a prosumer entity is power balance and power flow inside it. Since energy hub uses some energy carriers, a multi-energy balance and multi-energy power flow are needed. In other words, for each scenario, the sum of electrical/thermal loads must be equal to import powers, generation, and conversion of electrical/thermal power from the generators, converters, and storage systems. Thus, to satisfy (13) for each scenario, it is replaced by (15). It is noteworthy that all variables and parameters in this equation must be a function of scenarios.

$$L(t) = C.P(t,s) - Q^{ch}(t,s) + Q^{dis}(t,s) \tag{15}$$

Capacity limitations of converters are described by (4)-(6). However, constraints (5) and (6) should be modified as (16) and (17) in order to consider on/off state of converters.

$$I_{ik}(t,s).P_{ik}^{min} \le P_{ik}(t,s) \le P_{ik}^{max}.I_{ik}(t,s) \tag{16}$$

$$I_i(t,s).P_i^{min} \le P_i(t,s) \le P_i^{max}.I_i(t,s) \tag{17}$$

The charging/discharging of energy storages are described by (10)-(12). Moreover, state of charge and capacity limit of the energy storage system are defined by (8) and (9), respectively. All the constraints mentioned must be met for all scenarios and the solution must be feasible. Additionally, each converter may be subjected to some specific constraints based on its specifications that must be considered. For example, wind generation in time interval *t* is given as follow [23]:

$$P_w^{sw}(t,s) = \begin{cases} 0, & if\ v_{(t,s)}^{sw} \leq v_w^{ci}\ or\ v_{(t,s)}^{sw} \geq v_w^{co} \\ P_w^r \dfrac{v_{(t,s)}^{sw} - v_w^{ci}}{v_w^r - v_w^{ci}}, & if\ v_w^{ci} \leq v_{(t,s)}^{sw} \leq v_w^r \\ P_w^r, & otherwise \end{cases} \quad (17)$$

The other operational constraints such as minimum up/down time and ramp up/down can be included in the optimization problem. Due to the limited size and consequently low inertia of the assumed energy hub, they are neglected in this paper.

4. Case studies

4.1 Test system

The proposed optimal bidding strategy is implemented on an energy hub shown in Fig. 4. In this paper, a comprehensive structure of the energy hub is considered. The assumed energy hub has two energy inputs consisting of electricity and natural gas and two energy outputs consisting of electrical and thermal energy. Moreover, a wind turbine is also considered in this structure. The elements of the energy hub are CHP, EHP, auxiliary boiler, and electrical storage. Table 1 gives the elements and their input and output.

In order to form matrix model of energy flow in energy hub, linear model of each element is used. Efficiencies of each element [4, 8], capacities of elements, and specifications of the battery as an electrical storage are shown in Table 2, 3, and 4 respectively. It is assumed that forecasted data are available in advance. The forecasted data are electrical and thermal loads, wind generation, and day-ahead and real-time market prices. Electrical and thermal loads are shown in Fig.5 over time horizon which is 24 hours [4]. Day-ahead and real-time electricity prices [43] and natural gas price are shown in Fig. 6. In Fig. 7, wind generation data [44] are shown as forecasted wind. Note that forecasting process is beyond the scope of this paper. Since the size of the assumed energy hub is small compared with the grid size, it is considered a price-taker entity. The structure of optimization in the proposed strategy is shown in Fig. 8.

4.2 Case studies

In this section, the results of numerical simulation are presented and discussed. Optimal bidding problem is implemented on the described test system. The problem is formulated as a mixed integer linear problem. Numerical simulations are coded in GAMS software. In order to evaluate the proposed strategy, six case studies are considered:

Case 1: Applying the proposed bidding strategy to the energy hub

Case 2: Daily operation of energy hub without bidding

Case 3: Energy hub biding without considering real-time market

Case 4: Energy hub biding without considering prices uncertainties

Case 5: Energy hub biding without considering wind uncertainty

Case 6: Applying proposed bidding strategy considering elastic loads

The simulations are performed on the case studies and the results are compared with each other to prove the advantages of the proposed strategy. In case 6, elastic loads are considered to show the ability of the proposed strategy in handling them. The electrical demand is divided into two parts: 1) fixed load (80%) and 2) price elastic load (20%). The elasticity factor is 0.1 [45].

5. Simulation results and discussion

5.1 Results and evaluation

In the first case, the proposed strategy is implemented on the test system. Fig. 9 shows bidding curves of energy hub versus electricity price in the day-ahead market for selected hours. The selected hours are 4, 6, 9, 12, 16, 20, and 24. Since energy hub is a prosumer and can sell electricity to the market, the biddings include both buying and selling electricity in the day-ahead market. In Fig. 9 positive power means buying bid while negative power demonstrates selling bid. The increase in the market price leads to decrease in buying bid. Correspondingly, the increase in the market prices leads to increase in the selling bids. For example, in hour 12 with high price the bidding includes selling power that increases according to the market price while in hour 9, the bidding includes buying power from the main grid as expectations.

The behavior of the energy hub and its response to market prices can be justified according to Fig. 10. It shows that the natural gas consumption corresponds to the electricity input of the energy hub. During the high price hours, the electricity buying bids decreases or selling bids increase while, the natural gas consumption is increased. It is noteworthy that, the electrical load is high during the high electricity price hours. Therefore, the energy management system of energy hub increased production of electricity and heat from other resources that consume natural gas such as CHP systems. It is implies on the flexibility of energy hub explained in discussion section.

The energy hub submits the bids to day-ahead market. In real-time operation, the deviations from the day-ahead schedule are compensated by participating in the real-time market. The expectations of power exchanges in the day-ahead market over time horizon are shown in Fig. 11. In this figure, the deviations from the expectations are shown by vertical lines for each hour.

To indicate the necessity of a bidding strategy for an energy hub and also the efficiency of the proposed strategy, the operation of energy hub without bidding is simulated in Case 2. Since the energy hub may not participate in the day-ahead market without bidding, it must exchange power with real-time prices which is different with day-ahead prices. Therefore, energy management system adjusts the set points of converters based on the real-time prices. The power exchange in the second case is shown in Fig. 12.

Both the day-ahead and real-time market scenarios are considered in the proposed strategy. Therefore, the decisions about optimal bidding are made considering all prices scenarios. In Case 3, only the day-ahead market is considered in bidding problem to evaluate the advantages of considering both markets. The bidding curves of selected hours in this case are shown in Fig. 13. Due to ignoring the real-time market, the buying bids are increased and selling bids are decreased according to Fig 13.

In the proposed bidding strategy, three different uncertain parameters are considered. These parameters are day-ahead market prices, real-time market prices, and wind generation. In order to illustrate the advantage of stochastic optimization for bidding problem, day-ahead market prices and real-time market prices are considered as deterministic parameters in Case 4. Therefore, the objective function (14) is replaced by deterministic parameters. Consequently, the energy hub bids are formed based on the forecasted day-ahead market prices and real-time situation is ignored. In this case the deterministic optimization is performed and then the schedules are implemented in possible scenarios. The exchanged power with the main grid is shown in Fig.14. Since different operating scenarios in the real-time situation and deviations are not considered in the bidding problem, the exchanged power differs from Case 1. Comparison of Case 1 and Case 4 shows an increase in buying power and decrease in selling power, which affects the profit of energy hub.

In Case 5, wind generation forecasts are considered as deterministic parameters to illustrate another ability of the proposed strategy in handling uncertainties. Thus, the energy hub participates in the day-ahead market based on the deterministic wind generation and uncertain day-ahead and real-time prices. Therefore, the energy hub must participate in the real-time market to provide unbalances. The deviations of wind generation are imposed on the schedule. Fig. 15 compares the deviations in Case 5 and Case 1. The deviations are increased due to ignoring wind scenarios. As a result, the operation cost rises as expected.

In Case 6, elastic loads are considered in the bidding problem to the strategy is comprehensive. Therefore, the electrical loads are decreased with respect to electricity prices. Consequently, the operation cost is declined. Comparisons between operation with elastic loads and without elastic loads are presented in Fig. 16. According to this figure, the imported powers are decreased while exported powers are increased in this case as expected.

5.2 Discussion and comparison

Energy management system of energy hub as a price-taker entity receives forecasted parameters. It uses the bidding strategy to participate in the energy market. As a prosumer, the biddings consist of selling and buying electricity energy for each hour. The bids curves have a negative slope with respect to the prices. It means that, at high prices hours, energy management system decrease the bids in order to decrease the operating cost in realization day. The ability of energy hub in changing the bids is due to its access to the different types of energy as inputs. Thus, the energy management system can make the optimal decision for participating in the day-ahead market to decline the cost and correspondingly increases the profits. Participating in the day-ahead market requires submitting bids. Various inputs make difference between energy hub and other independent entities. The efficiency of the proposed bidding strategy is illustrated in Fig 9.

The effect of various types of inputs in different loads provision is demonstrated in Fig. 10. In the simulated energy hub, electricity and natural gas are supplying thermal and electrical loads in a coupled infrastructure. Energy management system adjusts set points of converters to optimize cost. To illustrate, exchanged electricity curve does not match the electrical load (Fig. 5) while the electrical load is served strictly without any changes in comfort level. Therefore, the coupling between loads may increase flexibility besides being a challenge. More flexibility may lead to improvement in the operation of energy hub. For example, according to Fig. 10, at high electricity price hours, energy management system changes the set points of converters toward more natural gas consumption considering both electricity and natural gas prices. Correspondingly, at low electricity prices hours, the consumption of electricity is increased. This flexibility makes advantages for participating in energy markets and demand response programs while comfort levels of consumers are satisfied. Thus, energy hub may use the flexibility by submitting bids to participate in the energy market.

Without a bidding strategy (Case 2), the energy hub must exchange total electricity energy with the real-time market. According to the forecasted curves of real-time and day-ahead markets prices (Fig. 6), it leads to an increase in operating cost in realization day. The operating cost in Case 2 is 340.8 $. It means about 6.8 $ (about 2 %) increase in operating cost compared with participating in day-ahead market through the proposed bidding strategy. Therefore, an optimal bidding strategy is required to participate in the day-ahead market.

Another advantage of the proposed strategy is considering both scenarios of the real-time and day-ahead markets simultaneously. In Case 3, real-time market scenarios are ignored. Thus, only the day-ahead market scenarios are used to form bid curves. As expected, the operating cost is increased to 364.2 $ (i.e. about 10% increase compared with the proposed strategy). In the proposed strategy, the energy hub makes an optimal decision via comparing scenarios of both markets, while in Case 3, the degree of freedom in decision-making is reduced.

Since bidding parameters such as forecasted prices and wind generation are not realized in solving time, the bidding problem is a stochastic problem. Therefore, the proposed model must handle uncertain parameters. If uncertainty is not considered in the proposed model, some scenarios may be ignored, which may leads to impose extra cost in realization day. If the prices are considered as deterministic parameters (Case 4), the operating cost is increased to 341 $ implying 2.1 % increase compared with the proposed strategy. Moreover, if wind generation scenarios are ignored while the prices are still uncertain (Case 5) the cost is increased to 358.96 $ suggesting about 7.4 % increase compared with the proposed strategy.

Table 5 summarizes the discussions about case studies. The operation cost in each case and the changes percentages are shown in the table. Comparing the results in the table shows the effectiveness of the proposed strategy.

6. Conclusion and future works

Multi-input vector and coupling between different types of loads make difference between energy hub and other active elements in the distribution grid. Although coupling between different types of loads and inputs is challenge in operation of energy hub, it increases the flexibility and improves the ability to participate in energy markets. Therefore, it is necessary to apply a strategy for optimal bidding. In this paper, a model for optimal bidding strategy for an energy hub is presented. In this model, the energy management system of energy hub submits the optimal bids to DSO in order to participate in the distribution day-ahead market. The problem optimizes the cost of energy hub while considers the operating constraints based on the forecasted data. Three uncertain parameters are considered in the problem consisting of day-ahead prices, real-time prices, and renewable generation. Therefore, a 3-satage stochastic optimization is used to handle the uncertainties. A generic model of energy hub is applied to prove the proposed model. Due to the multidisciplinary flexibility of supplying, the energy hub optimizes operating cost by participating in the day-ahead market instead of exchanging power with real-time prices. The simulation results show the flexibility of energy hub in bidding problem and the advantages of the model. Comparing the operation of energy hub, with and without participating in the day-ahead market, shows that the energy hub can decrease the cost about 2% by employing the proposed strategy. Moreover, the bidding model can be a base for natural gas consumption estimation.

Future research may focus on the behavior of each converter in detail. The effect of nonlinear loads on bidding problem may also be investigated. Moreover, the bidding problem for ancillary services might be an interesting issue. Furthermore, in grid point of view, the effect of multi-input aspect of energy hubs participated in the day-ahead market on the operation of distribution grid is crucial.

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Figures

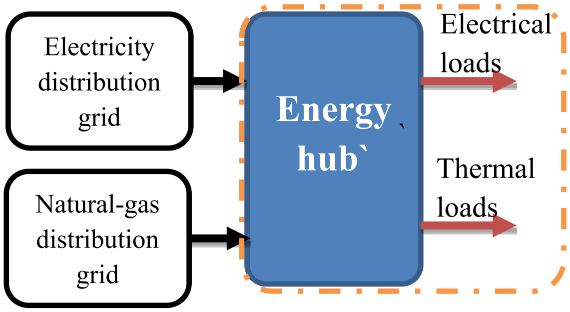

Fig. 1. A generic schematic of an energy hub

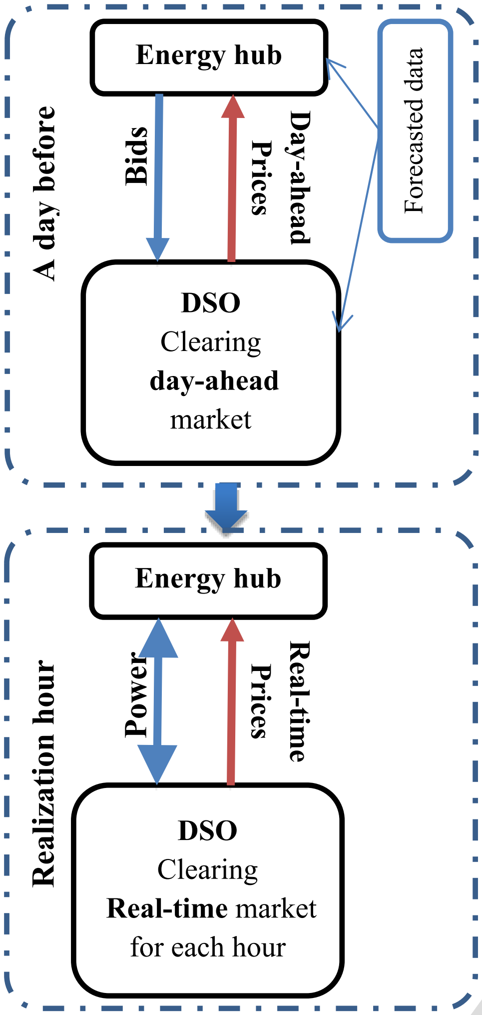

Fig. 2. Energy hub in the market

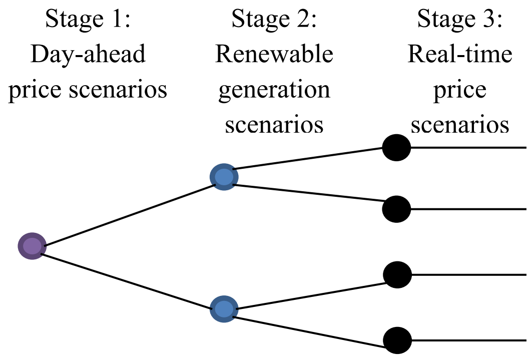

Fig. 3. Three-stage stochastic structure

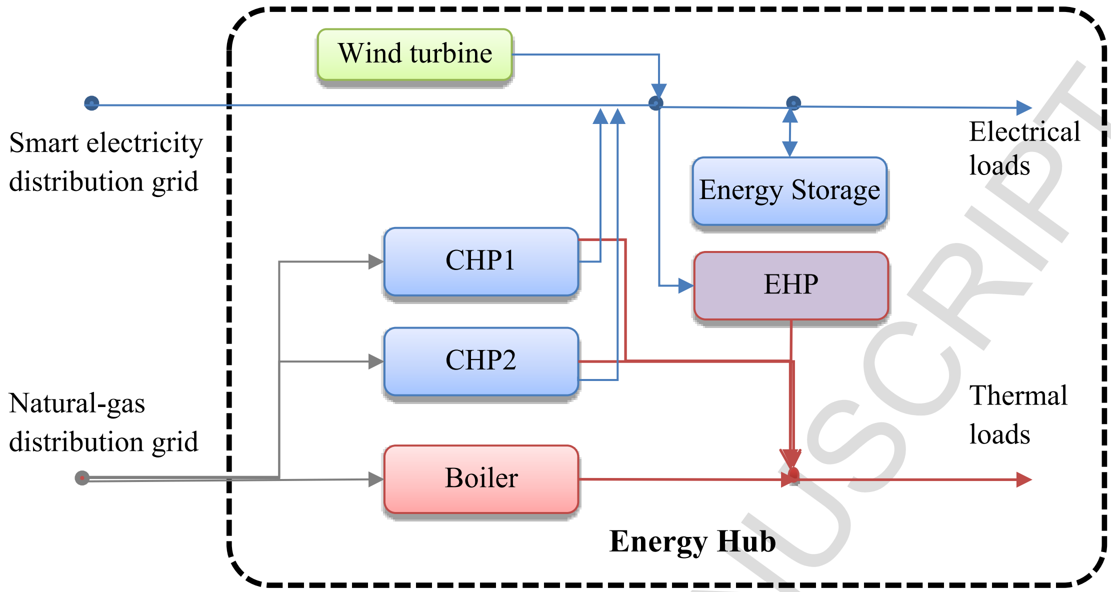

Fig. 4. Structure of the energy hub

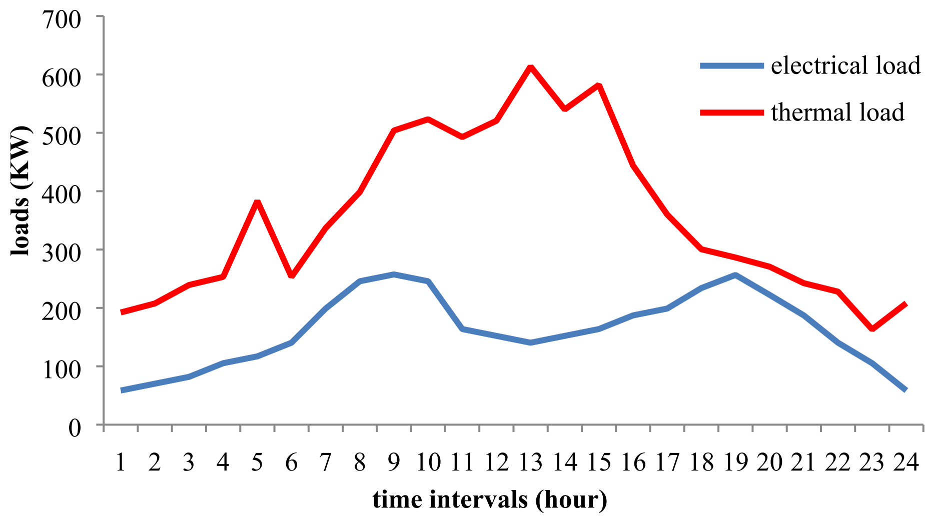

Fig 5. Electrical and thermal loads

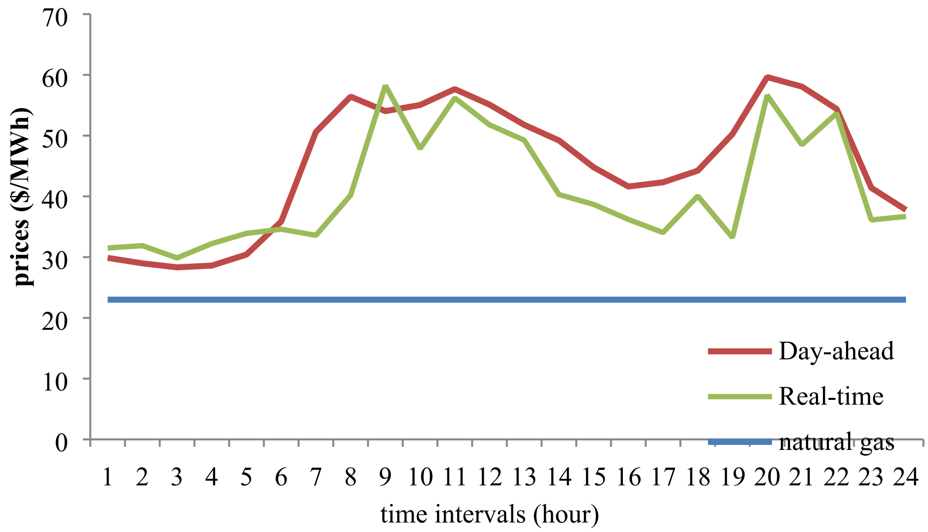

Fig. 6. Forecasted prices

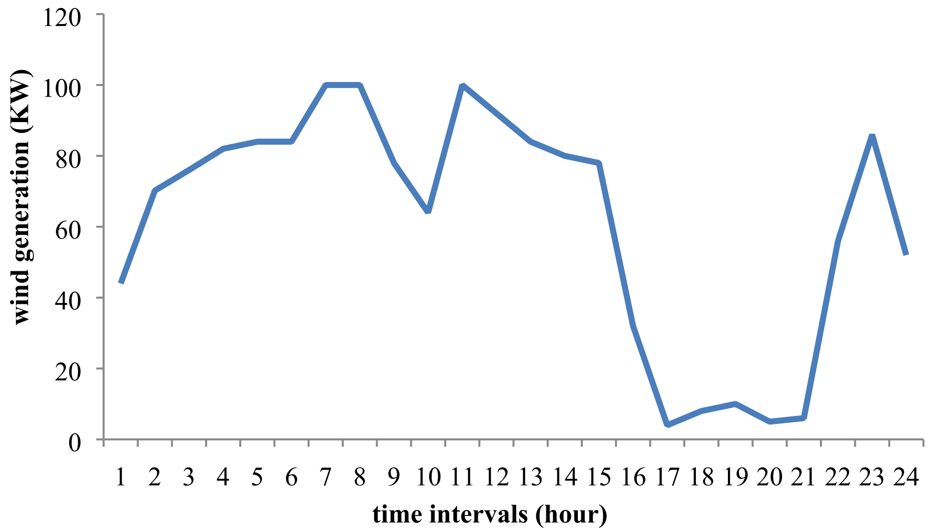

Fig. 7. Forecasted wind generation over time horizon

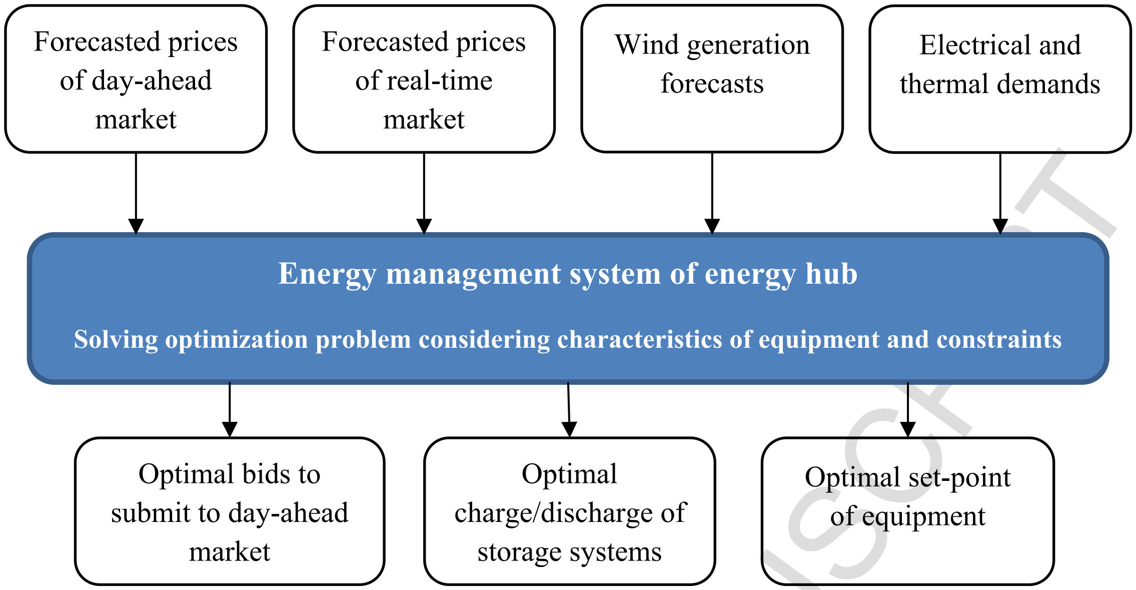

Fig. 8. Optimization structure of the proposed strategy

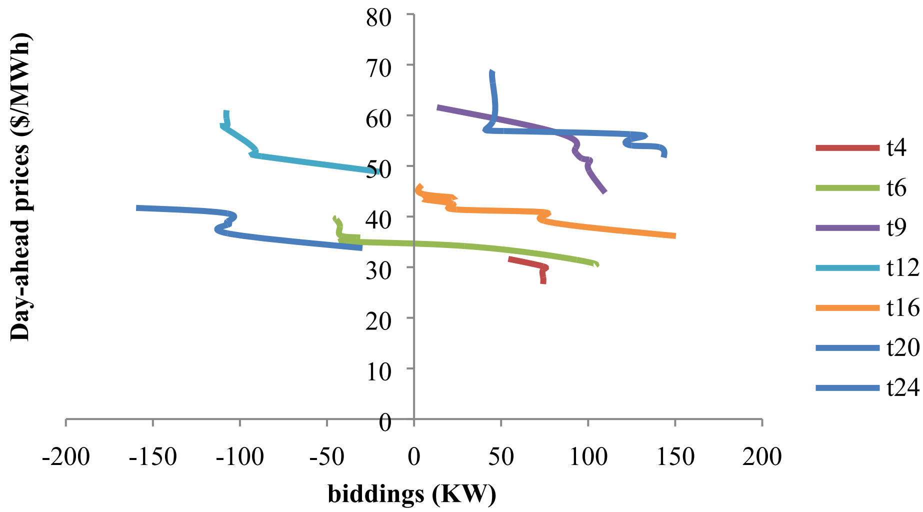

Fig. 9. Bidding curves for selected time intervals

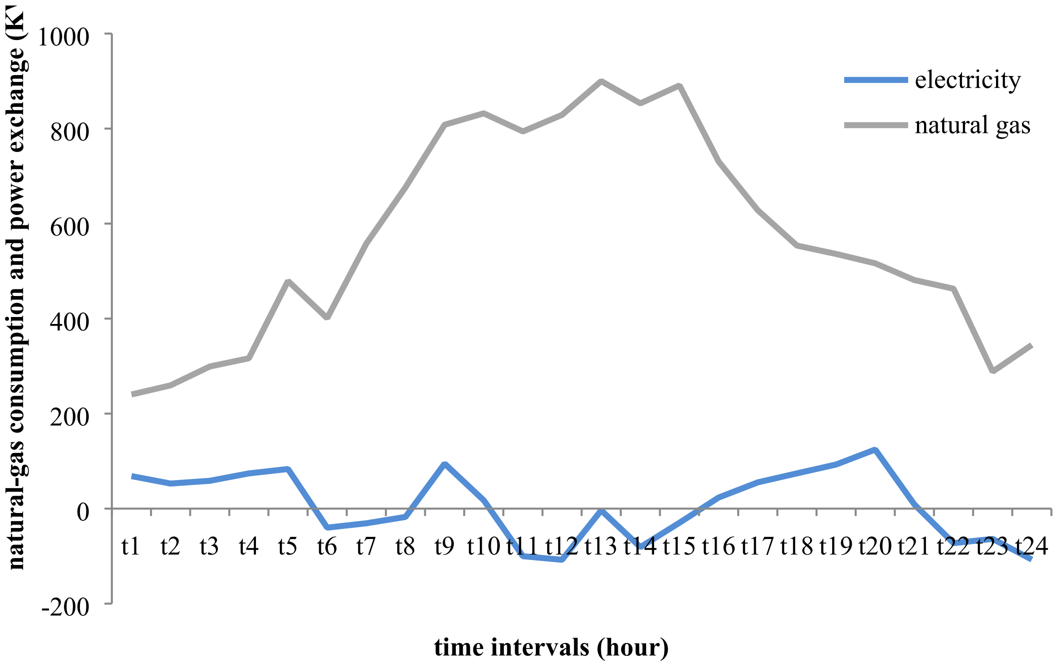

Fig. 10. Natural gas consumption and power exchange with the grid

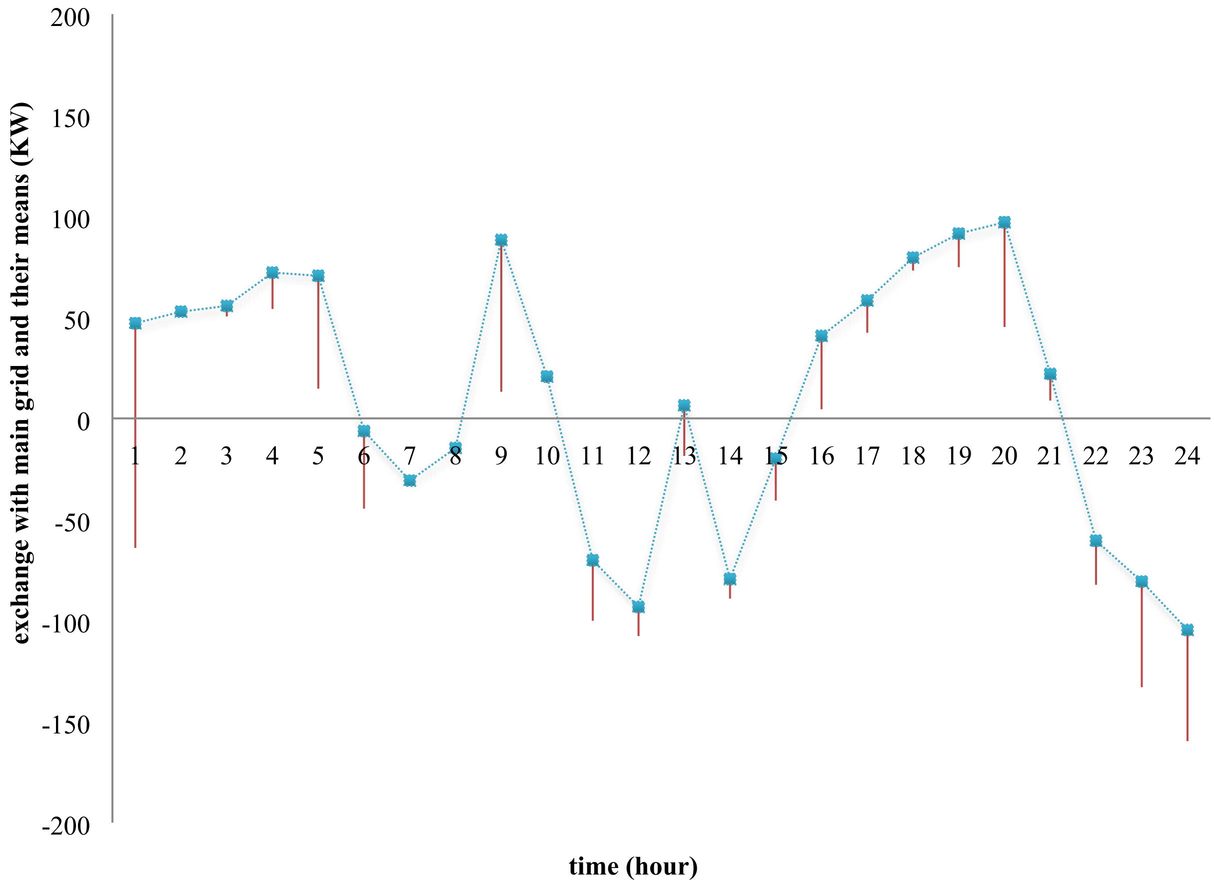

Fig. 11. Power exchange in day-ahead market and deviations

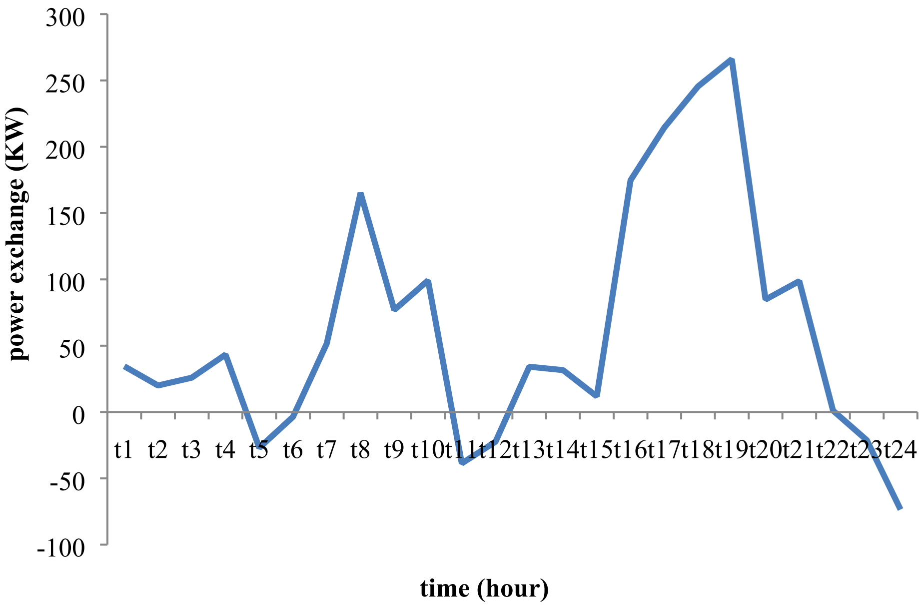

Fig. 12. Power exchange in real-time market without bidding (case2)

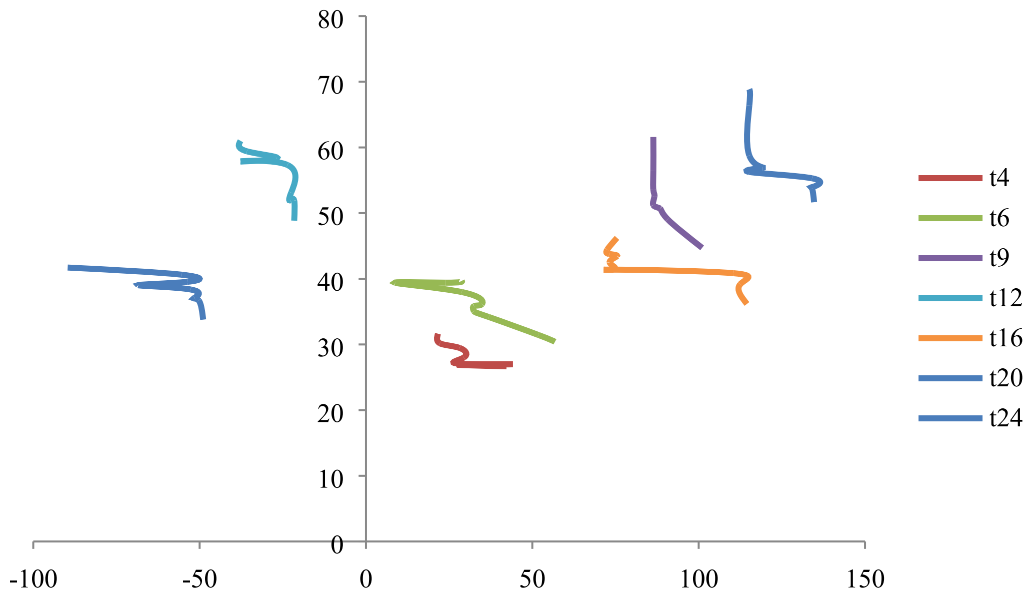

Fig. 13. Bidding curves in Case 3 for selected hours

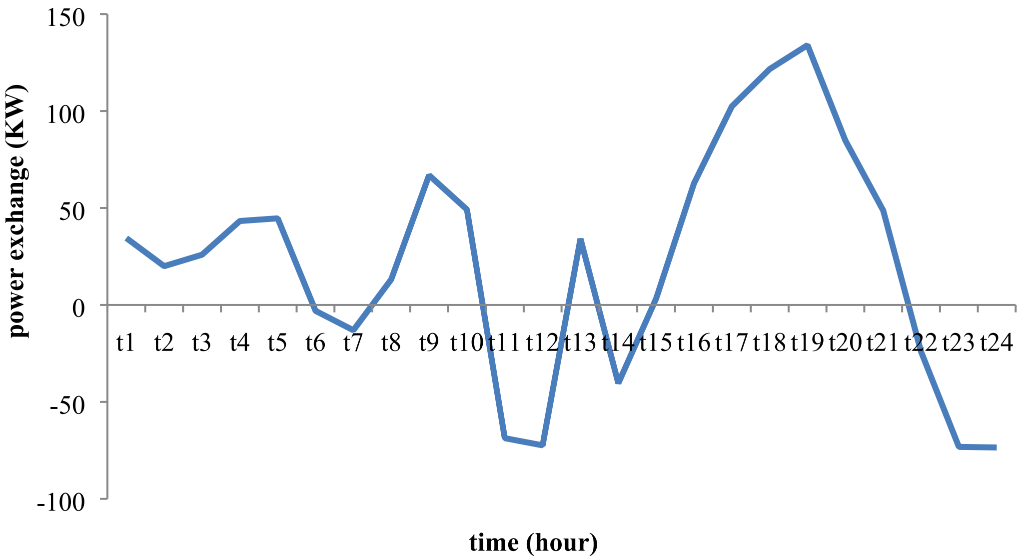

Fig. 14. Power exchange with the grid in Case 4

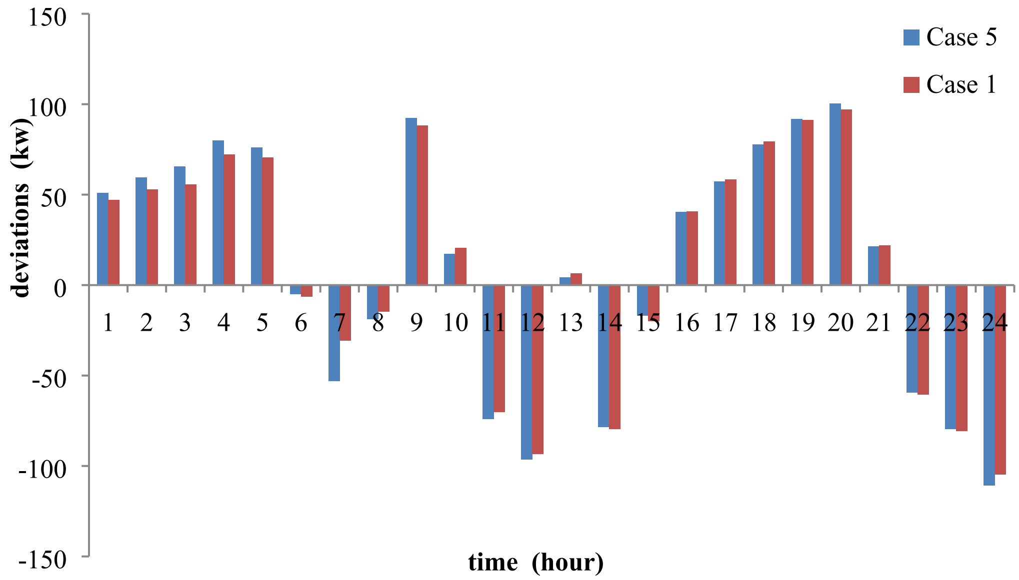

Fig. 15. Deviations in Case 5 and Case 1

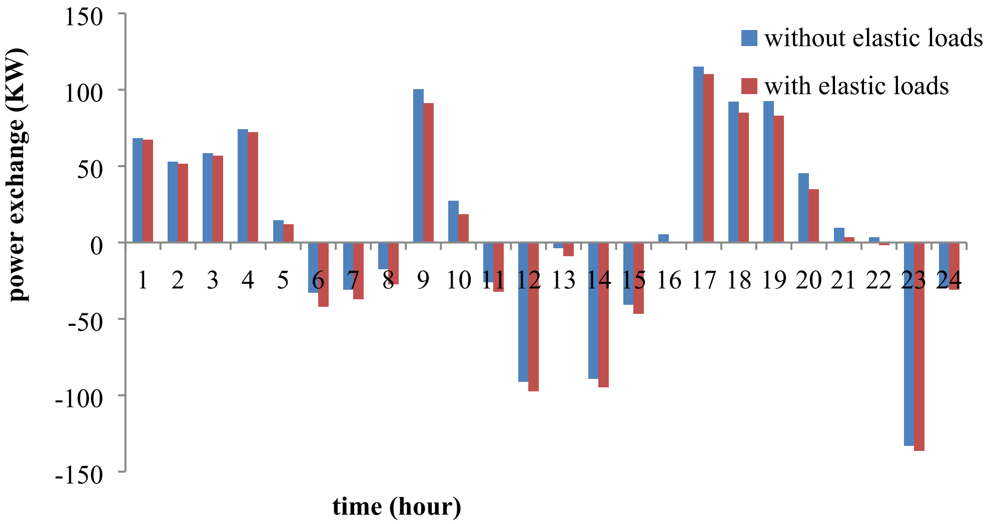

Fig. 16. Comparisons of exchanged power in Case 6 and Case 1

Highlights

- A model for optimal bidding strategy of energy hub is proposed.
- The model employs specific features such as multi-disciplinary and flexibility.
- A stochastic model is presented which is compatible for considering wind energy
- The model considers uncertainty of prices both in day-ahead and real-time markets.

Tables

Table 1
Elements of the energy hub

Element	Input	Output
CHP	Natural-gas	Electricity+heat
Auxiliary boiler	Natural-gas	Heat
Electrical heat pump (EHP)	Electricity	Heat
Energy storage	Electricity	Electricity

Table 2
Efficiencies of elements

Elements	Efficiency
CHP1	Electrical: 0.4 Thermal: 0.35
CHP2	Electrical: 0.35 Thermal: 0.3
Boiler	0.8
EHP	COP=2.5

Table 3
Input capacities of elements

Elements	Min. (KW)	Max. (KW)
CHP1	30	150
CHP2	30	150
Boiler	20	600
EHP	30	450

Table 4
Specification of energy storage

Parameter	Value
E^{max}	100 KWh
E^{min}	20 KWh
$Q^{ch,max}$	20 KW
$Q^{dis,max}$	20 KW
η^{ch}	0.9

Table 5
Comparison of cost in different cases

Cases	Cost ($)	Change percentage (%)
Proposed optimal bidding strategy	334	-----
Without bidding	340.8	+2
Ignoring real-time scenarios	364.2	+10
Deterministic prices	341	+2.1
Deterministic wind	358.96	+7.4