A Stochastic Bilevel Model for the Energy Hub Manager Problem

Arsalan Najafi, Hamid Falaghi, *Member, IEEE,* Javier Contreras, *Fellow, IEEE*, Maryam Ramezani, *Member, IEEE*

***Abstract*—A Bilevel Stochastic Programming Problem (BSPP) model of the decision-making of an energy hub manager is presented. Hub managers seek ways to maximize their profit by selling electricity and heat. They have to make decisions about: i) the level of involvement in forward contracts, electricity pool markets and natural gas networks and ii) the electricity and heat offering prices to the clients. These decisions are made under uncertainty of pool prices, demands as well as the prices offered by rival hub managers. On the other hand, the clients try to minimize the total cost of energy procurement. This two-agent relationship is presented as a BSPP in which the hub manager is placed in the upper level and the clients in the lower one. The bilevel scheme is converted to its equivalent single-level scheme using the Karush–Kuhn–Tucker (KKT) optimality conditions although there are two bilinear products related to electricity and heat. The heat bilinear product is replaced by a heat price-quota curve and the electricity bilinear product is linearized using the strong duality theorem. In addition, Conditional Value at Risk (CVaR) is used to reduce the unfavorable effects of the uncertainties. The effectiveness of the proposed model is evaluated in various simulations of a realistic case study.**

Index Terms —Bilevel stochastic programming, energy hub, hub manager, electricity pool, forward contract, Conditional Value at Risk.

NOMENCLATURE

Indices

ω	Scenario index
f	Forward contract index
t	Time index
k	Forward contract block
j	Heat price quota curve block
c	Client index
δ	Rival scenario index
r	Rival index

Variables

$C^P(\omega,t)$	Pool market purchase cost
$P^P(\omega,t)$	Purchased or sold energy in the pool
$P^f(f,t)$	Purchased energy from forward contracts
$C^F(t)$	Forward contract cost
$P_e^{CHP}(t,\omega)$	Electric energy produced by the CHP unit
$P_h^{Boil}(t,\omega)$	Heat energy produced by the boiler
$P_{CHP}^{gas}(t,\omega)$	Gas entering the CHP unit
$P_{Boil}^{gas}(t,\omega)$	Gas entering the boiler
$P_h^{CHP}(t,\omega)$	Heat generated by the CHP unit
$\lambda_{hs}^s(c,j)$	Offering heat price in each step
$\lambda_h^s(c)$	Heat price offered by the hub manager
$v(c,j)$	Binary variable associated with offering heat price
$v_f(f,k)$	Binary variable associated with forward contract
$v^{CHP}(t,\omega)$	Binary variable associated with CHP ON/OFF state
$\lambda_e^r(\delta)$	Electricity price offered by the rivals
$\lambda_h^r(c,r)$	Heat price offered by rivals
$\lambda_e^s(c)$	Electricity price offered by the hub manager
$P_e^s(c,\omega,t)$	Electric energy sold by the hub manager
$P_h^s(c,t,\omega)$	Heat energy sold by the hub manager
$x^m(c,\delta)$	Supported electricity by the hub manager
$x^r(c,\delta,r)$	Supported electricity by each rival

A. Najafi, H. Falaghi and M. Ramezani are with the Faculty of Electrical and Computer Engineering, University of Birjand, 97175 Birjand, Iran (e-mail: arsalan.najafi@birjand.ac.ir;falaghi@birjand.ac.ir; mramezani@birjand.ac.ir)

J. Contreras is with E.T.S. de Ingenieros Industriales, University of Castilla-La Mancha, 13071 Ciudad Real, Spain (e-mail: Javier.Contreras@uclm.es)

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$z^{m}(c)$	Supported heat by the manager under study
$z^{r}(c,r)$	Supported heat in percent supported by each rival manager
$H_{h}(c,t,\omega,j)$	Supported heat in each step of heat price-quota curve
$S_{h}(c,j)$	Percent of supporting heat demand in heat price-quota curve
$R(c,\omega,t)$	Revenue of selling electricity by the manager under study
$\mu_{e}(c,r)$	Dual variable associated with electricity
$\sigma_{h}(c)$	Dual variable associated with heat
$u^{r}(c,r,\delta)$	Binary variable used to linearize the complementary slackness electricity equation of the rivals
$k^{r}(c,r)$	Binary variable used to linearize the complementary slackness heat equation of the rivals
$u^{m}(c,\delta)$	Binary variable used to linearize complementary slackness electricity equation of the manager under study
$k^{m}(c)$	Binary variable used to linearize the complementary slackness heat equation of the manager under study
$CVaR$	Conditional value at risk
ξ	Value at risk
$\eta(\omega)$	Auxiliary variable for risk

Parameters

γ^{Boil}	Conversion efficiencies from gas to heat through the boiler
γ_{h}^{CHP}	Conversion efficiencies from gas to heat through the CHP unit
γ_{e}^{CHP}	Conversion efficiencies from gas to electricity through the CHP unit
ρ	Gas dispatch factor
$\hat{D}_{e}(c)$	Total expected electricity demands
$\hat{D}_{h}(c)$	Total expected heat demands
$\lambda^{p}(\omega,t)$	Electricity pool price
$\lambda^{f}(f,t)$	Forward contract price
$D_{h}(c,\omega,t)$	Heat demands
$D_{e}(c,\omega,t)$	Electrical demands
λ^{gas}	Gas price
$\pi(\omega)$	Scenario probability
$\tau(\delta)$	Rival scenarios probability
α	Confidence level
β	Risk coefficient
$P_{f,\max}$	Upper bound of forward contracts
$P_{f,\min}$	Lower bound of forward contracts
$\lambda_{h,\max}^{r}$	Maximum heat selling offer price by the hub manager
$\lambda_{h,\min}^{r}$	Minimum heat selling offer price by the hub manager
$\bar{\lambda}_{hs}^{s}(c,j)$	Maximum price of each block in heat price quota curve
$P_{h,\max}^{Boil}$	Maximum generation of heat energy by the boiler
M_{1},M_{2}	Sufficiently large numbers

Sets

F	Set of candidate contracts that can be signed
Ω	Number of scenarios
T	Number of time periods
J	Number of heat price-quota curve blocks
Δ	Number of rival scenarios
NC	Number of clients
R	Number of rival hub managers
K	Number of forward contract blocks

I. INTRODUCTION

An energy hub is a new concept used in multi-carrier energy systems. The energy hub is a simple model that can receive, send, convert and store different types of energy. These actions are done by various components such as a Combined Heat and Power (CHP) unit, heat and electrical storage, transformers, boilers and electronic devices. Linking multi-carrier energies is the main issue of an energy hub concept [1, 2]. An energy hub aims at feeding the loads via multi-energy inputs and outputs. Various types of energy at the input port of the energy hub provide the decision maker with more flexibility to satisfy the various energy loads. Hence, an energy hub provides the possibility of profiting from a number of prospective advantages over conventional decoupled energy supplies, adding more flexibility in load supplying or peak shaving [3]. In addition, energy hubs are not restricted to any system size. This enables the integration of an arbitrary number of energy carriers and products, allowing for high flexibility in system modeling [4]. In the past, only electric energy was important and retailers were intermediaries between producers and potential clients [5]. Currently, hub managers can play the same role, due to the emergence of multi-carrier energy systems or natural gas markets. Hence, maximizing the energy management profit is the main purpose of hub managers acting as retailers in restructured power systems. For a medium-term time horizon, retailers face uncertain pool prices and client demands. On the other hand, clients may choose a rival retailer to purchase electricity in a fully competitive environment. By extending the concept of the retailers' problem to allow for more energy carriers, energy hub managers have a similar role except for the different types of energy involved. Hub managers deal with more types of energy such as electricity, heat, wood energy, etc. They may also participate in another market, i.e., natural gas market. Therefore, hub managers have more difficulties in making decisions to procure and sell energy as well as how to make price offers for different types of energy. Thus, the medium-term decision making of a hub manager is about the optimal involvement in electricity and other markets, as well as the optimal selling prices to clients, in order to maximize the expected profit for a specific risk level of profit variability.

Decisions in restructured power systems have so far been limited to maximize the profit or to procure energy for consumers [6]. For instance, [7] has presented a general decision making framework for retailers and [8] has considered a single client providing a mixed-integer nonlinear decision-making procedure. Previously, numerous papers focused on various types of energies either in traditional or restructured power systems. This is known as the energy hub concept [9,10]. Few aspects of energy hubs have been investigated in several papers as follows. In [11], the planning of energy hubs in a region with natural gas and electric energies has been presented in order to determine the optimal number and size of the required components of the hub. Similarly, [12] has investigated the expansion planning of an energy hub. A model has been proposed in [13] to determine the best components to consider reliability and economic behavior of an energy hub where the maximum loss of load probability and adequacy indices have been studied under single contingency conditions. Some works have studied how to model the operational features in their research studies. Namely, [14] has studied an energy hub in a smart home considering a CHP unit and an electric vehicle. The main objective has been to minimize consumers' cost by controlling the usage of energy carriers. In relation to smart homes, similar papers can be found in [15] and [16]. The impact of small-scale energy storage has been investigated in [17]. Reference [18] has developed a model to consider the dynamic variations of the thermal loads in energy hubs using Markov chains and Monte Carlo simulation. A goal programming method has been proposed in [19] to optimize the power flow between interconnected power systems. Another formulation has been presented in [20] in order to model an energy hub using Mixed Integer Linear Programming (MILP). The proposed formulation has taken into account storage losses and operational limits. In [21], a model has been presented for the energy hub power flow. This model has been obtained from a set of nonlinear equations showing the hub connections. Reference [22] has developed a framework for the placement and control of residential energy systems using MILP considering electric energy and natural gas carriers. Economic dispatch considering uncertainty of wind turbines has been studied in [23]. In [24] energy management of hub inputs has been conducted aiming to minimize the total procured energy cost for a short-term time horizon using MILP. In addition, several papers have investigated other energy hub problems related to reliability and electric vehicles [25, 26].

In this paper, a model using bilevel stochastic programming to model an energy hub is proposed to consider both the hub manager's profit and the consumers' cost. This concept has been previously used in the retailer problem [27] and is extended here to model an energy hub containing more energy carriers. The proposed bilevel model takes into account the reaction of consumers to heat and electricity selling prices. Finally, the BSPP is converted to an equivalent single-level stochastic programming.

The main contributions of this paper are as follows:

- A bilevel stochastic programming model of an energy hub is defined, where the maximization of the profit of the hub manager and the minimization of the cost to the clients are the objectives of the upper and lower levels, respectively.
- A linear model is obtained to consider the bilinear terms from selling electricity and heat.
- The reaction of clients to heat and electricity selling prices in a fully competitive market is obtained.
- Risk aversion in the BSPP of the hub manager is considered to decrease the unfavorable effects of risk in the decision making process.

II. Bilevel Modeling Framework

The decision-making problems of the hub manager and the clients can be combined into a single bilevel stochastic programming problem. The BSPP is used to define a decision-making problem involving two optimization levels. In this case, the hub manager is at the upper level and the clients are at the lower one. The modeled hub manager tries to maximize their profit by selling heat and electric energy to the clients whilst the clients try to minimize their costs by procuring electric and heat energy from the hub manager and also from its rivals. The complexity of the decision making at the upper level is due to uncertainty in pool market prices and clients' demands. The hub manager procures the energy from two input carriers: electricity at uncertain prices and natural gas at a fixed price. These carriers have to offer heat and electricity prices to the clients to maximize their profit. Lower prices result in lower profits and higher prices result in a lesser willingness of the clients to deal with the manager and a greater willingness of the clients to deal with rival hub managers.

Fig. 1 depicts the upper and lower levels and the ways of procuring energy. The hub under study has a CHP unit and a boiler, which are self-production units fed by natural gas. The hub manager procures electricity in three ways: electricity pool market, forward contracts and a CHP unit. Heat is also obtained from a boiler and a CHP unit. Clients have access to the selling prices of heat and electricity and, consequently, decide to procure the energy in order to minimize their cost.

To create this model, some assumptions are made as follows:

- Clients cannot purchase energy from the electricity pool and only can procure their required energies by the managers.

- The electricity prices offered by the rivals are independent from the uncertainty in electricity pool prices.
- The electricity prices and heat prices offered by the hub manager are similar to the retailers' market rules and have fixed prices and are independent from the uncertainty in electricity pool prices but dependent on each client.
- The hub manager problem rules are assumed to be like a retailer one. Hence, the clients procure their required energies by fixed tariffs by extending retailer market rules.

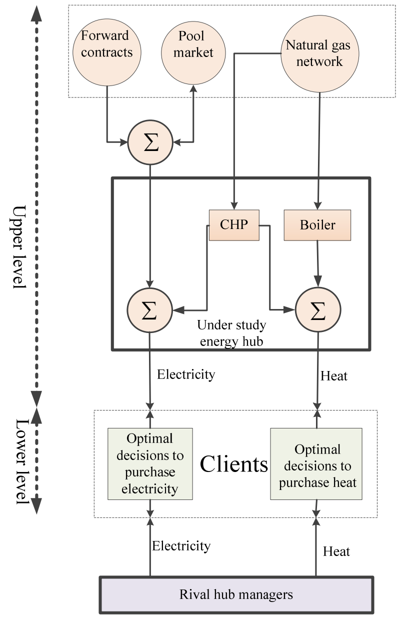

Fig. 1: Bilevel scheme of the problem.

III. Problem Modeling

A. Electricity pool market

The two ways of procuring electric energy by the hub manager are forward contracts and the electricity pool market. Retailers or hub managers may sell energy in the electricity pool in order to increase their profit. The cost or revenue of the energy traded in the pool is described as follows [28]:

$$C^P(\omega,t) = \lambda^p(\omega,t)P^P(\omega,t) \tag{1}$$

where $C^P(\omega,t)$, $P^P(\omega,t)$ and $\lambda^p(\omega,t)$ are the total cost or revenue of trading, the energy traded and electricity pool price in scenario ω and period t, respectively. $P^P(\omega,t)$ may be either positive or negative to represent the purchase or sale of energy, respectively.

Signing forward contracts is a conventional way to procure part of the clients' need for electric energy. In forward contracts, electricity is generated by an external agent and purchased by the hub managers. Forward contracts have fixed prices at the beginning of the decision making time horizon.

The method presented in [5] is used to model the forward contract as given in Fig. 2 and the following equation:

$$C^F(t) = \sum_{f \in Ft}\sum_{k=1}^{K} \lambda^f(f,t,k)P^f(f,t,k), \forall t \tag{2}$$

where $P^f(f,t,k)$ and $\lambda^f(f,t,k)$ are the power and price of block k at time t and contract f, respectively. $C^F(t)$ is the total cost of contracts at time t and K is the number of blocks. The amount of purchased power from contract f ($P^f(f,t)$) is obtained as follows:

$$P^f(f,t) = \sum_{k=1}^{K} P^f(f,t,k)v_f(f,k) \tag{3}$$

$$v_f(f,k) \in \{0,1\} \tag{4}$$

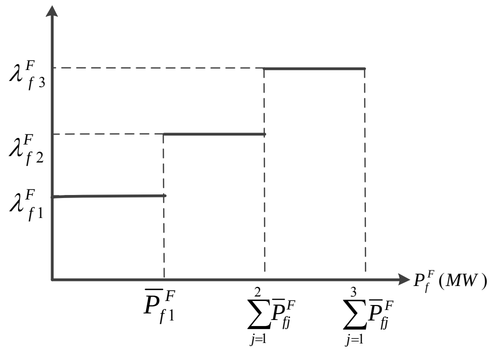

Fig. 2: Forward contract blocks.

B. CHP unit and boiler

Assume an energy hub as the one in Fig. 1. $P_e^{CHP}(t,\omega)$ is the electric energy produced by the CHP unit, which is defined as follows:

$$P_e^{CHP}(t,\omega) = \gamma_e^{CHP} P_{CHP}^{gas}(t,\omega) \tag{5}$$

where $P_{CHP}^{gas}(t,\omega)$ and γ_e^{CHP} are the gas entering the CHP unit and conversion efficiencies from gas to electricity through the CHP unit, respectively. The boiler is also fed by natural gas and generates heat. The relation between the input and the output of the boiler is described as follows:

$$P_h^{Boil}(t,\omega) = \gamma^{Boil} \cdot P_{Boil}^{gas}(t,\omega) \tag{6}$$

where $P_h^{Boil}(t,\omega)$, $P_{Boil}^{gas}(t,\omega)$ and γ^{Boil} are the heat produced by the boiler, the gas entering the boiler and the conversion coefficient from gas to heat through the boiler, respectively.

The amount of heat produced by the CHP unit, $P_h^{CHP}(t,\omega)$), is calculated as follows:

$$P_h^{CHP}(t,\omega) = \gamma_h^{CHP} P_{CHP}^{gas}(t,\omega) \tag{7}$$

where γ_h^{CHP} is the heat conversion coefficient through the CHP unit.

In addition, the dependency on the electrical and thermal outputs of the CHP unit is modeled by defining a feasible operation region bounded with coordinates $A(H_A,P_A)$, $B(H_B,P_B)$, $C(H_C,P_C)$ and $D(H_D,P_D)$, indicating the heat and electricity outputs at each point as presented in [28,32]. For instance, $A(H_A,P_A)$ are the heat and electricity outputs of the CHP unit in coordinate A.

C. Energy hub modeling

Energy hub is a concept describing a multi-carrier energy system including electric energy, gas, heat, etc., that can be converted, stored, and transmitted. An energy hub relates the input and output energies in a predefined area. Here, there are two inputs (gas and electric energy) and two outputs (heat and electric energy). The electric energy is transmitted to the output in two ways: directly from the input to the output or by a CHP unit. Heat output can also be produced through the boiler and the CHP unit (see Fig. 3).

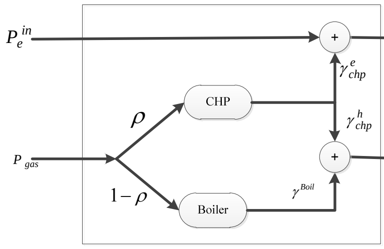

Fig. 3: A sample energy hub with two carriers in the input and output [32]

The coupling matrix is defined as follows:

$$\underbrace{\begin{pmatrix} P_e^{out} \\ P_h^{out} \end{pmatrix}}_{P^{out}} = \underbrace{\begin{pmatrix} 1 & \rho\,\gamma_e^{CHP} \\ 0 & \rho\gamma_h^{CHP} + (1-\rho)\gamma^{Boil} \end{pmatrix}}_{C} \underbrace{\begin{pmatrix} P_e^{in} \\ P_{gas} \end{pmatrix}}_{P^{in}} \tag{8}$$

where ρ is the dispatch factor to specify the share of natural gas, P_{gas} , entering the CHP unit or the boiler.

D. Offering heat price

The offering heat price, as a control variable, is very important to increase profit in the upper level. Higher prices decrease the clients' willingness to buy from the upper level and increase their tendency toward rival managers. Hence, the heat selling offer price by the hub manager is a stepwise function between $\lambda_{h,\min}^{r}$ and $\lambda_{h,\max}^{r}$ as shown in Fig. 4.

The minimum and maximum prices proposed by the rivals are the upper and lower bounds of the prices on the horizontal axis. By getting closer to $\lambda_{h,\max}^{r}$, the heat provided will decrease and vice versa.

$$\bar{\lambda}_{hs}^{s}(c,j-1)v(c,j) \le \lambda_{hs}^{s}(c,j) \le \bar{\lambda}_{hs}^{s}(c,j)v(c,j) \tag{9}$$

$$\sum_{j=1}^{J} v(c,j) = 1 \tag{10}$$

where $\lambda_{hs}^{s}(c,j)$ and $\bar{\lambda}_{hs}^{s}(c,j)$ are the offered price to client *c* and the maximum price of block *j*, respectively. Eq. (9) declares that $\lambda_{hs}^{s}(c,j)$ is positioned between minimum and maximum bounds of the blocks. Eq. (10) guaranties that only one block is selected.

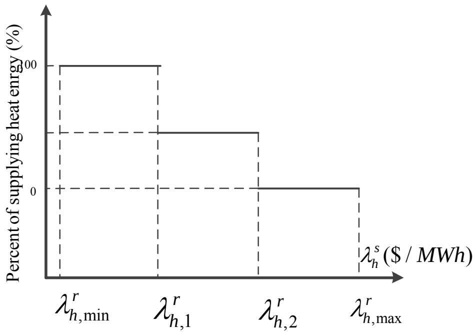

Fig. 4: Heat-price quota curve.

$$\lambda_h^s(c) = \sum_{j=1}^{J} \lambda_{hs}^{s}(c,j)v(c,j) \tag{11}$$

$$v(c,j) \in \{0,1\} \tag{12}$$

Each block shows a specific step of offering heat price. The offered prices represent the selected blocks. The manager can offer only one price. Therefore, only one block should be selected among all the blocks. In (12) $\lambda_h^s(c)$ is the price offered through all of the blocks and it is equal to the price of the selected block.

E. Uncertainty characterization

Three uncertainty sources are taken into account: electricity market prices, electricity demands and the prices offered to supply electricity by the rival managers. Heat demand uncertainty is neglected in the simulation for the sake of simplicity.

Due to the lack of information about the future, there is uncertainty in pool prices. Moreover, clients' demands and the electricity prices offered by the rivals are independent from the upper-level decisions. The uncertainty of the upper level is related to scenario ω, which includes pool prices and electricity and heat demands. Note that the summation of the probabilities over all scenarios has to be equal to 1. On the other hand, the prices offered by the rivals are a function of δ , which is described as follows:

$$\text{scenario}\,\gamma : \left\{\lambda_{e,1}^{r}(\delta),\ldots,\lambda_{e,NC}^{r}(\delta)\right\}$$

where scenario γ is the set of rivals' scenarios, $\lambda_{e,1}^{r}(\delta)$ is a random variable showing the price of electricity offered by rival *r* to client 1 in scenario δ which is unknown to the hub manager under study. *NC* is the total number of clients. The summation of probabilities of all rivals' scenarios has to be equal to 1:

$$\sum_{\delta=1}^{\Delta} \tau(\delta) = 1 \tag{13}$$

where Δ and $\tau(\delta)$ represent the total number of rival scenarios and the probability of rival scenario δ , respectively. Since we assume that gas price fluctuations are very low, gas and heat prices are considered to be fixed.

IV. Problem Formulation

A. Bilevel formulation

- *Upper level*

The hub manager under study tries to maximize their profit by selling heat and electric energy to the clients. The profit is defined as the revenue from selling heat and electricity minus the purchase cost of forward contracts, the electricity pool and natural gas. The upper-level stochastic programming problem is presented in (14)-(23). The decision variables of the upper level formulation are $\lambda_e^s(c)$, $P_e^s(c,\omega,t)$, $P_h^s(c,t,\omega)$, $\lambda_h^s(c)$, $P^P(\omega,t)$, $P^f(f,t)$, $P_{Boil}^{gas}(t,\omega)$, $P_{CHP}^{gas}(t,\omega)$, $v^{CHP}(t,\omega)$, ξ and $\eta(\omega)$.

$$\max \sum_{\omega=1}^{\Omega}\pi(\omega)\sum_{t=1}^{T}\begin{bmatrix}\sum_{c=1}^{NC}\lambda_e^s(c)P_e^s(c,\omega,t)+\sum_{c=1}^{NC}P_h^s(c,t,\omega)\lambda_h^s(c)-P^P(\omega,t)\lambda^p(\omega,t)\\ -\sum_{f\in F}P^f(f,t)\lambda^f(f,t)-\lambda^{gas}(P_{Boil}^{gas}(t,\omega)+P_{CHP}^{gas}(t,\omega))\end{bmatrix} \tag{14}$$

$$+\left[\beta(\xi-\frac{1}{1-\alpha})\sum_{\omega=1}^{\Omega}\pi(\omega)\eta(\omega)\right]$$

$$-\sum_{t=1}^{T}\begin{bmatrix}\sum_{c=1}^{NC}\lambda_e^s(c)P_e^s(c,\omega,t)+\sum_{c=1}^{NC}P_h^s(c,t,\omega)\lambda_h^s(c)-P^P(\omega,t)\lambda^p(\omega,t)\\ -\sum_{f\in F}P^f(f,t)\lambda^f(f,t)-\lambda^{gas}(P_{Boil}^{gas}(t,\omega)+P_{CHP}^{gas}(t,\omega))\end{bmatrix}+$$

$$\xi-\eta(\omega)\le 0 \tag{15}$$

$$\eta(\omega)\ge 0 \tag{16}$$

$$P_{f,\min}\le P^f(f,t)\le P_{f,\max} \tag{17}$$

$$P_e^{CHP}(t,\omega)+(\frac{P_A-P_B}{H_B})P_h^{CHP}(t,\omega)\le P_A v^{CHP}(t,\omega) \tag{18}$$

$$0\le P_h^{Boil}(t,\omega)\le P_{h,\max}^{Boil} \tag{19}$$

$$P_e^s(c,\omega,t)=D_e(c,\omega,t)\sum_{\delta=1}^{\Delta}\tau(\delta)x^m(c,\delta) \tag{20}$$

$$\sum_{c=1}^{NC}P_e^s(c,\omega,t)=\sum_{f\in F}P^f(f,t)+P^P(\omega,t)+P_{CHP}^{gas}(t,\omega)\gamma_e^{CHP} \tag{21}$$

$$P_h^s(c,t,\omega)=D_h(c,\omega,t)z^m(c) \tag{22}$$

$$\sum_{c=1}^{NC}P_h^s(c,t,\omega)=P_{Boil}^{gas}(t,\omega)\gamma^{Boil}+P_{CHP}^{gas}(t,\omega)\gamma_h^{CHP} \tag{23}$$

where α, β and $\eta(\omega)$ are the confidence level, risk coefficient and auxiliary variable, respectively. $D_e(c,\omega,t)$ and $D_h(c,\omega,t)$ are electricity and heat demands of client *c* in scenario ω at time *t*. $\lambda_e^s(c)$, $\lambda_h^s(c)$ and λ^{gas} are the prices offered for the electricity, heat and gas, respectively. Eq. (14) shows the objective function of the upper level, which includes two terms. The first term is the main profit objective and the second one is the CVaR. The weighting factor β is used to have a tradeoff between the expected profit and CVaR.

Eq. (15) and (16) are the constraints associated with the CVaR. Eq. (17) limits the forward contracts. The technical constraints of the CHP unit and boiler units are neglected and only the feasible operation region of the CHP unit and the maximum bounds of the boiler are considered in (18)-(19). $v^{CHP}(t,\omega)$ is a binary variable which shows the on/off state of the CHP unit. The amount of supplied electricity demand of client *c* at time *t* and scenario ω under the rivals' scenarios is modeled by (20). $x^m(c,\delta)$ determines the normalized amount of supplied electricity of client *c* under rival scenario price δ. This means part of clients demands are supplied by the hub manager and the rest by the rival managers. The supplied part can vary from 0 to 100% for each manager (either the one under study or a rival). Eq. (21) denotes the electricity sold by the hub manager, procured in the electricity pool and from forward contracts, as well as the energy produced by the CHP unit. Eq. (22) models the heat energy provided by the hub manager. Note that heat is produced by natural gas at a fixed tariff. Therefore, the rivals' heat prices are considered to have a fixed tariff in all the rivals' scenarios and, hence the normalized amount of supported heat, $z^m(c)$, is not a function of δ . The heat balance is also shown in (23).

- *Lower level*

At the lower level, the clients seek optimal ways to minimize the procurement cost of electric and heat energy. They are faced with the prices offered by the hub managers (including the hub manager and their rivals), and they seek optimal ways to minimize their purchasing cost. The decision variables of the lower level are the amount of electricity and heat to be purchased the hub manager and their rivals. The lower-level model is given in (24)-(27).

$$x^m(c,\delta)\,\text{and}\,z^m(c)\in\arg$$

$$\left\{\begin{matrix}\min\hat{D}_e(c)\sum_{\delta=1}^{\Delta}\tau(\delta)\left[\lambda_e^s(c)x^m(c,\delta)+\sum_{r=1}^{R}\lambda_e^r(c,\delta,r)x^r(c,\delta,r)\right]+\\ \hat{D}_h(c)\left[\lambda_h^s(c)z^m(c)+\sum_{r=1}^{R}\lambda_h^r(c,r)z^r(c,r)\right]\end{matrix}\right\} \tag{24}$$

$$x^m(c,\delta)+\sum_{r=1}^{R}x^r(c,\delta,r)=1 \tag{25}$$

$$z^m(c)+\sum_{r=1}^{R}z^r(c,r)=1 \tag{26}$$

$$x^m(c,\delta),x^r(c,\delta,r),z^m(c)\,\text{and}\,z^r(c,r)\ge 0 \tag{27}$$

Eq. (24) models the objective of the lower level including two terms. The first one shows the procurement cost of electricity and the second one that of heat energy. $\hat{D}_e(c)$ and $\hat{D}_h(c)$ are the total expected electricity and heat demands of each client that are calculated as follows:

$$\hat{D}_e(c)=\sum_{\omega=1}^{\Omega}\pi(\omega)\sum_{t=1}^{T}D_e(c,t,\omega) \tag{28}$$

$$\hat{D}_h(c)=\sum_{\omega=1}^{\Omega}\pi(\omega)\sum_{t=1}^{T}D_h(c,t,\omega) \tag{29}$$

Constraints (25) and (26) denote that all the electricity and heat demands should be supplied by the hub manager and their rivals for each client *c*. Eq. (27) shows the limits of the variables. Eq. (28) and Eq. (29) represent the average of the scenarios of total demands through all hours for each client.

B. Linearization and equivalent single-level optimization

In (14) the terms $\lambda_e^s(c)P_e^s(c,\omega,t)$ and $P_h^s(c,t,\omega)\lambda_h^s(c)$ are bilinear products. The heat bilinear product is linearized using the heat price-quota curve as follows:

$$H_h(c,t,\omega,j) = D_h(c,t,\omega) S_h(c,j) \tag{30}$$

where $S_h(c,j)$ is normalized amount of supplied heat in block *j*. Eq. (30) shows the amount of heat energy produced by the hub manager under study in block *j*. Then, the bilinear heat product becomes:

$$P_h^s(c,t,\omega)\lambda_h^s(c) = \sum_{j=1}^{J} H_h(c,t,\omega,j)\lambda_{hs}^s(c,j) \tag{31}$$

$z^m(c)$ is obtained by summing the supplied heat in all blocks of the heat price-quota curve as follows:

$$z^m(c) = \sum_{j=1}^{J} S_h(c,j) y(c,j) \tag{32}$$

Note that only one block is selected as in (10).

To have an equivalent linear single-level formulation, the lower-level problem is moved to the upper-level and the bilinear products and other nonlinearities are linearized as explained in [27]. The equivalent single-level MILP includes the objective function of the upper level, the constraints of the upper and lower levels and an equation resulting from equating the primal and dual objectives of the lower level.

The process of transforming the bilevel problem to an equivalent single-level one is as follows:

1) The bilevel problem is transformed to an equivalent single- level problem using KKT optimality conditions of the lower level problem [27].
2) The nonlinear products of step 1 are replaced with equivalent linear expressions [29].
3) The bilinear product of electricity is replaced using the strong duality theorem [30] (see Appendix).
4) The bilinear product of heat is linearized using the heat price-quota curve (30)-(32).

Finally, the equivalent single-level MILP is as follows:

$$\max \sum_{\omega=1}^{\Omega} \pi(\omega) \sum_{t=1}^{T} \sum_{j=1}^{J} \begin{bmatrix} R(c,\omega,t) + \sum_{c=1}^{NC} H_h(c,t,\omega,j)\lambda_{hs}^s(c,j) - \\ P^P(\omega,t)\lambda^p(\omega,t) - \sum_{f\in F} P^f(f,t)\lambda^f(f,t) - \\ \lambda^{gas}(P_{Boil}^{gas}(t,\omega) + P_{CHP}^{gas}(t,\omega)) \end{bmatrix} + \left[\beta(\xi - \frac{1}{1-\alpha})\sum_{\omega=1}^{\Omega}\pi(\omega)\eta(\omega)\right] \tag{33}$$

subject to:

(15)-(22),(25)-(27) and

$$R(c,t,\omega) = (D_e(c,t,\omega) / \hat{D}_e(c)) \cdot \begin{bmatrix} -\hat{D}_h(c)\cdot(\sum_{j=1}^{J}\lambda_{hs}^s(c,j)S_h(c,j) + \\ \sum_{r=1}^{R}\lambda_h^r(c,r)z^r(c,r)) + \\ \sum_{\delta=1}^{\Delta}\tau(\delta)(\mu_e(c,r)+\sigma_h(c)) \end{bmatrix} - D_e(c,t,\omega)\cdot\left[\sum_{r=1}^{R}\sum_{\delta=1}^{\Delta}\tau(\delta)\lambda_e^r(c,r,\delta)x^s(c,r,\delta)\right] \tag{34}$$

$$\sum_{c=1}^{NC}\sum_{j=1}^{J} H_h(c,t,\omega,j) y(c,j) = P_{Boil}^{gas}(t,\omega)\gamma^{Boil} + P_{CHP}^{gas}(t,\omega)\gamma_h^{CHP} \tag{35}$$

$$\hat{D}_e(c)\lambda_e^r(c,r) - \mu_e(c,r) \le M_1 u^r(c,r,\delta) \tag{36}$$

$$\hat{D}_h(c)\lambda_h^r(c,r) - \sigma_h(c) \le M_1 k^r(c,r) \tag{37}$$

$$\hat{D}_e(c)\lambda_e^s(c) - \mu_e(c,r) \le M_1 u^m(c,\delta) \tag{38}$$

$$\hat{D}_h(c)\sum_{J}\lambda_{hs}^s(c,j) - \sigma_h(c) \le M_1 k^m(c) \tag{39}$$

$$x^r(c,\delta,r) \le M_2\left[1 - u^r(c,r,\delta)\right] \tag{40}$$

$$z^r(c,r) \le M_2\left[1 - k^r(c,r)\right] \tag{41}$$

$$x^m(c,\delta) \le M_2\left[1 - u^m(c,\delta)\right] \tag{42}$$

$$\sum_{j=1}^{J} S_h(c,j) y(c,j) \le M_2\left[1 - k^m(c)\right] \tag{43}$$

$$u^r(c,r,\delta), k^r(c,r), u^m(c,\delta) \text{ and } k^m(c) \in \{0,1\} \tag{44}$$

where $\mu_e(c,r)$, $\sigma_h(c)$ are dual variables and M_1 and M_2 are large numbers. Eq (34) results from equating the primal and dual objectives of the lower level.

V. Numerical Results and Discussion

A. Test case

To evaluate the proposed formulation, a test case with realistic electricity market prices is considered for a medium-term, four-week time horizon in a sample energy hub as shown in Fig. 1. Each sample time is assumed to be two hours long which turns a 672-hour period into a shorter 336-hour one, therefore, decreasing the CPU time. The pool prices and the electricity demands are two uncertainty sources that are considered using scenarios. Pool prices have variable average and variance with respect to time. Therefore, pool price scenarios are created for the New York City electricity market prices [31]. The pool price time series presented in [32] is used to create 75 price scenarios. Electricity demand scenarios are also generated with respect to the pool price scenarios because of the correlation between the electricity demands and pool prices. In this regard, the model in [27] is used to generate the electricity demand scenarios for the clients. This means each pool scenario provides an electricity demand scenario. The generated scenarios of electricity prices and demands are available in [33]. Note that the rivals' price scenarios are related to the lower level and they are not combined with the upper level scenarios. A total number of three scenarios is also considered for the rivals.

Fig. 5 depicts the generated electricity price scenarios. Two sample scenarios, 14 and 65, are selected among all the scenarios in order to show the difference between the two scenarios, graphically. It should be noted that other/more scenarios could be selected. However, only two scenarios are selected in order to prevent crowding data in the figures. Three rival hub managers are available in a fully competitive environment. It is assumed that the amount of the electricity and heat demands are known by the clients. The heat data is obtained from the HOMER software as presented in Fig. 6 and [34]. The prices offered by the 7 rivals for heat and electricity are generated randomly and they are provided in Tables I and II, respectively. Table III presents the prices of the blocks and the upper and lower bounds and time duration of the forward contracts. The lower and upper bounds of each contract are specified as $P_{f,\min}$ and $P_{f,\max}$ in the table. The gas price and boiler efficiency are considered 20$/MWh and 0.75, respectively. Other features of the energy hub are also given in [32]. The coordinates of the CHP unit feasible operation region are selected from [28].

The BSPP is formulated as an equivalent MILP problem and solved with CPLEX in the GAMS software environment [35]. The problem has 306,387 variables. The computational time is 9 minutes and 41 seconds, on a computer with 4 Giga Bytes of RAM and Ci5 CPU.

TABLE I
ELECTRICITY PRICES OFFERED BY RIVAL HUB MANAGERS

Client	Scenario	Price ($/MWh)						
		Rival						
		1	2	3	4	5	6	7
1	1	37.5	37	35.5	32.6	38.1	33.5	36.2
	2	32.6	38.9	31.4	38.4	32.4	32	34.7
	3	35.1	39.6	31.5	32.5	39.3	32.5	33.5
2	1	86.1	78.9	85.9	79.6	87.3	81.8	86.2
	2	76.6	77.9	78.3	80.8	87.9	80.9	87.1
	3	77.5	88.5	91	79.6	75.7	84.9	77.5
3	1	58.4	76	70.7	64.9	64.3	71.5	58.6
	2	62.5	62	60.5	56	63.1	60.5	61.2
	3	71.5	61.5	55.2	78.1	62.4	74.6	69.5

TABLE II
HEAT PRICES OFFERED BY RIVAL HUB MANAGERS

Client	Price ($/MWhth)						
	Rival						
	1	2	3	4	5	6	7
1	43.9	44.4	39.8	44.5	42.8	39.6	40.7
2	43.6	44.9	44.9	42.5	44.9	44.9	43.5
3	45.3	42.2	46.2	46.7	45.4	45.8	45.7

TABLE III
AVAILABLE FORWARD CONTRACTS TO BE SIGNED

Contract	Price ($/MWh)	$P_{f,min}$	$P_{f,max}$	Time
1	35.2	0	50	4 weeks
2	29.8	0	45	4 weeks
3	29	0	40	First 2 weeks
4	28.8	0	50	Last 2 weeks
5	26	0	38	Last 2 weeks
6	40.5	0	50	4 weeks

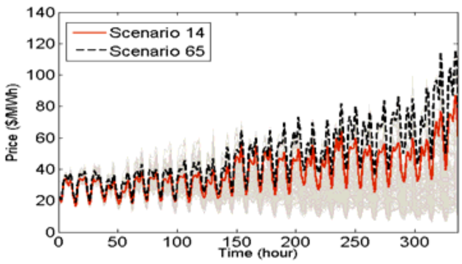

Fig. 5: Electricity pool price scenarios.

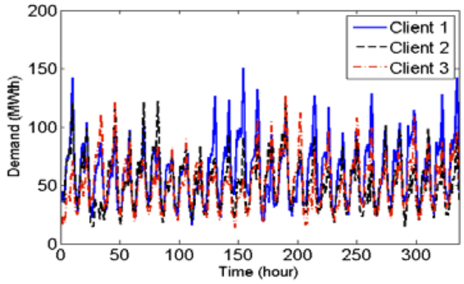

Fig. 6: Heat demands.

B. Simulations and discussion

The values of α and β are 0.95 and 1, respectively. Electricity market prices and electricity load demands of the clients are subject to uncertainty. As mentioned, heat demand uncertainty is neglected for the sake of simplicity. The percentages of the supplied electricity and heat as well as the prices offered by the hub manager under study and their rivals are provided in Tables IV and V. The electricity price offered to client 1 is high, thus all client 1's electricity is supplied by their rivals. This occurs because their offered prices are lower than those offered by the hub manager. The two-level optimization shows that the hub manager supplies most of the heat energy. For instance, the heat price offered by the hub manager for client 2 is higher than the one offered by rival 4 but lower than the other rivals' prices (see Table II). This offered price makes the hub manager supply 71.6% of the heat for client 2 and 85.8% of the heat of clients 1 and 3, where the remaining heat percentage is produced by the rival managers.

The decisions related to forward contracts are shown in Table VI. The average purchased electricity in the contracts' time periods and utilized hours in each contract are shown in the table. More energy is procured in case of low-priced contracts. For example, the lowest amount of energy is purchased in contract 6 because of its high price, while contract 5 is signed for most of its duration, which has the minimum price among all the contracts. Table VII illustrates the expected gas entering the CHP and boiler units in scenarios 14 and 65. The amount of gas entering the CHP unit (generated heat and electricity) in scenario 65 is higher than in scenario 14. This shows that, by increasing the price of the electricity pool, the generation of electricity with natural gas, a cheaper source, increases. In addition, the gas entering the boiler in the two scenarios is similar. This is because the heat demands are deterministic. Finally, the resulting expected profit and CVaR are shown in Table VIII.

TABLE IV
ELECTRICITY SUPPLIED BY THE HUB MANAGER AND ITS RIVALS

Client	Scenario	Supplied electricity (%)		Offered price by hub manager ($/MWh)
		Hub manager	Rivals	
1	1	0	100	118.5
	2	0	100	
	3	0	100	
2	1	100	0	75.4
	2	100	0	
	3	91	9	
3	1	66	34	58.4
	2	0	100	
	3	0	100	

TABLE V

HEAT SUPPLIED BY THE HUB MANAGER AND ITS RIVALS

Client	Supplied heat (%)		Offered price by hub manager ($/MWhth)
	Hub manager	Rivals	
1	85.8	14.2	40
2	71.6	28.4	42.9
3	85.8	14.2	42.7

TABLE VI
DECISIONS RELATED TO FORWARD CONTRACTS IN ALL PERIODS

Time duration	All Periods			First two weeks	Last two weeks	
Contract	1	2	6	3	4	5
Average purchased energy (MWh)	29.3	33.9	18.4	13.5	21.9	18.7
Number of utilized hours	197	253	129	113	147	165

TABLE VII
AMOUNT OF EXPECTED GAS ENTERED TO THE CHP AND BOILER

Scenario	CHP	Boiler
14	1.4	174.7
65	6.4	171.8

TABLE VIII
SIMULATION RESULTS WITH FIXED VALUES OF α AND β

Average indices	Expected profit ($)	Expected risk ($)
Value	8,552,573	5,471,790

C. Sensitivity analysis

Sensitivity analysis is carried out using CVaR in order to investigate the effects of β. This parameter represents a tradeoff between profit and risk. The value of β can range from 0 to 10 and the results are provided in Fig. 7. Increasing β decreases the expected profit and increases CVaR. A negative CVaR for β=0 means there is a possibility of a negative profit in some scenarios. As can be seen in Fig. 8, most of the energy traded in the electricity pool and the lowest price contract takes place in a risk-neutral environment.

By increasing β, the willingness to participate in the electricity market decreases and the willingness to participate in a forward contract increases. This means that the deterministic nature of the forward contract is used to decrease the uncertainty of participating in the electricity pool market. Fig. 9 plots the profit of the scenarios with and without risk.

When risk is considered ($\beta=1$), the farthest profits to the mean profit are eliminated from both sides. This shows the applicability of the CVaR concept in which lower-profit scenarios with a low probability are not considered in the decision making process, when risk is considered. CVaR results in an average value with a higher probability and a lower variance with respect to the risk-neutral case. This is observed in the figure by dashed and continuous lines.

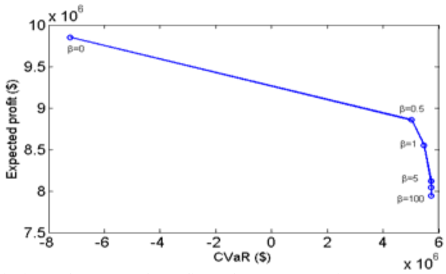

Fig. 7: Variation of expected profit and CVaR varying β

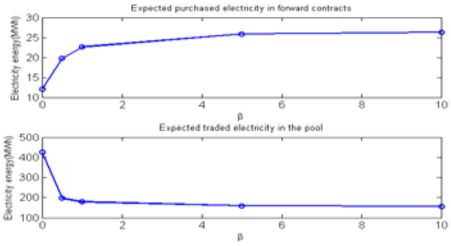

Fig. 8: Variation of the average energy purchased from the pool and the forward contract varying β

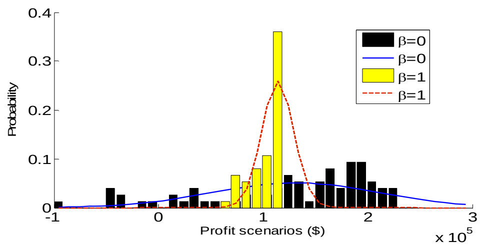

Fig. 9: Profit in all scenarios with respect to β

VI. CONCLUSIONS

In this paper, a bilevel formulation for the problem faced by an energy hub manager supplying energy clients subject to rival hub managers is proposed. The hub manager under study is placed in the upper level and the clients in the lower level. The bilevel nonlinear stochastic program is transformed into an equivalent linear single level one, using the KKT optimality conditions and the strong duality condition. Uncertainty is considered in pool prices, electricity demands and the electricity prices offered by the rival managers. Natural gas prices and, consequently, heat energy prices are assumed to have fixed tariffs. The heat price offered in the upper level is modeled with a heat price quota curve. The results show the energy traded in the pool increases when the electricity demands are increased and vice versa. Additionally, more energy is purchased from low-priced contracts. On the other hand, the clients choose the lowest electricity and heat energy prices in order to minimize their cost. Finally, the use of CVaR shows the effects of risk in the trading decisions of the hub manager.

APPENDIX

LINEARIZING THE BILINEAR ELECTRICITY PRODUCT BY THE STRONG DUALITY FEASIBILITY CONDITION

Expression $\lambda_e^s(c)P_e^s(c,\omega,t)$ should be replaced by its equivalent linear expression in order to linearize the objective function. Based on duality theorem, each linear objective function has a dual objective. By using strong duality theorem, the lower-level objective function is considered as the primal objective and its dual is obtained as follows [36]:

$$\text{Dual objective} : \max \sum_{r=1}^{R} \mu_e(c,r) + \sigma_h(c) \qquad \text{(A. 1)}$$

To obtain the optimal solution the dual and primal objectives should be equal, based on the strong duality theorem as follows:

$$\begin{aligned} &\sum_{r=1}^{R} \mu_e(c,r) + \sigma_h(c) = \\ &\hat{D}_e(c) \sum_{\delta=1}^{\Delta} \tau(\delta) \left[\lambda_e^s(c) x^m(c,\delta) + \sum_{r=1}^{R} \lambda_e^r(c,\delta,r) x^r(c,\delta,r) \right] + \qquad \text{(A. 2)} \\ &\hat{D}_h(c) \left[\lambda_h^s(c) z^m(c) + \sum_{r=1}^{R} \lambda_h^r(c,r) z^r(c,r) \right] \end{aligned}$$

By extracting $\lambda_e^s(c) x^m(c,\delta)$ and using Eq. (31), the equivalent expression for the bilinear product is obtained. In addition, $\lambda_h^s(c) z^m(c)$ is replaced by Eq. (32). Finally, the equivalent expression is derived as follows:

$$R(c,t,\omega) = \left({D_e(c,t,\omega)} \Big/ {\hat{D}_e(c)} \right) \cdot \begin{bmatrix} -\hat{D}_h(c) \cdot (\sum_{j=1}^{J} \lambda_{hs}^s(c,j) S_h(c,j) + \\ \sum_{r=1}^{R} \lambda_h^r(c,r) z^r(c,r)) + \\ \sum_{\delta=1}^{\Delta} \tau(\delta)(\mu_e(c,r) + \sigma_h(c)) \end{bmatrix} - \qquad \text{(A. 3)}$$
$$D_e(c,t,\omega) \cdot \left[\sum_{r=1}^{R} \sum_{\delta=1}^{\Delta} \tau(\delta) \lambda_e^r(c,r,\delta) x^r(c,r,\delta) \right]$$

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