Chapter 5
Risk Averse Energy Hub Management Considering Plug-in Electric Vehicles Using Information Gap Decision Theory

Alireza Soroudi and Andrew Keane

Abstract The energy hub is defined as the multi-input multi-output energy converter. It usually consists of various converters like thermal generators, combined heat and power (CHP), renewable energies and energy storage devices. The plug-in electric vehicles as energy storage devices can bring various flexibilities to energy hub management problem. These flexibilities include emission reduction, cost reduction, controlling financial risks, mitigating volatility of power output in renewable energy resources, active demand side management and ancillary service provision. In this chapter a comprehensive risk hedging model for energy hub management is proposed. The focus is placed on minimizing both the energy procurement cost and financial risks in energy hub. For controlling the undesired effects of the uncertainties, the Information gap decision theory (IGDT) technique is used as the risk management tool. The proposed model is formulated as a mixed integer linear programming (MILP) problem and solved using General Algebraic Modeling System (GAMS). An illustrative example is analyzed to demonstrate the applicability of the proposed method.

Keywords Energy hub · Information gap decision theory · Uncertainty modeling · Wind power · Plug-in electric vehicle

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Nomenclature

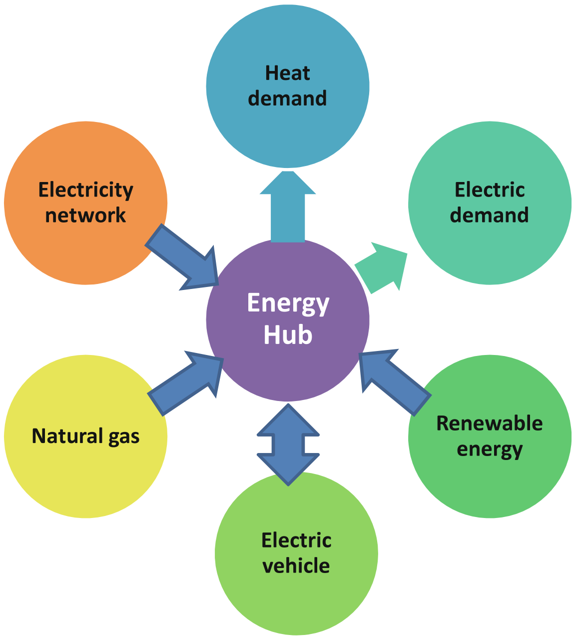
$Uc(t,v)$	Binary variable indicating the charging state
Ud(t,v)	Binary variable indicating the discharging state
η_{chp}^{ge}	CHP efficiency in converting gas to electricity
η_{chp}^{gh}	CHP efficiency in converting gas to heat
Pc(t,v)	Charged power of vehicle v in time t
η_v^c	Charging efficiency of vehicle v
$Pd(t,v)$	Discharged power of vehicle v in time t
η_d^v	Discharging efficiency of vehicle v
Le(t)	Electric load in time t
λ_t^e	Electricity price
η_f^{gh}	Furnace efficiency in converting gas to heat
λ_g	Gas price
Lh(t)	Heat load in time t
Pw(t)	Injected wind power
$Pc_{\min/\max}^v$	Min/max charging limits of vehicle v
$Pd_{\min/\max}^v$	Min/max discharging limits of vehicle v
OF	Objective function
Pg(t)	Purchased gas power
$Pe_b(t)$	Purchased electricity power
α_{Le}	Radius of uncertainty for electric load
α_{Lh}	Radius of uncertainty for heat load
α_w	Radius of uncertainty for wind power generation
$Pe_s(t)$	Soled electricity power
SOC(t,v)	State of charge of vehicle v in time t
$Pg_{chp}(t)$	Share of purchased gas power to feed into CHP
$Pg_f(t)$	Share of purchased gas power to feed into furnace
$P_{tr}(t,v)$	Traveling requirement of vehicle v in time t

5.1 Introduction

The concept of energy hub was first introduced in [1]. It is defined as a combination of energy conversion units which satisfy different types of energy demands. Figure 5.1 illustrates an example of energy hub, which provides an interface between the different inputs and outputs energy carriers.

A relevant number of recent researches have proposed some models for energy hub concept. These models describe the energy hubs as a combination of nuclear plants, wind turbines, solar panels, biomass reactors, electrolyzers, fuel cells [2] and energy storage devices. Different optimization techniques are available for solving

Fig. 5.1 The general concept of energy hub



the optimal management of energy hubs like Simulated Annealing algorithm [3], genetic algorithm [4] and multi-objective goal programming [5]. The optimal operating schedule of an energy hub highly depends on the input parameters of the model. Usually these input parameters are subject to uncertainty due to various reasons. For example, renewable power generations are volatile because of their natural primary resource like wind speed, solar radiation, temperature and etc. Another important uncertain input parameter is the demand whether it is electrical or heat which should be treated properly [6]. It is highly dependent on the consumer behavior which cannot be predicted easily. The last important uncertain parameter is the electricity price which directly affects the payments or benefits of the decision maker. The electricity prices in deregulated electricity markets are uncertain due to various reasons like: competition between the price maker generating companies, contingencies and etc.

There are different types of uncertainty modeling in energy hub management. The most famous technique is stochastic method [7, 8]. The Monte Carlo Simulation (MCS) [9] is used in uncertainty modeling of energy prices [10]. The shortcoming of this technique is that it is computationally expensive and it also requires the probability density functions (PDF) of uncertain parameters. Without them the problem cannot be solved. The second issue is that using the Monte Carlo simulation gives the decision maker the expected value of objective function and also its variance. It's more useful in assessment applications rather than optimization applications. The scenario based modeling which defines some discrete scenarios with specific probabilities and then tries to minimize the expected values. It improves the computational burden significantly compared to MCS.

In [11], this method is used to handle the uncertainty of wind, price and electricity demand. The conditional value at risk (CVaR) [12] is also used for risk controlling. Another uncertainty modeling technique is robust optimization [13]. This technique does not require the PDF of the uncertain parameters. Instead, it uses an interval for uncertain parameters. It tries to find the optimal decision variables while some predefined degree of conservativeness is taken into account. This technique is used for uncertainty modeling of energy prices, energy demand and also the converter efficiencies of energy hubs [14]. To cope with the increasing volatile renewable generation in energy hubs it is possible to use energy storage [15]. Different energy storage technologies have been used in energy hubs such as solid hydrogen storage [3], water electrolyzers for hydrogen production [16], thermal energy storage [17], Hydrogen-Natural Gas Co-Storage [18] and plug-in electric vehicles (PEV) [19]. The PEVs have recently attracted a great deal of attention in energy system management strategies. The advents of these new technologies have changed the original operating philosophy of PEVs from pure transportation into important energy system flexibility providers. They can be used as an energy storage device when not in use for transportation purposes. In this chapter, a risk averse Information Gap Decision Theory (IGDT) [20] framework is proposed for optimal energy management of an energy hub. This technique is exact and does not require the PDF of the uncertain parameters. This hub purchases energy from different resources and converts them to different output forms. It also uses the flexibilities that PEV may provide. The problem is analyzed with the following constraints, decision variables and objective function:

- Decision variables:
  - Electricity purchase from the electricity market
  - Electricity sell to the electricity market
  - Gas purchase from the gas network
  - Operation schedule of energy conversion devices
  - Operation charging and discharging of PEV
- Constraints:
  - Uncertainty of thermal demand
  - Uncertainty of electricity demand
  - Uncertainty of energy production of renewable resources
  - Technical constraints of energy conversion/storage of PEVs
  - Different demand balance
  - Risk of energy management strategy due to different uncertainties

Objective function: it is defined as the total payments regarding the energy management.

5.2 IGDT Based Uncertainty Modeling

The decision makers need some strong tools in order to handle the severe uncertainties. Specially when not enough information is available from the uncertain input parameters (like probability density function or membership function). The information gap decision theory provided such a tool which is computationally efficient and it is robust against the prediction errors. It has been successfully applied on various energy system applications such as:

- Energy procurement in distribution networks [20]
- Risk-constrained self-scheduling of GenCos [21]
- Multi-objective robust transmission expansion planning [22]
- Optimal bidding strategy of generation station in power market [23]

In this chapter, an IGDT based model [8] is proposed to handle the uncertainty of wind power generation, electric load and heat load. The mathematical formulation of risk hedging IGDT framework is as follows:

$$\min_X f(X, \psi) \tag{5.1}$$

$$H_i(X, \psi) \leq 0, \quad i \in \Gamma \tag{5.2}$$

Γ is the set of all constraints. ψ is the vector of input uncertain parameters. In this work, an IGDT based energy management is formulated as:

$$\max_X \hat{\ell} \tag{5.3}$$

$$H_i(X, \psi) \leq 0, \quad i \in \Gamma \tag{5.4}$$

$$\hat{\ell} = \{\max_\ell | f(X, \psi) - \Lambda_c \leq 0\} \tag{5.5}$$

$$\psi \in U(\bar{\psi}, \ell) = \{\psi : |\frac{\psi - \bar{\psi}}{\bar{\psi}}|\} \leq \ell \tag{5.6}$$

Λ_c is the critical value of objective function (for a given value of X) which can be exceeded when the realized values are not the same as forecasted ones. $\bar{\psi}$ is the forecasted value of ψ. ℓ is the unknown radius of uncertainty.

5.3 Problem Formulation

The general operating concept of an energy hub can be described as follows:

$$OF = \sum_t \lambda_\gamma(t) P_\gamma^{in}(t) \tag{5.7}$$

$$P_\gamma^{out}(t) = AP_\gamma^{in}(t) \tag{5.8}$$

where, γ is the set of energy carriers. $P_\gamma^{in}(t)$, $P_\gamma^{out}(t)$ denote the input and output energy carriers of the hub, respectively. $\lambda_\gamma(t)$ is the price of energy carrier γ at time t. The matrix A is the core function of the energy hub which defines the conversion, storage and distribution of different energy carriers. The energy hub under study in this chapter is depicted in Fig. 5.2.

This energy hub has three inputs as the supplying resources namely electric power purchased from electricity market ($Pe_b(t)$), wind power generation ($Pw(t)$) and finally natural gas ($Pg(t)$). The output of energy hub has three different parts namely electric load ($Le(t)$), heat load ($Lh(t)$), power sold to energy market ($Pe_s(t)$) and power charge/discharge for PEV ($Pd(t, v), Pc(t, v)$). The question is how to optimally exploit the energy hub in order to minimize the payments for energy procurement.

The performance of the described energy hub in Fig. 5.2 can be modeled as follows:

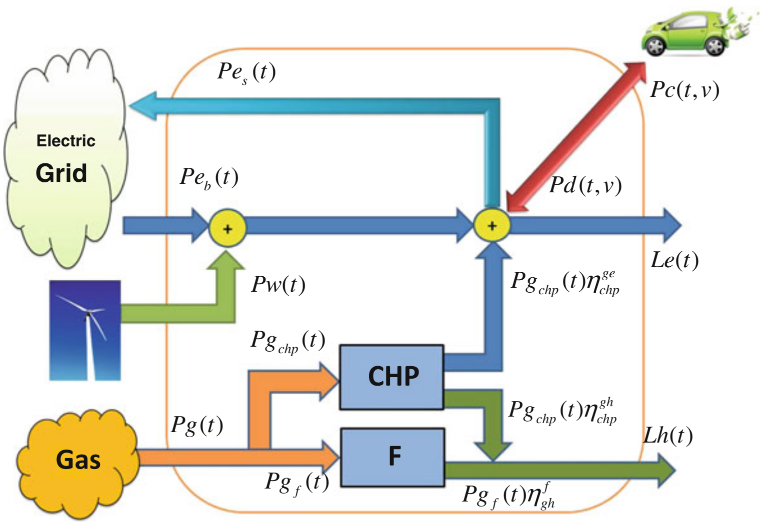


Fig. 5.2 The energy hub under study

$$Pe_b(t) + Pw(t) + Pg_{chp}(t)\eta_{chp}^{ge} + \sum_v Pd(t,v) = Le(t) + Pe_s(t) + \sum_v Pc(t,v) \tag{5.9}$$

$$0 \le Pe_b(t) \le Pe_b^{\max} \tag{5.10}$$

$$0 \le Pe_s(t) \le Pe_s^{\max} \tag{5.11}$$

$$Pw(t) \le (1-\alpha_w)\,\bar{P}w(t)Cap_w \tag{5.12}$$

$$Le(t) = (1+\alpha_{Le})\,\bar{L}e(t)Le_{\max} \tag{5.13}$$

$$Lh(t) = (1+\alpha_{Lh})\,\bar{L}h(t)Lh_{\max} \tag{5.14}$$

$$Pg(t) = Pg_{chp}(t) + Pg_f(t) \tag{5.15}$$

$$Lh(t) = Pg_f(t)\eta_f^{gh} + Pg_{chp}(t)\eta_{chp}^{gh} \tag{5.16}$$

The electric balance is modeled in (5.9). This means that the electric output of the energy hub $(Le(t) + Pe_s(t) + \sum_v Pc(t,v))$ is fed using $Pe_b(t) + Pw(t) + Pg_{chp}(t)\eta_{chp}^{ge} + \sum_v Pd(t,v)$. The third term is the converted gas to electricity in CHP units. The purchased gas $Pg(t)$ is divided into two streams $Pg_{chp}(t), Pg_f(t)$. The $Pg_{chp}(t)$ is fed into the CHP unit and the $Pg_f(t)$ is fed into the furnace unit as described in (5.15). Finally, the heat load $(Lh(t))$ is supplied using furnace and CHP units as given in (5.16).

The operation modeling of PEV is described in (5.17–5.23).

$$\mathrm{SOC(t, v)} = \mathrm{SOC(t-1,\ v)} + \eta_v^c Pc(t,\mathrm{v}) - \frac{Pd(t,\mathrm{v})}{\eta_v^d} - \mathrm{P}_{tr}(\mathrm{t,v}) \tag{5.17}$$

$$\mathrm{SOC(t,v)} = \mathrm{E}_v^0 + \eta_v^c Pc(t,v) - \frac{Pd(t,v)}{\eta_v^d} - \mathrm{P}_{tr}(\mathrm{t,v}) \tag{5.18}$$

$$\mathrm{SOC}_{\min}^v \le \mathrm{SOC(t,v)} \le \mathrm{SOC}_{\max}^v \tag{5.19}$$

$$\mathrm{P}_{tr}(\mathrm{t,v}) = \Delta\mathrm{D(t,v)}\ \Omega_v \tag{5.20}$$

$$\mathrm{Pc}_{\min}^v Uc(t,v) \le Pc(t,v) \le \mathrm{Pc}_{\max}^v Uc(t,v) \tag{5.21}$$

$$\mathrm{Pd}_{\min}^v Uc(t,v) \le Pd(t,v) \le \mathrm{Pd}_{\max}^v Uc(t,v) \tag{5.22}$$

$$Uc(t,v) + Ud(t,v) \le 1 \tag{5.23}$$

The state of charge in *vth* PEV at time t $(SOC(t,\ v))$ depends on the state of charge at time t − 1 $(SOC(t-1,\ v))$. as well as the charging/discharging or traveling state of the PEV as modeled in (5.17) and (5.18). The relation between the required energy for traveling of vth PEV (P_{tr}(t,v)) depends on the traveling distance (ΔD(t,v)) and also the efficiency of the vehicle (Ω_v) as described in (5.20). The state of charge should be kept between operating limits as (5.20). The charging and discharging rate of each PEV are limited by technical characteristics as well as the operating state as enforced by (5.22) and (5.23). It is assumed that each PEV is either in charging ($Uc(t,v) = 1$)/discharging state $Ud(t,v) = 1$ or traveling state ($Uc(t,v) + Ud(t,v) = 0$) as described in (5.23).

The objective function is defined as the total payments regarding the energy purchase as follows:

$$OF = \sum_t Pg(t)\lambda^g + \lambda_t^e(Pe_b(t) - Pe_s(t)) \tag{5.24}$$

If the OF is negative in (5.24) it means the energy hub is making profit in the electricity market.

5.4 Simulation Results

The proposed mixed integer linear programming (MILP) model is implemented in GAMS [24] environment solved by CPLEX solver running on an Intel® Xeon® CPU E5-1620 @ 3.6 GHz PC with 8 GB RAM. The predicted hourly electric/heat demand, wind power, electricity price pattern are depicted in Fig. 5.3. The wind

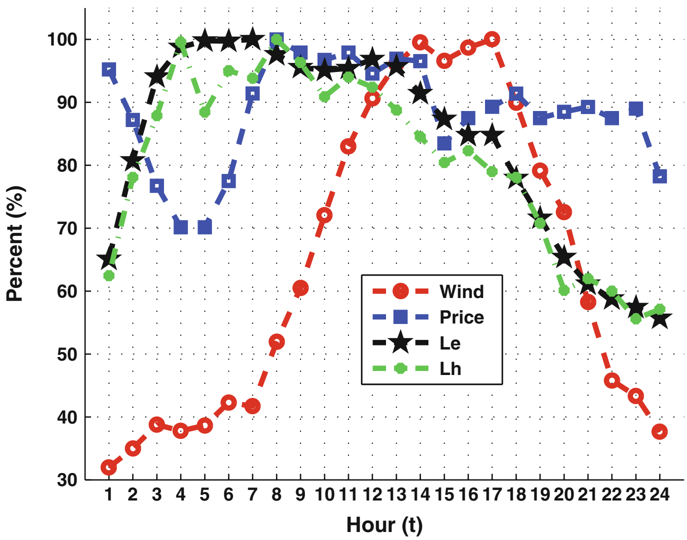


Fig. 5.3 The hourly electric/heat demand, wind power, electricity price pattern

Table 5.1 Energy hub characteristics and data

Parameter	Value	Unit
η_{chp}^{ge}	35	%
η_{chp}^{gh}	45	%
η_{f}^{gh}	75	%
$Pe_{s}^{\max}$	7	kW
$Pe_{b}^{\max}$	7	kW
η_{v}^{d}	93	%
η_{v}^{c}	90	%
E_{v}^{0}	3	kWh
$SOC_{\max}^{v}$	25	kWh
$SOC_{\min}^{v}$	1	kWh
$P(c/d)_{\min}^{v}$	0	kW
$P(c/d)_{\max}^{v}$	12.5	kW
Ω_{v}	$\frac{1}{6}$	$\frac{\text{kW}}{\text{km}}$

capacity is assumed to be $Cap_w = 15\,\text{kW}$. The energy hub characteristics and data are described in Table 5.1. The peak electric and heat load is $Le_{\max} = 5\,\text{kW}$, $Lh_{\max} = 4.5\,\text{kW}$, respectively. The peak value of electric price is $47\frac{\$}{\text{kWh}}$. The gas price is assumed to be constant and equal to $\lambda^{g} = 30\frac{\$}{\text{kWh}}$.

The travel pattern of PEV (km) are given in Table 5.2.

In order to demonstrate the applicability and strength of the proposed approach different scenarios are considered as follows:

- Base case (no uncertain parameter exists in the model)
- Wind uncertainty (α_w)
- Electric load uncertainty (α_{Le})
- Heat load uncertainty (α_{Lh})

5.4.1 Base Case

In this case, it is assumed that no uncertain parameter exists in the model. The objective function to be minimized is the energy procurement cost. It is called the base cost (benefit) OF_b. The following optimization is solved:

$$\min_{DV_b}\ \text{OF}_b = \text{OF} \tag{5.25}$$

Subject to: (5.9–5.24)

Table 5.2 The travel patterns of PEVs (km)

Time (h)	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10
t1	0	0	0	4.6	0	0	0	4	0	0
t2	0	3.6	0	1.8	0	2	0	0	0	0
t3	0	5	0	0	0	2.2	0	0.6	0	2
t4	0	0	0	0	3.6	0	0	1.2	0	0
t5	2.4	0	0	0	1.8	4.2	2.8	3.6	0	4.4
t6	0	4.8	0	0	1.4	1.8	0	0	0	0
t7	0	0	0	0	1.6	2.6	0	0	0	0
t8	4.8	0	1	2	0	3.8	0	0	0	2
t9	0	0	0	0	1.2	3	1.2	0.8	0	1.2
t10	0	2.4	0	4	0	0	3.4	0	0	1
t11	0	0	0	4.6	2.4	0	0	4.4	0	0.4
t12	4	0	0	0	4.2	3	0	1.2	0	0
t13	0	0	0	0	2	0	3.4	0	4.2	0
t14	0	0	0	0	3	0	0	4	0	0
t15	0	0	0	0	0	1.4	0	0	3.8	0
t16	3.6	0	0	4.6	0	0	3.8	0	0	4
t17	0	0	3.6	0	1.6	0	0	3	0	4
t18	0	0	0	4	0	0	0	1.8	0	0
t19	0	0	4	0	2.2	2.6	0	0	2	4
t20	0	0	0	0	3	0	4.2	3.2	2.2	0
t21	0	0	4.8	3.8	0	0	0	2.6	1	1
t22	0	0	0	0	3.8	0	0	0.4	0	0
t23	0	4.8	0	0	0	0	0	0	0	2.2
t24	0	0	0	0	2.2	0	3.2	0	0.4	0

$$\alpha_{Lh} = \alpha_{Le} = \alpha_w = 0 \tag{5.26}$$

$$\mathrm{DV}_b = \left\{ \mathrm{Pe}_b(\mathrm{t}), \mathrm{Pe}_s(\mathrm{t}), \mathrm{Pw}(\mathrm{t}), \mathrm{Pg}_{chp}(\mathrm{t}), \mathrm{Pg}_f(\mathrm{t}), \mathrm{Pd}(\mathrm{t}, \mathrm{v}), \mathrm{Pc}(\mathrm{t}, \mathrm{v}), \mathrm{Ud}(\mathrm{t}, \mathrm{v}), \mathrm{Uc}(\mathrm{t}, \mathrm{v}) \right\} \tag{5.27}$$

The total costs would be $\mathrm{OF}_b = -\$0.480165$. The hourly total charge and discharge pattern of PEVs is shown in Fig. 5.4.

The hourly gas input to CHP and furnace is shown in Fig. 5.5.

The hourly purchased/sold power from/to electric grid is shown in Fig. 5.6.

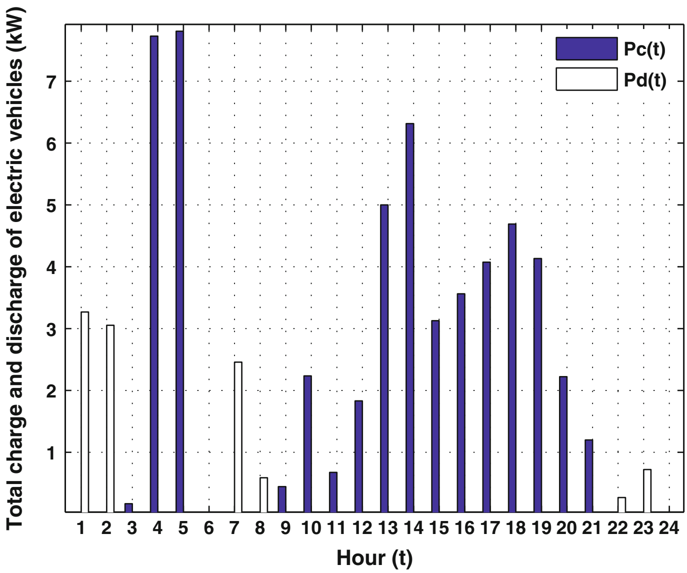


Fig. 5.4 The hourly total charge and discharge pattern of PEVs in base case

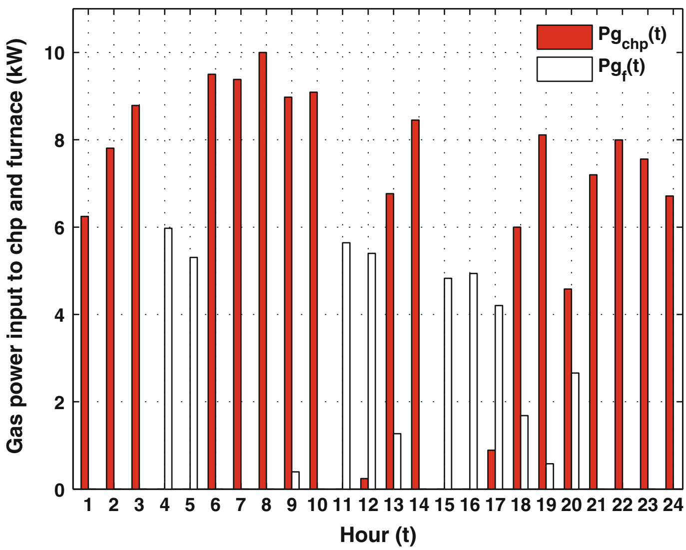


Fig. 5.5 The hourly gas input to CHP and furnace in base case

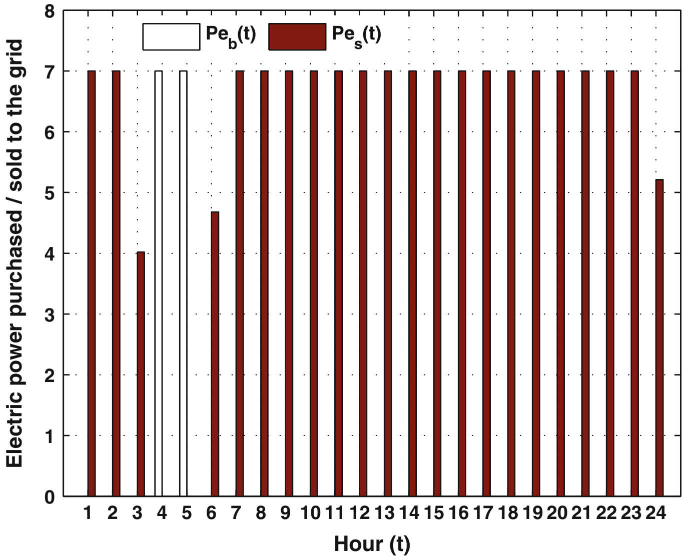


Fig. 5.6 The hourly purchased/sold power from/to electric grid in base case

5.4.2 Uncertain Wind ($\alpha_w \neq 0$)

In this case, it is assumed that the only uncertain parameter existing in the model is wind power generation. The objective function in this case is radius of wind power uncertainty (not the total cost (benefit)). The following optimization is solved:

$$\max_{DV_w} \alpha_w \tag{5.28}$$

$$\mathrm{OF} \leq \mathrm{OF}_b + \beta|\mathrm{OF}_b| \tag{5.29}$$

Subject to: (5.9–5.24)

$$\alpha_{Lh} = \alpha_{Le} = 0 \tag{5.30}$$

$$\mathrm{DV}_w = \{\mathrm{DV}_b, \alpha_w\} \tag{5.31}$$

The interpretation of each β value is simply defined as the relaxation degree of objective function. The objective function is defined as α_w and the decision maker tries to maximize it for a given β value. In this way, the traditional objective function OF would be immune against the wind uncertainty. This means even if the forecasted value of wind doesn't come true, the total payments do not increase more than β percent of the base case costs OF_b. The β is increased from 0 to 1 and the variation of different variables (DV_w) versus β is shown in Fig. 5.7.

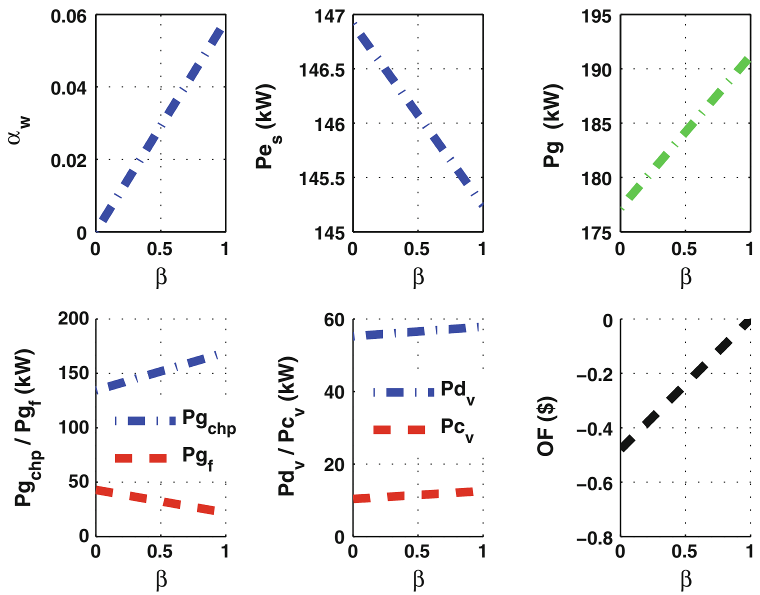


Fig. 5.7 The variation of different variables versus β (uncertain wind)

In this way, the decision maker has a portfolio of the decision variables (DV_w) for each β. The simulation results show that the α_w varies from 0 to 5.829 %. This means that if the total cost is 100 % increased then the decision maker can be immune up to 5.829 % error in wind power prediction. In order to increase the immunity of the objective function against the wind power uncertainty, $Pe_s(t)$, $Pg_f(t)$ are decreased and $Pg_{chp}(t)$ is increased. Both charging and discharging of PEVs ($Pd(t, v)$, $Pc(t, v)$) are increased. For clarification, the decision variables DV_w are given in Table 5.3 for $\beta = 30\,\%$. In this table, the hourly optimal schedule of energy hub $\beta = 30\,\%$ under $Pw(t)$ uncertainty are described. The total payments would be OF = − \$0.3361 and the maximum wind uncertainty that can be tolerated would be $\alpha_w = 1.748692\,\%$.

5.4.3 Uncertainity Electric Load Missing ($\alpha_{Le} \neq 0$)

In this case, it is assumed that the only uncertain parameter existing in the model is electric load. The objective function in this case is radius of electric load uncertainty [not the total cost (benefit)]. The following optimization is solved:

Table 5.3 The hourly optimal schedule of energy hub $\beta = 30\,\%$ under Pw(t) uncertainty

Time (h)	$Pe_b(t)$	$Pe_s(t)$	$Pg(t)$	$Pg_{chp}(t)$	$Pg_f(t)$	$\sum_v Pc(t,v)$	$\sum_v Pd(t,v)$
t1	0	7	6.245	6.245	0	0	3.353
t2	0	7	7.808	7.808	0	0	3.145
t3	0	3.729	8.787	8.787	0	0.36	0
t4	7	0	5.974	0	5.974	7.63	0
t5	7	0	5.306	0	5.306	7.708	0
t6	0	4.569	9.502	9.502	0	0	0
t7	0	7	9.385	9.385	0	0	2.568
t8	0	7	10	10	0	0	0.724
t9	0	7	9.044	8.159	0.885	0	0
t10	0	7	9.091	9.091	0	2.048	0
t11	0	7	8.387	6.866	1.522	2.862	0
t12	0	7	5.544	0	5.544	1.511	0
t13	0	7	7.214	4.718	2.496	4.031	0
t14	0	7	6.536	3.663	2.874	4.378	0
t15	0	7	6.183	3.391	2.792	4.061	0
t16	0	7	8.23	8.23	0	6.186	0
t17	0	7	6.603	4.656	1.947	5.129	0
t18	0	7	8.807	8.807	0	5.439	0
t19	0	7	5.448	0	5.448	1.087	0
t20	0	7	9.011	9.011	0	3.582	0
t21	0	7	6.002	4.207	1.795	0	0
t22	0	7	8	8	0	0	0.389
t23	0	7	7.558	7.558	0	0	0.835
t24	0	5.113	6.713	6.713	0	0	0

$$\max_{DV_w} \alpha_{Le} \tag{5.32}$$

$$\mathrm{OF} \leq \mathrm{OF}_b + \beta|\mathrm{OF}_b| \tag{5.33}$$

Subject to: (5.9–5.24)

$$\alpha_{Lh} = \alpha_w = 0 \tag{5.34}$$

$$\mathrm{DV}_{Le} = \{\mathrm{DV}_b,\ \alpha_{Le}\} \tag{5.35}$$

The objective function is defined as α_{Le} and the decision maker tries to maximize it for a given β value. In this way, the traditional objective function OF would be immune against the electric load uncertainty. This means that even if the forecasted value of electric load is not equal to the real value, the total payments do not increase more than β percent of the base case costs OF_b. The β is increased from 0 to 1 and the variation of different variables versus β is shown in Fig. 5.8.

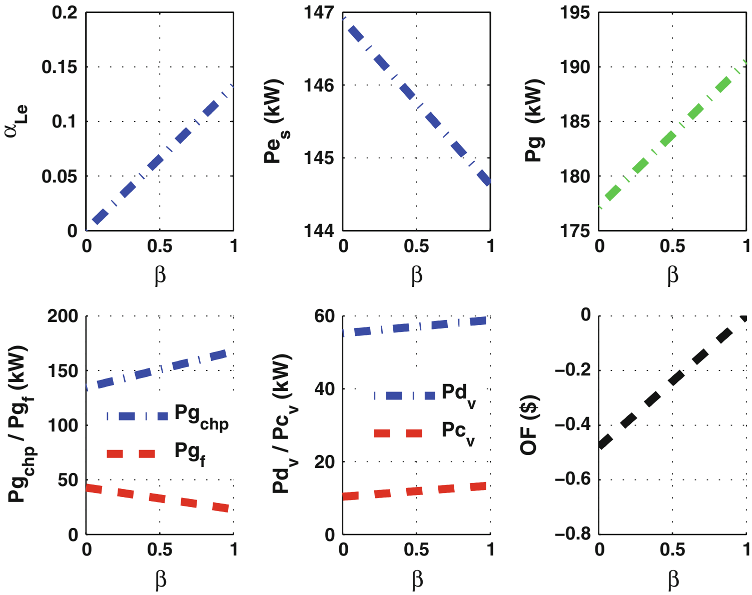


Fig. 5.8 The variation of different variables versus β (uncertain electric load)

In this way, the decision maker has a portfolio of the decision variables (DV_{Le}) for each β. For clarification, the decision variables are given in Table 5.4 for $\beta = 30\,\%$. In this table, the hourly optimal schedule of energy hub $\beta = 30\,\%$ under Le(t) uncertainty are described. The total payments would be OF = − \$0.336115 and the maximum wind uncertainty that can be tolerated would be $\alpha_{Le} = 3.963492\,\%$.

5.4.4 *Uncertain Heat Load* ($\alpha_{Lh} \neq 0$)

In this case, it is assumed that the only uncertain parameter existing in the model is heat load. The objective function in this case is radius of heat demand uncertainty (not the total cost (benefit)). The following optimization is solved:

$$\max_{DV_{Lh}} \alpha_{Lh} \tag{5.36}$$

$$\mathrm{OF} \leq \mathrm{OF}_b + \beta|\mathrm{OF}_b| \tag{5.37}$$

Subject to: (5.9–5.24)

Table 5.4 The hourly optimal schedule of energy hub $\beta = 30\,\%$ under Le(t) uncertainty

Time (h)	$Pe_b(t)$	$Pe_s(t)$	$Pg(t)$	$Pg_{chp}(t)$	$Pg_f(t)$	$\sum_v Pc(t,v)$	$\sum_v Pd(t,v)$
t1	0	7	6.245	6.245	0	0	3.398
t2	0	7	7.808	7.808	0	0	3.213
t3	0	3.645	8.787	8.787	0	0.359	0
t4	7	0	5.974	0	5.974	7.533	0
t5	7	0	8.843	8.843	0	10.707	0
t6	0	4.482	9.502	9.502	0	0	0
t7	0	7	9.385	9.385	0	0	2.657
t8	0	7	10	10	0	0	0.781
t9	0	7	9.079	8.246	0.832	0	0
t10	0	7	9.091	9.091	0	2.048	0
t11	0	7	9.402	9.402	0	3.778	0
t12	0	7	5.544	0	5.544	1.557	0
t13	0	7	5.327	0	5.327	2.442	0
t14	0	7	8.452	8.452	0	6.134	0
t15	0	7	4.826	0	4.826	2.955	0
t16	0	7	7.247	5.774	1.473	5.417	0
t17	0	7	4.74	0	4.74	3.594	0
t18	0	7	8.343	7.646	0.697	5.114	0
t19	0	7	7.686	5.595	2.091	3.111	0
t20	0	7	5.407	0	5.407	0.489	0
t21	0	7	7.199	7.199	0	1.079	0
t22	0	7	8	8	0	0	0.385
t23	0	7	7.558	7.558	0	0	0.835
t24	0	5.101	6.713	6.713	0	0	0

$$\alpha_{Le} = \alpha_w = 0 \tag{5.38}$$

$$\mathrm{DV}_{Lh}=\{\mathrm{DV}_b, \alpha_{Lh}\} \tag{5.39}$$

The interpretation of each β value is simply defined as the relaxation degree of objective function. The objective function is defined as α_{Lh} and the decision maker tries to maximize it for a given β value. In this way, the traditional objective function OF would be immune against the heat load uncertainty. This means that even if the forecasted value of heat load is not equal to the real value, the total payments do not increase more than β percent of the base case costs OF_b. The β is increased from 0 to 1 and the variation of different variables (DV_{Lh}) versus β is shown in Fig. 5.9.

In this way, the decision maker has a portfolio of the decision variables (DV_{Lh}) for each β. For clarification, the decision variables are given in Table 5.5 for $\beta = 30\,\%$. In this table, the hourly optimal schedule of energy hub $\beta = 30\,\%$ under

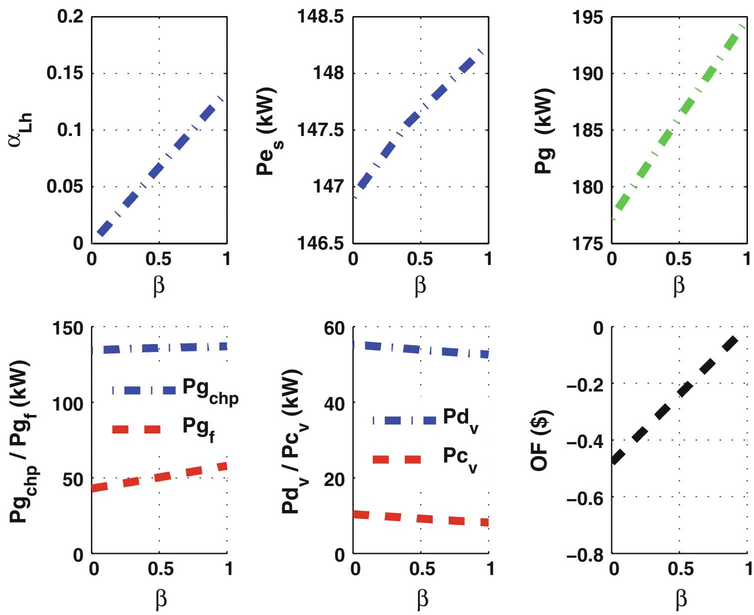


Fig. 5.9 The variation of different variables versus β (uncertain heat load)

Lh(t) uncertainty are described. The total payments would be OF = − $0.336115 and the maximum wind uncertainty that can be tolerated would be $\alpha_{Lh} = 4.040376\,\%$.

5.5 Comparison and Discussion

In this section, the four assessed cases are compared and discussed. The simulation results show that in order to increase the robustness of the decision variables against the wind uncertainty, some actions should be taken. Selling electricity to the pool should be reduced. This holds also for reducing the undesired impacts of electric demand uncertainty. In contrary to these two cases, the energy selling to the pool market should be increased in order to avoid the financial risks due to uncertainty of heat load. Increasing the amount of gas purchase would have positive impacts on reducing the risks of all uncertain parameters (including wind power generation, electric and heat load). However in order to make the objective function immune to uncertainty of wind and electric load, the share of the natural gas which is fed into the CHP unit is increased and the furnace share is decreased. The decision maker should increase the share of furnace unit to avoid the risks of uncertain heat demand. The amount of PEVs in charging and discharging should be increased in order to handle the uncertainties of wind and electric load in contrary to the

Table 5.5 The hourly optimal schedule of energy hub $\beta = 30\,\%$ under Lh(t) uncertainty

Time (h)	$Pe_b(t)$	$Pe_s(t)$	$Pg(t)$	$Pg_{chp}(t)$	$Pg_f(t)$	$\sum_v Pc(t,v)$	$\sum_v Pd(t,v)$
t1	0	7	6.497	6.497	0	0	3.181
t2	0	7	8.123	8.123	0	0	2.943
t3	0	4.272	9.142	9.142	0	0.042	0
t4	7	0	6.331	0.29	6.041	7.831	0
t5	7	0	5.52	0	5.52	7.809	0
t6	0	4.814	9.886	9.886	0	0	0
t7	0	7	9.764	9.764	0	0	2.326
t8	0	7	10.404	10.404	0	0	0.447
t9	0	7	9.096	7.705	1.391	0	0
t10	0	7	9.458	9.458	0	2.365	0
t11	0	7	5.869	0	5.869	0.677	0
t12	0	7	5.768	0	5.768	1.749	0
t13	0	7	5.542	0	5.542	2.632	0
t14	0	7	8.793	8.793	0	6.435	0
t15	0	7	8.369	8.369	0	6.057	0
t16	0	7	5.137	0	5.137	3.564	0
t17	0	7	8.219	8.219	0	6.639	0
t18	0	7	7.553	5.138	2.415	4.391	0
t19	0	7	8.295	6.565	1.729	3.593	0
t20	0	7	5.625	0	5.625	0.619	0
t21	0	7	6.002	3.771	2.231	0	0
t22	0	7	8.323	8.323	0	0	0.156
t23	0	7	7.864	7.864	0	0	0.615
t24	0	5.307	6.984	6.984	0	0	0

uncertain head load case. The comparison between different cases and the actions to be taken is shown in Fig. 5.10.

Some lines of future research can be concluded from this work, as follows:

- To consider more elements (like energy conversion and storage units) in energy hub
- To consider other uncertain parameters affecting the performance of the energy hub
- To consider the possibility of participating in other markets in addition to energy market
- To assess the Impacts of smart grids on energy hub energy management policies
- To analyze the reliability issues of elements in energy hub
- To develop a model for describing the interaction of multiple energy hubs from technical and economical points of view
- To incorporate the grid (gas and electric) integration constraints of energy hubs

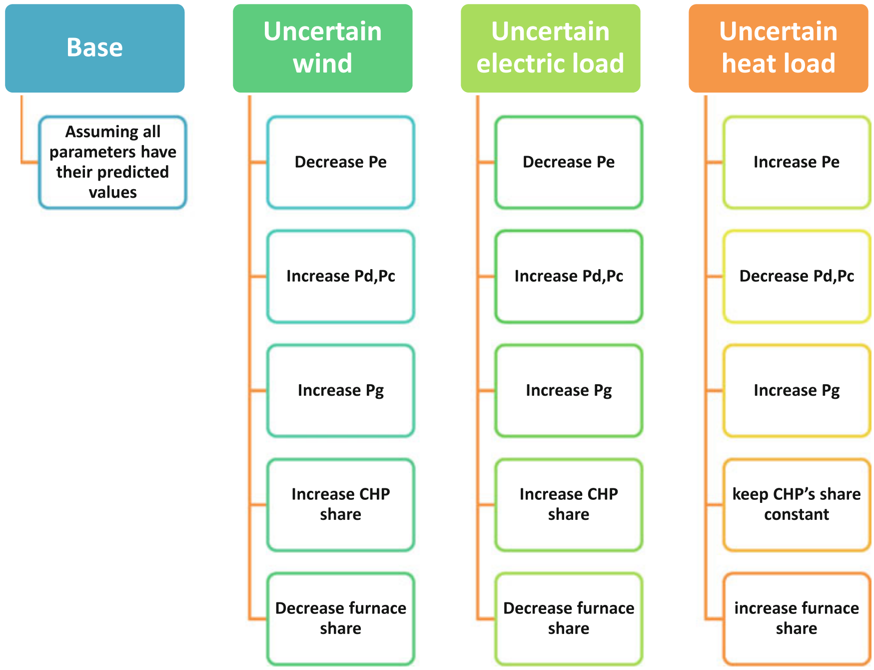


Fig. 5.10 The comparison between different cases and the actions to be taken

5.6 Conclusions

The problem of considering the input uncertainties within the context of the energy hub management has been addressed in this chapter. An IGDT based technique was proposed to obtain the optimal operating strategy of the energy hub. The PEVs have been used as the energy storage device in order to maximize the flexibility of decision making framework. The optimal energy procurement from different resources is determined taking into account the influence of electric/heat demand as well as the wind power generation uncertainties. The obtained results from the proposed risk-averse strategy assures the decision maker that although the predicted values of the uncertain input parameters are not exact, the outcome of the proposed model (payments) would be immune against the prediction error to some controlled extent. The method can be extended to consider the risk seeking behavior of opportunistic decision maker.

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