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Short-term Scheduling Strategy for Wind-based Energy Hub: A Hybrid Stochastic/IGDT Approach

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***Abstract*— This paper evaluates the scheduling problem for energy hub system consisting of wind turbine, combined heat and power units (CHP), auxiliary boilers and energy storage devices via hybrid stochastic/information gap decision theory (IGDT) approach. Considering that energy hub plays an undeniable role as the coupling among various energy infrastructures, still it is essential to be investigated in both modeling and scheduling aspects. On the other hand, penetration of wind power generation is significantly increased in energy infrastructures in recent years. In response, this paper aims to focus on the hybrid stochastic/IGDT optimization method for the optimal scheduling of wind integrated energy hub considering the uncertainties of wind power generation, energy prices and energy demands explicitly in a way that not only global optimal solution can be reached, but also volume of computations can be lighten. In addition, by the proposed hybrid model, the energy hub operator can pursue two different strategies to face with price uncertainty, i.e., risk-seeker strategy and risk-averse strategy. This method optimizes energy hub scheduling problem in uncertain environment by mixed-integer non-linear programming (MINLP). This formulation is proposed to minimize the expected operation cost of energy hub where different energy demands of energy hub would be efficiently met. The forecast errors of uncertainties related to wind power generation and energy demands are modeled as a scenario, while an IGDT optimization approach is proposed to model electricity price uncertainty.**

***Index Terms*— Energy hub, wind power generation, information gap decision theory (IGDT), stochastic optimization, uncertainty.**

NOMENCLATURE

Indices:

m	Index for boilers, from [1: *M*].
n	Index for CHP units, from [1: *N*].
s	Index for scenarios, from [1: *S*].
t	Index for time periods, from [1: *T*].
k	Index for cost deviation factor steps, from [1: *K*].

Parameters:

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$EL_{Min/Max}^{CHP_n}$	Lower/upper limits of the CHP units outputs.
$TH_{Min/Max}^{Boiler_m}$	Lower/upper limits of the boilers outputs.
$ES_{Min/Max}$	Minimum/ maximum stored energy of electrical energy storage.
$TS_{Min/Max}$	Minimum/maximum stored energy of thermal energy storage.
$\lambda^{e/g}$	The price of the electricity /natural gas.
$\tilde{\lambda}^{e}$	Forecasted electricity price.
$Z_{\cos t}^{0}$	The basic cost of the stochastic optimization.
HV	Heat value of the natural gas.
HPR_n	Heat to power ratio of the CHP units.
η_{HE}	Efficiency of the heat exchanger.
MCC	Maintenance cost coefficient.
$EL^{Ramp-up/Ramp-down}$	Ramp-up/ramp-down rates of the CHP units.
SUC, SDC	The start-up and shut-down cost of CHP units.
π_s	Probability of scenario *s*.
η^{CHP}	Electrical efficiency of the CHP units.
η^{Boiler}	Efficiency of boilers.
$\eta^{ES/TS}$	Standby efficiency of the electrical/thermal energy storage.
$VOLL$	The value of lost load.
$P_{s,t}^{wind}$	Power generation of wind turbine at scenario *s* and time *t*.
$ED_{s,t}$, $TD_{s,t}$	Electrical and thermal demands at scenario *s* and time *t*.

Variables:

$OC_{s,t}, OB_{s,t}$	Operation cost of CHP units and boilers at scenario *s* and time *t*.
$PC_{s,t}$	Penalty cost at scenario *s* and time t.
$STUC_t$, $SHDC_t$	Startup and shutdown costs of the CHP units at time *t*.
$FC_{s,n,t}$, $MC_{s,n,t}$	Fuel and maintenance costs of the n^{th} CHP unit at scenario *s* and time *t*.

$FB_{s,m,t}$, $MB_{s,m,t}$	Fuel and maintenance costs of the m^{th} boiler at scenario *s* and time *t*.
$EL_{s,n,t}^{CHP}$	Electricity generation of the n^{th} CHP unit at scenario *s* and time *t*.
$TH_{s,m,t}^{Boiler}$	Thermal generation of the m^{th} boiler at scenario *s* and time *t*.
$ES_{s,t}$	Amount of stored energy in the electrical energy storage at scenario *s* and time *t*.
$ES_{s,t}^{ch}$, $ES_{s,t}^{dch}$	Electrical input and output of the electrical energy storage at scenario *s* and time *t*.
$TS_{s,t}$	Amount of stored energy in the thermal energy storage at scenario *s* and time *t*.
$TS_{s,t}^{ch}$, $TS_{s,t}^{dch}$	Thermal input and output of the thermal energy storage at scenario *s* and time *t*.
$EL_{s,t}^{Grid,in/out}$	Amount of imported/exported electricity at scenario *s* and time *t*.
$ESH_{s,t}$, $TSH_{s,t}$	Amount of electrical and thermal curtailed loads at scenario *s* and time *t*.
EB_s	Cost of buying electricity from local grid at scenario *s*.
ES_s	Income of selling electricity to local grid at scenario *s*.

Functions:

$U\left(\tilde{\lambda}_t^e, \alpha\right)$	Uncertainty model in IGDT method.
$\hat{\alpha}(EL, Z_w^{\cos t})$	Robustness function.
$\hat{\beta}(EL, Z_k^{\cos t})$	Opportunity function.

I. Introduction

A. Motivation and Problem Description

As the penetration of intermittent renewable energy resources increase substantially in energy infrastructures, renewable generation intermittency and variability causes big challenges on energy infrastructure scheduling. Among the renewable energy resources, wind generation assigns a remarkable portion of the renewable generations, due to energy balance efficiency and low marginal operating costs [1]. However, one possibility to smooth the effect of limited predictability and uncertainty of wind generation as well as convert potential possibility of these kinds of resources into actual solutions is coordinating different energy infrastructures [2]. An energy hub can be defined as an interface between various energy infrastructures such as electricity and natural gas networks [3-5]. On the other hand, an energy hub can reduce consumption of primary energy, the sequential pollutant emissions and the cost of energy consumption [4, 6]. Towards the goal of supplying energy demands in an economical, environmentally friendly and reliable way, planning, operation, and energy management of energy hub systems have been extensively investigated recently. An essential problem of the associated planning and scheduling tasks is to consider the effect of uncertainties associated with wind power, energy demands and energy market tariffs so that total energy demands can be served, while the cost of serving energy to customers is minimized.

B. Literature Review

Many studies have investigated energy hub scheduling and planning assessments based on numerical and simulation methods [4, 7-9]. Optimization of a long-term energy hub expansion planning model for multiple energy networks consisting of electricity, natural gas, and district is studied in [4], which determines the least-cost planning schedule of candidate CHPs, generating units, transmission lines, and natural gas furnaces. In [7], a mathematical optimization models for residential energy hubs in presence of smart grid and automated decision making technologies is proposed, which not only minimize energy demands and total cost of energy consumption but can also reduce emissions and peak load of the hubs. All these efforts build the scheduling models on deterministic optimization and do not take into account uncertainties of renewable resources. Considerable efforts have been devoted to the operational and economic impact of wind power uncertainty on the energy hub planning and scheduling problems. In [10], an optimal operation model for an energy hub considering uncertainty of wind, price and demand is proposed. The wind power generation and energy prices changes in combination with energy demand variations have been envisaged using two stage stochastic programming method. A new model for medium-term energy hub management problem in restructured power systems is proposed in [11], in which focusing on uncertain nature of pool prices and wind turbine production in an energy hub has been studied. Conditional value at risk (CVaR), a well-known risk measure, is employed to determine the best strategy for hub operator to cover the uncertainties in a secure way and reduce the unfavorable risk of different options. In [12], a stochastic approach to design an energy hub consisting of intermittent resources, storage devices, and combined heat and power (CHP) system is proposed. In addition, in order to secure operation and supply energy demands with desirable reliability level, reliability indices such as loss-of-load expectation (LOLE) and expected energy not supplied (EENS) are considered in the energy hub design problem. The uncertain parameters, including the power output of the renewable resources, energy demands and the random outages of the energy hub system components are modeled via scenarios based upon historical data using the Monte Carlo simulation method. In [13], an optimization and modeling framework for multi energy carrier (MEC) systems online economic dispatch is pinpointed, where the authors offer multiagent genetic algorithm (MAGA) as a promising approach to deal with economic dispatch problem in the cases of energy hubs. Furthermore, a decomposed model is introduced to reduce the computational burden of the online economic dispatch optimization model. A new framework to coordinate the charging process of plug-in hybrid electric vehicles (PHEVs) in the context of energy hubs is proposed in

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TABLE I
COMPARING THE PROPOSED METHOD WITH DIFFERENT STUDIES

References	Study field	Uncertainties			Uncertainty modeling
		Wind	Electricity price	Demand	
[15]	Operation	✖	✖	✔	Stochastic
[12]	Planning	✔	✖	✔	Stochastic
[16]	Operation	✔	✖	✔	IGDT
[17]	Operation	✔	✖	✖	Robust
[18]	Operation	✖	✖	✖	Robust
Proposed	Operation	✔	✔	✔	Hybrid stochastic/IGDT

[14]. Optimal charging patterns of PHEVs are derived from the vehicle owners' and system operator's viewpoint. The optimization problem is formulated as a multiobjective particle swarm optimization and applied to the modified IEEE 34-node test system. Additionally, in the proposed model, uncertainties of scheduling problem are modeled by the 2-point estimation method.

Due to that the uncertain nature of renewable energy, demand and price plays an important role in increasing volume of computations in stochastic programming approach, the information gap decision theory (IGDT) technique and robust optimization, which can handle the forecast errors of uncertainties related to energy systems scheduling, has been the subject of keen considerations in the past papers [16-18]. A comprehensive risk hedging model for energy hub management problem is proposed in [16] for minimizing both the energy procurement cost and financial risks in energy hub. In [17], a robust optimization model is used to analyze interdependencies of various energy infrastructures, such as electricity, coal and natural gas considering their technical constraints and wind power uncertainties. An optimization-based framework to manage household demand in a renewable-based residential energy hub environment is proposed in [19]. The model includes a micro-CHP unit, a PHEV, a heat storage unit, generic electrical appliances, heating appliances, and rooftop solar panels. The uncertainty related to the output power of solar panels is modeled using two-point estimate method. In [15], a daily scheduling of smart grid using smart energy hubs framework is presented. The most important innovation of this paper is applying stochastic demand response. Customers participating and the selection of different carriers by the customers are the main sources of uncertainty. A probabilistic energy flow analysis framework for integrated electrical and gas systems is proposed in [20]. Different aspects of couplings between electrical and gas systems such as gas-fired generators, electric-driven compressors and energy hubs integrated with power to gas units are investigated. Table I summarizes taxonomy of proposed methodologies in modeling and studying of energy hub systems.

C. Contributions

When it comes to modeling the scheduling problem in the energy hubs, a main challenge arises in addressing the unavoidable uncertainties imposed by the renewable resources and reducing the computational volume of finding the global optimal of the problem. Motivated by the aforementioned facts, this paper endeavors to outline an optimization and modeling framework for scheduling problem of energy hubs. To the best of authors' knowledge, no similar hybrid model for energy hub scheduling problem has been proposed in the past literature. The main contribution of this paper is to propose a new hybrid stochastic/IGDT optimization model for the energy hub scheduling problem. Compared to existing methods, the proposed hybrid stochastic/IGDT optimization approach is considered as a promising approach not only in achieving the high-quality solutions but also in reducing computational burden of optimization problems. The main contributions of this work can be summarized as follows.

1) Integrating renewable resources into the modern energy systems requires risk-cognizant dispatch of resources to account for the stochastic availability of renewable energies. Toward this goal, a new model for energy hub scheduling is proposed in this paper based on the hybrid stochastic/IGDT optimization method.

2) The proposed hybrid method takes the advantages of both the stochastic and IGDT optimization approaches. It can provide an energy hub scheduling decision that can lead to a minimum expected total cost while modeling the error between the practical and forecasted amount of the uncertain parameters.

3) It can provide two different strategies for the energy hub operator to face with price uncertainty, i.e., risk-seeker strategy and risk-averse strategy.

D. Paper Organization

The rest of this paper is laid out as follows. Section II introduces and discusses the mathematical modeling of energy hub scheduling problem based on hybrid stochastic/IGDT method. Section III presents the results of an application case. Finally, the conclusion drawn from this paper is provided in Section IV.

II. Energy Hub Scheduling Based on Hybrid Stochastic/IGDT Optimization

The stochastic nature of wind power generation, electrical and thermal loads and the uncertainty relevant to electricity price make a challenge for the energy hub systems to schedule the operation of the CHP units and other facilities in an optimal way. By taking this challenge, in this paper, three sets of possible scenarios for modeling wind generation, electrical and thermal loads uncertainties are considered and the IGDT

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method for modeling electricity price uncertainty in the optimal operation problem is applied.

A. Scheduling strategy based on stochastic programming

This section describes a scheduling framework for energy hub based on pure stochastic optimization. The stochastic programming is an appropriate approach to make decisions under probabilistic and uncertain situation [21]. The energy hub operator applies the stochastic optimization to determine the optimal production schedules of combined heat and power (CHP) units and auxiliary boilers, amount of imported and exported electricity in the market, as well as the charging and discharging states of the energy storages. The uncertainties related to wind power generation and electrical and thermal loads are characterized via different scenarios based on forecast results or historical data [22]. Additionally, an effective scenario reduction method is also used to reduce the number of scenarios and the computational burden of the scheduling problem.

The Monte Carlo simulation method is used to generate a set of possible scenarios for modeling uncertainties associated with the energy hub system. One of the principal advantages of the Monte Carlo simulation method is that the required number of samples for a given accuracy level is totally independent of the scale of simulation and system size. Since computational burdens of solving the stochastic programming optimization problems significantly depend on the number of scenarios, it is crucial to exert a proper scenario reduction method for solving large scale stochastic problems.

1) Wind power modeling

Due to the great flexibility, the Rayleigh or Weibull PDF has been generally used to model the intermittency and the volatility of wind speed [23, 24]. In this paper, the Rayleigh PDF is applied to model the variation of wind speed, υ [25]:

$$\mathrm{PDF}(\upsilon)=\left(\frac{\upsilon}{c^2}\right)exp\left[-\left(\frac{\upsilon^2}{2c^2}\right)\right] \tag{1}$$

The wind generation is dependent on wind speed and can be formulated as follows:

$$P_s^{wind}(\upsilon)=\begin{cases}0 & \text{if } \upsilon\le\upsilon_{in}^c \text{ or } \upsilon\ge\upsilon_{out}^c\\ \dfrac{\upsilon-\upsilon_{in}^c}{\upsilon_r-\upsilon_{in}^c}P_s^r & \text{if } \upsilon_{in}^c\le\upsilon\le\upsilon_r\\ P_s^r & 0\end{cases} \tag{2}$$

Where P_s^r is rated output power of wind turbine and also, υ_{in}^c , υ_r and υ_{out}^c are the cut-in, rated and cut-out wind speed, respectively.

2) Demands modeling

Usually demand uncertainty can be modeled by the normal of Gaussian PDF [23]. It is assumed that the mean and standard deviation of the normal distribution related to the electrical and thermal demands are known.

3) Scenario reduction

Since computational necessity for solving optimization problems with a lot of scenarios appertain to the number of scenarios, it is necessary to reduce number of scenarios with an impressive scenario reduction method. The reduction technique is a scenario-based approximation to keep required features of the primary scenarios [26]. In this work, the SCENRED tool for scenario reduction process, which is provided by the General Algebraic Modeling System (GAMS), has been applied [24]. In the current paper, at the first, two stages stochastic scheduling problem of the proposed energy hub is solved based on the forecasted electricity price, $\tilde{\lambda}_t^e$.

4) Stochastic optimization model

The objective function minimizes the net cost of energy hub scheduling problem based on the forecasted electricity price. The terms of the optimization are the generation costs of the CHP units and boilers, the cost and benefit of the buying and selling electricity to local grid, unsupplied demands penalty cost, startup and shutdown costs of the CHP units in each scenario and time blocks of scheduling horizon (3).

$$Min\ Z^{\cos t}=Min\sum_{t=1}^{T}\sum_{s=1}^{S}\pi_s\times\Big\{OC_{s,t}+OB_{s,t}+\left(EL_{s,t}^{Grid,in}\times\lambda_t^e\right)-\left(EL_{s,t}^{Grid,out}\times\lambda_t^e\right)+PC_{s,t}\Big\}+STUC_t+SHDC_t \tag{3}$$

CHP units' constraints:

The operation costs of CHP units which consist of fuel cost (*FC*) and maintenance cost (*MC*) are shown by (4).

$$OC_{s,t}=\sum_{n=1}^{N}\left(FC_{s,n,t}+MC_{s,n,t}\right) \tag{4}$$

Fuel and maintenance cost functions of the CHP units are formulated as (5) and (6).

$$FC_{s,n,t}=EL_{s,n,t}^{CHP}\times\left(\frac{\lambda_t^g}{\eta_n^{CHP}\times HV}\right) \tag{5}$$

$$MC_{s,n,t}=EL_{s,n,t}^{CHP}\times MCC_n^{CHP} \tag{6}$$

It should be noted that the power and thermal outputs of the CHP units are interrelated and could not be regulated separately. Limitations of the electrical and thermal generations of the CHP units are given by (7) and (8), respectively.

$$EL_{\min}^{CHP_n}\le EL_{s,n,t}^{CHP}\le EL_{\max}^{CHP_n} \tag{7}$$

$$TH_{s,n,t}^{CHP}=EL_{s,n,t}^{CHP}\times HPR_n\times\eta_{HE} \tag{8}$$

It should be mentioned that the power and thermal outputs of the CHP units cannot fluctuate too rapidly. Therefore, Ramp-up and ramp-down constraints are expressed as (9) and (10), respectively.

$$EL_{s,n,t}^{CHP}-EL_{s,n,t-1}^{CHP}\le u_{n,t-1}\times EL^{Ramp-up}+x_{n,t}\times EL_{Min}^{CHP_n} \tag{9}$$

$$EL_{s,n,t-1}^{CHP}-EL_{s,n,t}^{CHP}\le u_{n,t}\times EL^{Ramp-down}+y_{n,t}\times EL_{Min}^{CHP_n} \tag{10}$$

In the above equations $u_{n,t}$ is the binary variable which

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equals to 1 if each of the CHP units be in the ON state and 0 otherwise. Likewise, start-up and shut-down status of the CHP units are shown by $x_{n,t}$ and $y_{n,t}$ which are binary variables. In addition, equations (11) and (12) explain CHP unit's start-up and shut-down costs.

$$STUC_t = \sum_{n=1}^{N}\left(x_{n,t} \times SUC\right) \tag{11}$$

$$SHDC_t = \sum_{n=1}^{N}\left(y_{n,t} \times SDC\right) \tag{12}$$

Moreover, constraints (13)-(17) are introduced to ensure that binary variables take the correct values.

$$0 \le x_{n,t} \le u_{n,t} \tag{13}$$

$$u_{n,t} - u_{n,t-1} \le x_{s,n,t} \le 1 - u_{n,t-1} \tag{14}$$

$$0 \le y_{n,t} \le u_{n,t-1} \tag{15}$$

$$u_{n,t-1} - u_{n,t} \le y_{n,t} \le 1 - u_{n,t} \tag{16}$$

$$u_{n,t-1} - u_{n,t} + x_{n,t} - y_{n,t} = 0 \tag{17}$$

Boiler system operation cost and constraints:

The operation costs of boilers are similar to CHP units and are defined by (18)-(20):

$$OB_{s,t} = \sum_{m=1}^{M}\left(FB_{s,m} + MB_{s,m}\right) \tag{18}$$

$$FB_{s,m,t} = TH_{s,m,t}^{Boiler} \times \left(\frac{\lambda_t^g}{\eta_m^{Boiler} \times HV}\right) \tag{19}$$

$$MB_{s,m,t} = TH_{s,m,t}^{Boiler} \times MCC_m^{Boiler} \tag{20}$$

The range of boilers outputs are expressed by (21). In the following equation TH_{Max}^{Boiler} and TH_{Min}^{Boiler} are the maximum and minimum limits of the boilers outputs, respectively.

$$TH_{Min}^{Boiler_m} \le TH_{s,m,t}^{Boiler} \le TH_{Max}^{Boiler_m} \tag{21}$$

Electrical energy storage (EES) system constraints:

Equation (22) indicates the storage transition function in the EES. Limitation of the electrical energy, which can be stored in the EES, is shown in (23). Equations (24) and (25) refer to maximum and minimum charging and discharging capacity of the EES, respectively.

$$ES_{s,t} = \left(ES_{s,t-1} \times \eta^{ES}\right) + \left(ES_{s,t}^{ch} \times \eta_{ch}^{ES}\right) - \left(ES_{s,t}^{dch} / \eta_{dch}^{ES}\right) \tag{22}$$

$$ES_{Min} \le ES_{s,t} \le ES_{Max} \tag{23}$$

$$ES_{Min}^{ch} \le ES_{s,t}^{ch} \le ES_{Max}^{ch} \tag{24}$$

$$ES_{Min}^{dch} \le ES_{s,t}^{dch} \le ES_{Max}^{dch} \tag{25}$$

Where, $\eta_{ch/dch}^{ES}$, $ES_{Min/Max}^{ch}$ and $ES_{Min/Max}^{dch}$ are charging/discharging efficiency and minimum/maximum range of the charging and discharging of the EES, respectively.

Thermal energy storage (TES) system constraints:

The constraints of the TES are similar to EES system constraints that are explained in (26)-(29).

$$TS_{s,t} = \left(TS_{s,t-1} \times \eta^{TS}\right) + \left(TS_{s,t}^{ch} \times \eta_{ch}^{TS}\right) - \left(TS_{s,t}^{dch} / \eta_{dch}^{TS}\right) \tag{26}$$

$$TS_{Min} \le TS_{s,t} \le TS_{Max} \tag{27}$$

$$TS_{Min}^{ch} \le TS_{s,t}^{ch} \le TS_{Max}^{ch} \tag{28}$$

$$TS_{Min}^{dch} \le TS_{s,t}^{dch} \le TS_{Max}^{dch} \tag{29}$$

Likewise, $\eta_{ch/dch}^{TS}$, $TS_{Min/Max}^{ch}$ and $TS_{Min/Max}^{dch}$ are charging/discharging efficiency and minimum/maximum range of charging and discharging of the TES, respectively.

Local grid connection constraints:

Cost and benefit of the buying/selling electrical energy from/to the local grid are formulated by (30) and (31).

$$EB_s = \sum_{t=1}^{T} \lambda_t^e \times EL_{s,t}^{Grid,in} \tag{30}$$

$$ES_s = \sum_{t=1}^{T} \lambda_t^e \times EL_{s,t}^{Grid,out} \tag{31}$$

The limitations on the capacity of the connection lines between energy hub and local grid in each time blocks of scheduling are defined by (32) and (33). Equation (34) prevents electrical energy being sent to and received from local grid. In the following equations $EL_{\max}$ shows electrical cable line capacity, as well as i and j are binary variables which illustrate buying and selling electricity status, respectively.

$$EL_{s,t}^{Grid,in} \le i_{s,t} \times EL_{Max}^{Grid,in} \tag{32}$$

$$EL_{s,t}^{Grid,out} \le j_{s,t} \times EL_{Max}^{Grid,out} \tag{33}$$

$$i_{s,t} + j_{s,t} \le 1 \tag{34}$$

Power balancing constraints:

The following constraints express that the supplied electrical and thermal power by the energy hub components and the grid must satisfy the electrical and thermal demands in the scheduling horizon.

$$ED_{s,t} - ESH_{s,t} \le \sum_{n=1}^{N} EL_{s,n,t}^{CHP} + EL_{s,t}^{Grid,in} - EL_{s,t}^{Grid,out} + ES_{s,t}^{ch} - ES_{s,t}^{dch} + P_{s,t}^{wind} \tag{35}$$

$$TD_{s,t} - TSH_{s,t} \le \sum_{n=1}^{N} TH_{s,n,t}^{CHP} + \sum_{m=1}^{M} TH_{s,m,t}^{boiler} + TS_{s,t}^{ch} - TS_{s,t}^{dch} \tag{36}$$

In addition, ESH and TSH are electrical and thermal loads which are curtailed.

Penalty cost:

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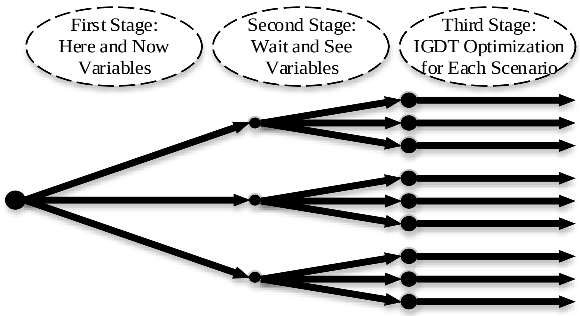

Fig.1. Decisions structure of proposed hybrid stochastic/IGDT optimization approach.

The cost of unsupplied electrical and thermal demands is added to the total energy hub operation cost represented by (37) as a penalty cost based on $VOLLs$.

$$PC_{s,t} = ESH_{s,t} \times VOLL^{E} + TSH_{s,t} \times VOLL^{TH} \tag{37}$$

Where, $VOLL^{E}$ and $VOLL^{TH}$ are the value of electrical and thermal curtailed loads, respectively.

B. Hybrid Stochastic/IGDT Optimization

In this work a hybrid stochastic/IGDT scheduling model is proposed and formulated to minimize the expected net cost. The proposed hybrid stochastic/IGDT scheduling is premier from sheer stochastic scheduling because of two reasons. On one hand, in the pure scenario-based stochastic scheduling, since the computational burden is a function of the number of scenarios, the scale of the model increases dramatically by adding a more uncertain parameter to the problem. While, the IGDT scheduling methods, model the error between the practical and forecasted amount of the uncertainty parameters [27]. On the other hand, by the proposed hybrid model, the energy hub operator can pursue two different strategies to face with price uncertainty: risk-seeker strategy and risk-averse strategy.

In the current paper, the electricity price $\left(\tilde{\lambda}_t^e\right)$ is uncertain therefore the IGDT method tries to solve the third stage of the scheduling problem. The uncertainty set can be formulated as follows:

$$\forall \alpha \in U\left(\tilde{\lambda}_t^e, \alpha\right) = \left\{ \lambda_t^e : \left| \frac{\lambda_t^e - \tilde{\lambda}_t^e}{\tilde{\lambda}_t^e} \right| \le \alpha \right\} \tag{38}$$

Where α is the uncertainty horizon parameter, $\tilde{\lambda}_t^e$ and λ_t^e are the forecasted electricity price and actual price, respectively.

In the proposed energy hub model, IGDT method tries to find an interval for electricity price to study the robustness and opportunity functions. The schematic of the proposed hybrid stochastic/IGDT optimization is depicted in Fig. 1. The first stage decisions (here and now) are those that have to be made before the actual realization of the uncertainties and are not affected from the information arriving in second stage. Subsequently, the second stage decisions (wait and see) are conducted when the uncertain data become known as time evolves. The third stage ensures that results are immune regarding price uncertainties.

In the proposed model due to the electrical demand of the energy hub, it is clear that amount of electricity which is purchased from local grid by energy hub system is more than its components production. Therefore, net cost of the system is dependent on electricity price.

The schematic of the proposed hybrid stochastic/IGDT optimization method is shown in Fig. 2. The cost deviation factor is indicated by d and step of cost deviation factor is denoted by k .

1) Deriving the risk-averse strategy function

Risk-averse strategy desires to schedule in a way to be immune against higher cost due to unfavorable price deviations from the forecasted values. This can be represented as follows:

$$\hat{\alpha}(EL, Z_w^{\cos t}) = Max \left\{ \alpha : \left(\underset{\lambda_t^e}{Max} \quad Z(EL, \lambda_t^e) \le Z_w^{\cos t} \right) \right\} \tag{39}$$

Where, $Z_w^{\cos t}$ is a cost target for the robustness function. The objective of the risk-averse scheduling is to maximize the uncertain variable, α , while the required constraints are satisfied.

$$\hat{\alpha}(EL, Z_w^{\cos t}) = Max \ \ \alpha \tag{40}$$

Subject to:

$$Z_w^{\cos t} = (1 + d_r) Z_{\cos t}^{0} \ge Max \ Z_{\cos t} \tag{41}$$

$$\begin{aligned} Max \ Z_{\cos t} = & Max \sum_{t=1}^{T} \sum_{s=1}^{S} \pi_s \times \Big\{ OC_{s,t} + OB_{s,t} + \left(EL_{s,t}^{Grid,in} \times \lambda_t^e \right) \\ & - \left(EL_{s,t}^{Grid,out} \times \lambda_t^e \right) + PC_{s,t} \Big\} + STUC_t + SHDC_t \end{aligned} \tag{42}$$

$$(1-\alpha)\tilde{\lambda}_t^e \ \le \ \lambda_t^e \le (1+\alpha)\tilde{\lambda}_t^e \tag{43}$$

(4)-(37) (44)

Where, α is the uncertain variable, d_r is a cost deviation factor, $\tilde{\lambda}_t^e$ and λ_t^e are the forecasted electricity price and actual price, respectively. Let's call the result of (3), the basic cost of the stochastic optimization $(Z_{\cos t}^{0})$.

Due to the electrical demand of the energy hub, it is clear that amount of electricity which is purchased from local grid by energy hub system is more than its components production. Therefore, net cost of the system is dependent on electricity price. Also, it is expected that net cost increases with the increase of electricity price. It should be noted the IGDT-based proposed method generally known as bi-level in the studies which can be solved by the typical solutions for bi-level models. The interested readers are referred to [28] for more details and information. In addition, in certain circumstances, the IGDT-based models can be divided into two single level problems [27]. In the proposed scheduling

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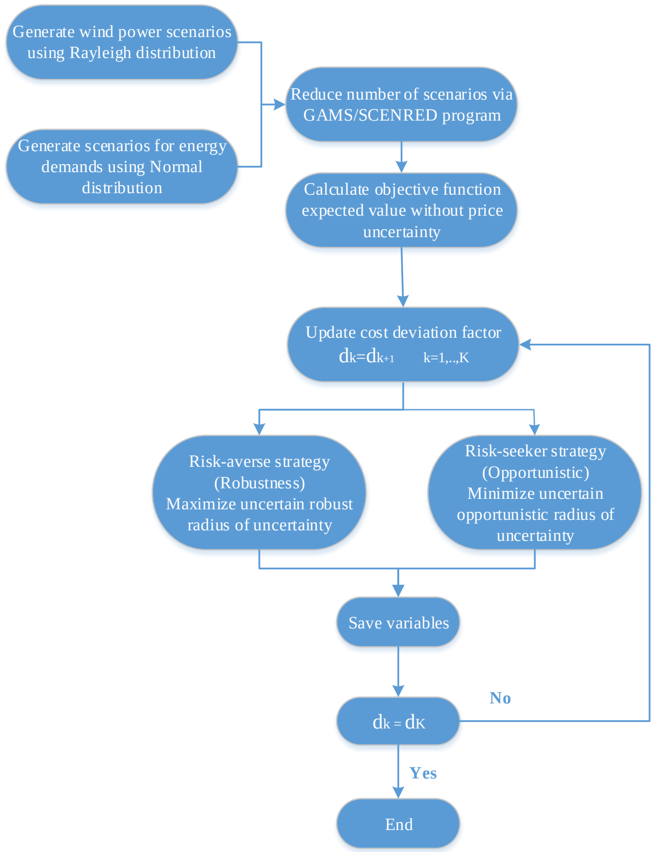

Fig. 2. Schematic of the proposed hybrid stochastic/IGDT optimization method.

problem, amount of imported electricity is definitely more than exported electricity due to that CHPs and wind turbine cannot cover the electrical demand without exchanging with grid. Therefore increasing electricity price has a positive impact on the scheduling cost. In other words, if the market price drops, then the scheduling cost will decrease as well or vice versa if the electricity price increases, the cost will certainly increase. So, the proposed hybrid stochastic/IGDT model can be divided into single level problem in line with [29-31]. With this background, using (38), the electricity price can be illustrated as (45):

$$\lambda_t^e = \tilde{\lambda}_t^e + \alpha\tilde{\lambda}_t^e \tag{45}$$

The maximum net cost in (41) is readily seen to occur for the highest electricity price which the optimization problem related to (40) can be simplified as (46)-(49):

$$\hat{\alpha}(EL, Z_w^{cost}) = Max\ \ \alpha \tag{46}$$

Subject to:

$$Z_w^{cost} = (1+d_r)Z_{cost}^{0} \geq Max\ \ Z_{cost} \tag{47}$$

$$\begin{aligned} Max\ Z_{cost} = & \sum_{t=1}^{T}\sum_{s=1}^{S}\pi_s \times \Big\{OC_{s,t} + OB_{s,t} + \Big(EL_{s,t}^{Grid,in} \times \big(\tilde{\lambda}_t^e + \alpha\tilde{\lambda}_t^e\big)\Big) \\ & - \Big(EL_{s,t}^{Grid,out} \times \big(\tilde{\lambda}_t^e + \alpha\tilde{\lambda}_t^e\big)\Big) + PC_{s,t}\Big\} + STUC_t + SHDC_t \end{aligned} \tag{48}$$

(4)-(37) (49)

It is clear that using Eq. 48 for calculating Z_{cost} will make the model non-linear due to multiplying variables $EL_{s,t}^{Grid}$ and α. The above optimization scheduling problem will give a result that guarantees a maximum cost of Z_w^{cost} if all forecasted errors are less than maximized errors, $\hat{\alpha}$.

2) Deriving the risk-seeker strategy function

When the presented energy hub follows risk-seeker strategy, it is optimistically treating with uncertain parameters that may have positive effects on the objective function. The operation cost of the proposed system is dependent on electricity price, so, the net cost is decreases with the low prices. Risk-seeker strategy desires to schedule at low cost by using these variations and an opportunity function. Actually, this strategy describes the opportunity of obtaining lower costs. The opportunity function in scheduling problem can be formulated as (50):

$$\hat{\beta}(EL, Z_k^{cost}) = Min\left\{\alpha : \left(\underset{\lambda_t^e}{Min}\ \ Z(EL, \lambda_t^e) \leq Z_k^{cost}\right)\right\} \tag{50}$$

Where, Z_k^{cost} is a cost target that the energy hub hopes to operate at this cost in the event of favorable electricity prices. It is noteworthy target cost Z_k^{cost} is generally smaller than Z_w^{cost}. Likewise, a similar formulation can be driven for opportunity function (51)-(55).

$$\hat{\beta}(EL, Z_k^{cost}) = Min\ \ \alpha \tag{51}$$

Subject to:

$$Z_k^{cost} = (1-d_o)Z_{cost}^{0} \geq Min\ Z_{cost} \tag{52}$$

$$\begin{aligned} Min\ Z_{cost} = Min & \sum_{t=1}^{T}\sum_{s=1}^{S}\pi_s \times \Big\{OC_{s,t} + OB_{s,t} + \Big(EL_{s,t}^{Grid,in} \times \lambda_t^e\Big) \\ & - \Big(EL_{s,t}^{Grid,out} \times \lambda_t^e\Big) + PC_{s,t}\Big\} + STUC_t + SHDC_t \end{aligned} \tag{53}$$

$$(1-\alpha)\tilde{\lambda}_t^e \ \leq\ \lambda_t^e \leq (1+\alpha)\tilde{\lambda}_t^e \tag{54}$$

(4)-(37) (55)

As mentioned in the previous subsection the minimum net cost in (52) is readily seen to occur for the lowest price, which is equal to $\tilde{\lambda}_t^e\,(1-\alpha)$. So the bi-level the scheduling problem related to (50) can be reformulated as a single level problem:

$$\hat{\beta}(EL, Z_k^{cost}) = Min\ \ \alpha \tag{56}$$

Subject to:

$$Z_k^{cost} = (1-d_o)Z_{cost}^{0} \geq Min\ Z_{cost} \tag{57}$$

$$\begin{aligned} Min\ Z_{cost} = & \sum_{t=1}^{T}\sum_{s=1}^{S}\pi_s \times \Big\{OC_{s,t} + OB_{s,t} + \Big(EL_{s,t}^{Grid,in} \times \big(\tilde{\lambda}_t^e - \alpha\tilde{\lambda}_t^e\big)\Big) \\ & - \Big(EL_{s,t}^{Grid,out} \times \big(\tilde{\lambda}_t^e - \alpha\tilde{\lambda}_t^e\big)\Big) + PC_{s,t}\Big\} + STUC_t + SHDC_t \end{aligned} \tag{58}$$

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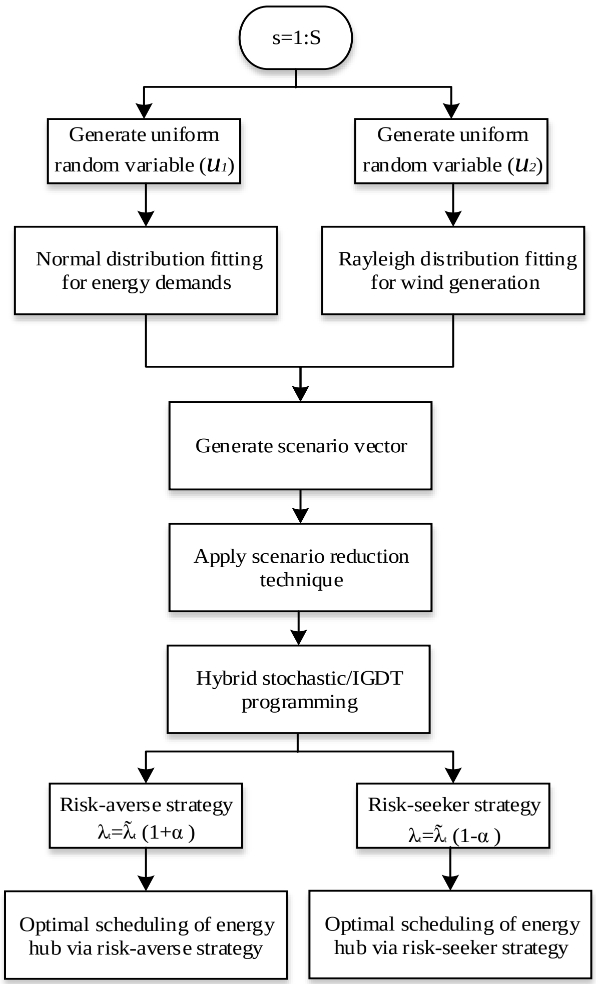

Fig.3. Decisions structure of proposed hybrid stochastic/IGDT optimization approach.

$$(4)\text{-}(37) \tag{59}$$

Note that, $\widehat{\beta}$ is the lowest required electricity price variations that make Z_k^{cost} accessible. The flowchart of the proposed hybrid stochastic/IGDT model has been illustrated in Fig. 3.

III. Simulation Results and Discussions

In this section, the method presented in this paper has been implemented in two comprehensive examples to assess the effectiveness and applicability of the proposed hybrid stochastic/IGDT model.

A. *Case Study I: An Illustrative Example*

In this subsection, to illustrate the effectiveness of the main concept of the paper, some representative results are presented through running the proposed hybrid stochastic/IGDT model on a sample energy hub. To this end, the inputs of energy hub are considered as wind-originated electricity, local grid-received electricity and natural gas, while the outputs are electrical and thermal demands. The generation facilities consist of two CHP units, two boilers, EES and TES as well as the local electricity and natural gas grid connection. Characteristics of the CHP units, boilers, EES and TES are provided in Table II, Table III and Table IV, respectively. The average VOLLs for electrical and heat loads equal 5 $/kWh and 3 $/kWh, respectively. The wind turbine capacity is considered 400 kW. Also, the parameters of wind generation are taken from [32]. Furthermore, the standard deviation of energy demands forecasting are considered to be 3% of the mean value. Monte Carlo simulation approach is used to generate proper scenarios. SCENRED contains two reduction algorithms: The backward method and forward method. The backward method has the best expected performance with respect to response time. On the other hand, the results of the forward method are more accurate, but at the expense of higher computing time [33, 34]. In addition, there are two options in SCENRED for specifying the desired reduction. *Red_num_leaves* which determines the desired number of preserved scenarios and *red_percentage* which works based on the relative distance between the initial and reduced scenarios [35]. In this paper fast backward reduction method is chosen based on the running time and performance accuracy as well as *red_num_leaves* factor is set to be 10. The base value of electrical and thermal energy demands are 1600 and 2950kW, respectively. In addition, 0.4 $/kWh and 0.1 $/m^3 are chosen for base values of electricity and natural gas prices, respectively. Variation of hub different loads and the prices of energy carriers in different hours are depicted in Fig. 4 and Fig. 5, respectively. Finally, with respect to all above assumptions, the proposed hybrid stochastic/IGDT model was solved by the non-linear programming solver SBB using the GAMS platform [36].

By solving the scheduling problem based on proposed hybrid model for d=0.01 to d=0.05, the optimum robustness and opportunity functions expected values $\widehat{\alpha}$ and $\widehat{\beta}$ as well as critical costs Z_w^{cost} and Z_k^{cost} are founded and shown in Fig. 6 and Fig. 7, respectively. As presented in Fig. 6, it is clear that impact of price changes on net cost is extremely low. For example, for $d_r = 0.03$, an expected critical cost of $Z_{cost} = 14666.97\$$ is guaranteed while the price changes are not more than 17.6% or $\alpha = 0.176$. On the hand, risk averse and risk seeker are the key strategies which affecting scheduling problem. For example, Fig. 8 and Fig. 9 display the variation of electrical output of CHP units for d=0.02 and d=0.05.

TABLE II
SPECIFICATION OF CHP UNITS 1 AND 2

Max/Min output (kW)	Conversion efficiency (%) Elec.	Conversion efficiency (%) Th.	Ramp-up/down (kW/h) Elec.	Ramp-up/down (kW/h) Th.	Start-up/ Shut-down cost($)	Maintenance cost ($/kWh)
2000/200	40	45	400	450	55/55	0.259

TABLE III
SPECIFICATION OF BOILERS 1 AND 2

Nominal capacity (kW)	Energy efficiency (%)	Start-up/ Shut-down cost($)	Maintenance cost ($/kWh)
1200	75	14	0.259

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TABLE IV
SPECIFICATION OF STORAGE DEVICES

Storage type	Maximum energy (kWh)	Maximum input & output (kW)	Charge & discharge efficiency (%)	Standby efficiency (%)
Electrical	2000	500	95	98
Thermal	1000	300	90	95

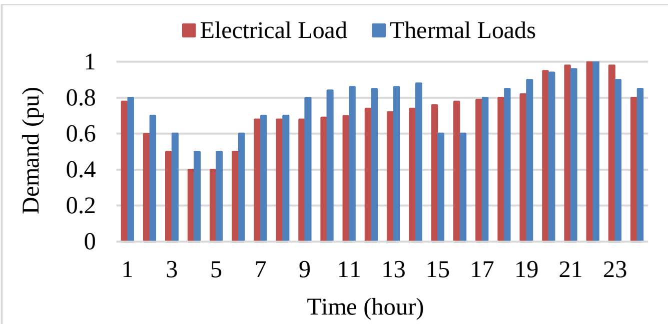

Fig. 4. Variation of electrical and heat load in different hours.

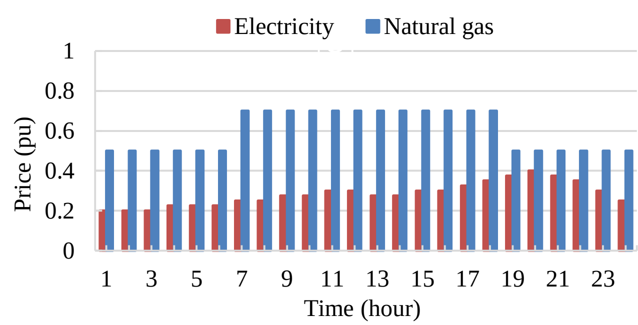

Fig. 5. Variation of electricity and natural gas prices in different hours.

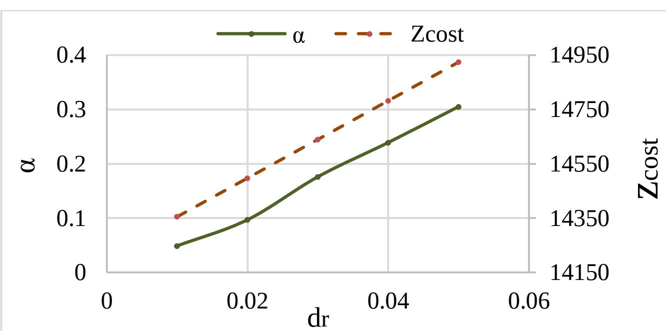

Fig. 6. Robustness function of α vs. cost deviation factor (d) in case study I.

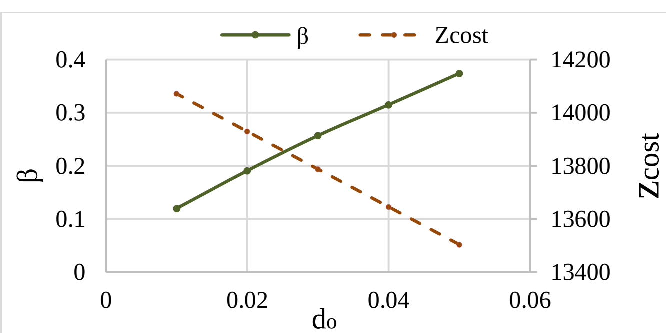

Fig. 7. Opportunity function of β vs. cost deviation factor (d) in case study I.

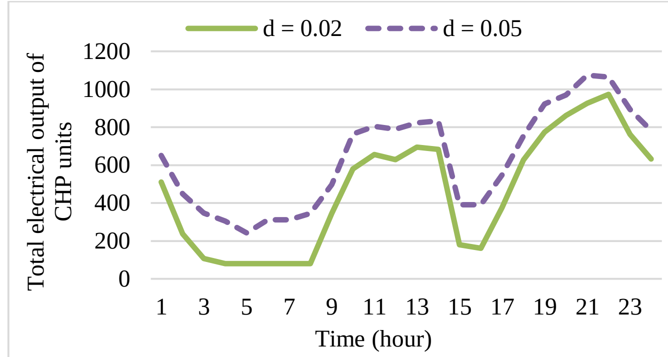

Fig. 8. Total electrical output of CHP units at risk-averse strategy in case study I.

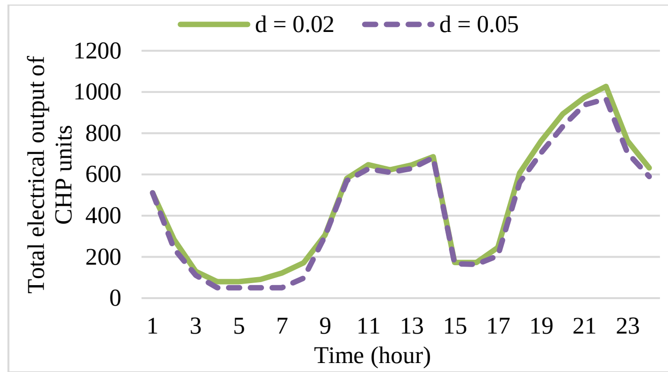

Fig. 9. Total electrical output of CHP units at risk-seeker strategy in case study I.

B. Case Study II: A modified IEEE 34-node test system

The proposed hybrid stochastic/IGDT model is implemented and examined using the modified IEEE 34-node test system [14]. In this paper, the test system is modeled as a residential energy hub. The single line diagram of this system is depicted in Fig. 10, and its data are available in [37]. The sizes of CHP units, boilers and wind turbine are respectively considered to be 2000 kW, 1200 kW and 600 kW. The required number of samples for a given accuracy level is independent of the system size when adopting the Monte Carlo simulation method. So we still simulate this system with the number of scenarios like case study I and then reduce the number of scenarios to 10 after scenario reduction. Also, other characteristics of hub units are similar to the case study I as shown in Table II, Table III and Table IV. Applying the proposed hybrid stochastic/IGDT method for adequacy studies of the given energy hub, expected critical cost for different cost deviation factor were found taking into consideration different operating strategies of the energy hub decision maker, i.e., risk-seeker strategy and risk-averse strategy. The optimum robustness and opportunity functions expected values $\hat{\alpha}$ and $\hat{\beta}$ as well as critical costs Z_w^{cost} and Z_k^{cost} are delineated in Fig. 11 and Fig. 12, respectively. The optimum robustness and opportunity function values are optimized for pursuing risk-averse and risk-seeker strategies by energy hub operator. The results shown in Fig. 11 indicate that, the robustness parameter starts to rise as d_r increases, implying that a higher range of price forecast errors can be endured at the expense of higher cost expectations. That is, a higher

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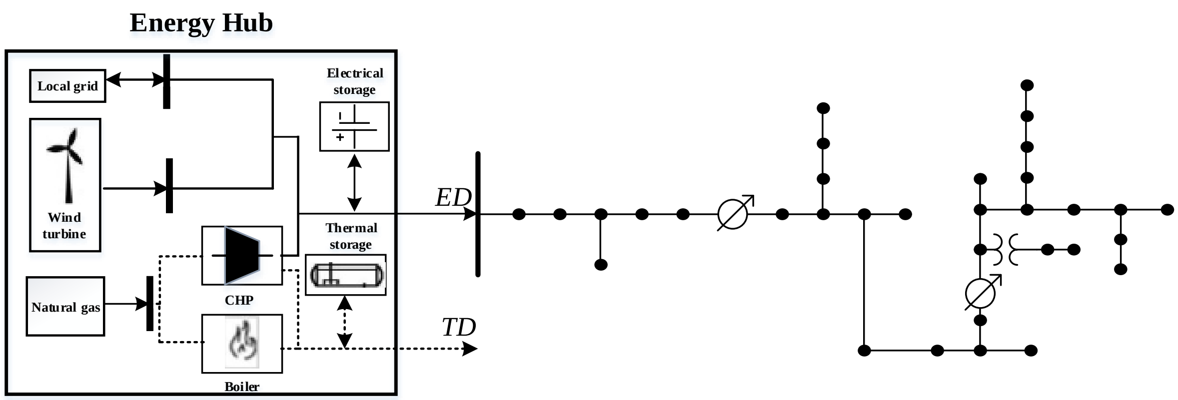

Fig. 10. Single-line diagram of the modified IEEE 34-node test system.

robustness strategy by the energy hub operator leads to a higher cost. Conversely, a higher cost of the energy hub indicates a state of being more risk averse and the higher robustness of the strategy taken by the energy hub operator. As it is shown in Fig. 11, for $d_r = 0.04$ the net cost for risk-averse strategy would be $Z_{cost} = 16294.09\$$ and the maximum electricity price uncertainty that can be tolerated would be $\hat{\alpha} = 0.233$.

As depicted in Fig. 12, it can be observed that a lower target cost requires greater favorable price deviations from the forecast values. For instance, to reach a cost 4% lower than Z^0_{cost}, i.e., $Z_{cost} = 15005.32\$$, the observed prices have to be 30.9% lower than the forecast prices.

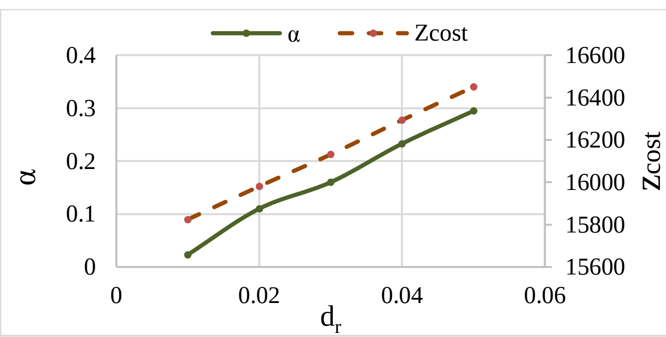

Fig. 11. Robustness function of α vs. cost deviation factor (d) in case study II.

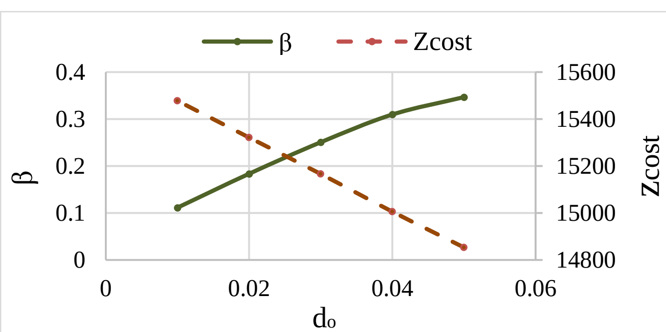

Fig. 12. Opportunity function of β vs. cost deviation factor (d) in case study II.

C. Comparison of proposed hybrid method with deterministic and pure stochastic approaches for actual prices

In this subsection, in order to demonstrate usefulness and efficiency of proposed hybrid method, deterministic and pure stochastic methods are applied to the scheduling problem. However, in deterministic method the fluctuations and prediction errors are not considered in the scheduling problem and in pure stochastic approach all uncertainty resources are modeled with different scenarios. In addition, the analysis of the case study I is repeated using the actual and forecasted prices ,which are generated by Monte Carlo model, for an arbitrary week in electricity market. The actual and forecasted prices for this week are illustrated in Fig. 13.

The calculated values of total operation cost of proposed energy hub for the risk-seeker strategy, the risk-averse strategy, pure stochastic and deterministic models based on the actual market prices are presented in Table V. As presented in Fig. 13, during the first four days, prices are underestimated by the model whereas during the rest of the days, the prices are mostly overestimated. Table V displays the results for this week and also confirm that for an underestimating circumstance, the robust model results lower cost whereas for an overestimating circumstance the opportunistic model yields economical operation. Additionally, the risk-averse scheduling in this case gives lower overall weekly cost. This lies in the fact that in four out of seven days, the prices are mainly underestimated by the forecasting model.

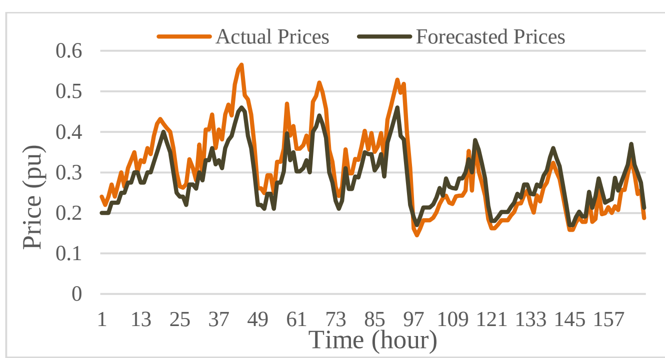

Fig. 13. Hourly actual prices for an arbitrary day in electricity market.

TABLE V
COMPARISON OF SCHEDULING COSTS FOR DIFFERENT METHODS

Day	Z_k^{cost} (\$)	Z_w^{cost} (\$)	Z_s^{cost} (\$)	Z_d^{cost} (\$)
1	15093.342	14959.732	15295.689	15457.620
2	15214.425	15010.394	15741.813	15934.230
3	14720.691	14433.989	15081.549	15283.721
4	14425.913	14289.173	14518.158	14867.654
5	11503.590	11611.616	12259.020	12747.791
6	11268.570	11317.227	11484.513	11722.028
7	10415.078	10549.474	10834.446	11155.249
Total	92641.609	92171.605	95215.188	97168.293

IV. CONCLUSION

In this paper, a scheduling strategy for an energy hub system based on hybrid stochastic/IGDT optimization is proposed. The uncertain outputs of wind generation and energy demands are modeled via scenarios, while an IGDT optimization is implemented to find an interval for electricity price to study the robustness and opportunity functions. By the proposed hybrid model, the energy hub operator can track risk-averse and risk-seeker strategies to face with price uncertainty. By implementing the hybrid stochastic/IGDT optimization method for the optimal scheduling of wind integrated energy hub, the computation burden of the problem is decreased. Finally, the numerical results obtained from the studied cases verified the appropriateness and usefulness of the proposed method, where it is shown that by applying different strategies such as risk-averse and risk-seeker strategies provided by hybrid stochastic/IGDT model grants additional degree of freedom in deregulated energy markets for energy hub operator.

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