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A Robust/Stochastic Hybrid Technique

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Published in:
e-Prime: Advances in Electrical Engineering, Electronics and Energy

DOI (link to publication from Publisher):
10.1016/j.prime.2022.100028

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

e-Prime - Advances in Electrical Engineering, Electronics and Energy 2 (2022) 100028

Contents lists available at ScienceDirect

e-Prime - Advances in Electrical Engineering, Electronics and Energy

journal homepage: www.elsevier.com/locate/prime

Transactive energy strategy for energy trading of proactive distribution company with renewable systems: A robust/stochastic hybrid technique

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A R T I C L E I N F O

Keywords:
Hybrid stochastic and robust approach
Transactive energy
Optimal operation of the PDISCO
Renewable energy sources
Uncertainty modeling
Demand response program

A B S T R A C T

Given the unsuitability of the previous strategies in procuring affordable conditions for the proactive distribution company (PDISCO) participation in the power market interactions, this article benefits transactive energy advantages to manipulate an innovative model for addressing this challenge. The proposed model enables the PDISCO to undertake optimal energy exchanges for maximizing its profit while creating equality between power supply and demand in the renewable-based system. A robust/stochastic hybrid technique is developed considering the uneven changes' pattern to properly model uncertainties in the studied system. In this process, probabilistic scrutinizing of whole elements of the sample space is done by applying the Latin Hyperbolic Sampling method, while the selection process of the elements with a high existence probability is completed using the fast forward selection method. Moreover, the system robustness is intended by exerting robust optimization. The demand response program is advanced by using the elasticity properties of the shiftable loads. The modified version of the IEEE 33-bus test system is intended for verifying the effectiveness of the developed model. The results demonstrated a 23.197% diminution in the profit while procuring an acceptable degree of robustness for the system as well as guaranteeing the reach of a certain profit by operating the PDISCO under the suggested model rather than the base one.

1. Introduction

1.1. Motivation and background

Nowadays, proactive distribution companies (PDISCOs) are taken into account as active agents for energy networks, which are responsible for delivering reliable electricity to various types of consumers and operating distribution networks [1]. As the most important goal in the short-term exploitation of the distribution grid, PDISCOs are targeted to maximize the difference between the revenue of electricity selling to consumers and energy supplying costs [2]. By developing electricity markets and turning them into a competitive environment, PDISCOs have been faced with significant challenges in realizing their goals [3]. On the other hand, by growing renewable systems (RSs) as pollutant-free energy production units [4] in line with the pathway towards the energy network decarbonization [5], a large number of uncertainties have been recognized in the power grid [6]. This issue has made the adopting process of optimal decisions on all participants in the electricity market challenge [7]. Therefore, the PDISCO needs effective solutions for maximizing its profits in a deregulated environment with a high penetration of RSs. Although this issue is critical for the PDISCO's successful participation in competitive energy markets in the highly renewable-penetrated system, the holistic model is not offered yet for the PDISCO's energy interactions in the uncertain environment. Therefore, this work is aimed to propose a practical solution for addressing the aforementioned challenge by relying on the application of transactive energy technology. In other words, this study benefits the transactive energy for developing a sustainable energy sharing strategy for the PDISCO's energy interactions aiming to optimally pursue its economic and technical objectives.

1.2. Literature review and research gaps

Recently, several studies have been carried out with the aim of determining various solutions for the effective participation of the PDISCO in energy interactions of the electricity market. For example, the authors in [8] modeled a strategic behavior of the PDISCO with the aim of maximizing their profits in the wholesale and reserve electricity markets. In this study, bi-level optimization is applied considering the independent system operator and the PDISCO's operation problem as the lower

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https://doi.org/10.1016/j.prime.2022.100028
Received 17 October 2021; Received in revised form 19 November 2021; Accepted 4 January 2022

Nomenclature

Indices

t	index of time periods
s	index of generated scenarios
i, j	index of the electric power system buses

Parameters

$P_{i,t}^{Load}$	the amount of load shedding
γ_t^{Sell}	selling energy price to the consumers
γ_t^{LSh}	load shedding price
γ_t^{RT}	real-time (RT) energy trading price
$Co_{i,t}^{SU}, Co_{i,t}^{SD}$	the startup and shut down costs for DGs
ξ_s	probability of the scenario
N_s	number of generated scenarios
B	number of buses
$\varsigma_{1,2,3,i}^{DG}$	cost coefficients of DGs
$P_{i,t}^{DG,Gas}$	gas demand of DGs
$Rup_i^{DG}/Rdown_i^{DG}$	the ramp up/down limit for DGs
HR_{Gas}^{DG}	the gas heat rate
MUT_i^{DG}/MDT_i^{DG}	the minimum up/down time limit for DGs
$\Upsilon_{i,t-1}^{DG,on}/\Upsilon_{i,t-1}^{DG,off}$	number of on/off hours for DGs
$\bar{P}_i^{Wind}$	the upper limit of the wind turbine output
ω_i^{Rat}, ω_t	the rated and forecasted amounts of the wind velocity
$\omega_i^{Cout}, \omega_i^{Cin}$	the cut-out and cut-in amounts of the wind velocity
$P_{it}^{RTI}, P_{i,t}^{RTE}$	the RT inelastic and elastic portions of the electrical load
$\bar{P}_{i,t}^{LSh}, \underline{P}_{i,t}^{LSh}$	the upper and lower bounds for the load shedding
$\bar{P}_{i,t}^{Load}, \underline{P}_{i,t}^{Load}$	The upper and lower limits for the electricity demand
PV_i^{Size}, PV^{η}	the PV panel's size and efficiency
PV_t^{SR}	the solar radiation at time t
$Q_{i,t}^{Load}$	the reactive power load

Variables

$P_{i,t,s}^{LSh}$	the amount of load shedding
$P_{t,s}^{RT}$	the amount of energy traded in the RT market
$U_{i,t}^{DG}$	the binary variable indicating DGs' ON/OFF status
$U_{i,t}^{SU}, U_{i,t}^{SD}$	the binary variables indicating DGs' startup and shut down status
$Co_{i,t,s}^{DG}$	energy production cost of DGs
$P_{i,t,s}^{DG}$	power production of DGs
ψ_t, ϕ	the dual variables in the robust optimization method
Γ	the budget of uncertainty related to the robust optimization method
$P_{i,t}^{Wind}$	the wind turbine output
$P_{i,t}^{PV}$	the PV panel output
$Ploss_t$	the power losses in the distribution lines
$y_{i,t}, x_{i,t}$	the virtual generation and consumption of the electricity demand
$P_{i,t}^{Flow}, Q_{i,t}^{Flow}$	the active and reactive power injection
$Q_{i,t}^{C}$	the reactive power produced by a shunt compensator
$S_{i,j,t}$	the complex power flow
$\theta_{i,t}, V_{i,t}$	the phase angle and voltage magnitude

and upper-level problems, respectively. The simulation results proved the strategic role of the PDISCO in both the reserve and wholesale energy markets. In another work [9], a multipored energy acquisition model is investigated using a bi-level programming model for maximizing PDISCO's revenue in the upper-level while reducing the energy generation cost in the lower subproblem. The results indicated that the solution algorithm and proposed model can help the PDISCO to adopt optimal plans for energy purchasing in various conditions. In [10], an equilibrium problem with equilibrium constraints (EPEC) technique was employed for modeling the operational decision-making of the PDISCO with the aim of minimizing their operation cost at the lower level and maximizing social welfare in the upper-level problem. The results show that the PDISCO can reduce the feeder losses and operation costs using the distributed generators (DGs) units and interrupted load options while it can effectively participate in the wholesale power market interactions. Beside the aforementioned studies, some other valuable works, including a novel day-ahead (DA) energy acquisition model for maximizing the expected benefit of the PDISCOs in [11], a two-level decision-making model for PDISCO's profit maximization in the DA market [12], multi-objective particle swarm optimization approach for maximizing the profit of the PDISCO and DGs owners in [13], and a probabilistic sequential framework for PDISCO's profit maximization in [2] have been conducted regarding the PDISCO with various goals and different methods.

Because distribution networks are integrated with stochastic producers such as RSs, the stochastic modeling of distribution networks has also been scrutinized in recent literature. For instance, a stochastic bi-level model is presented in [14] to maximize PDISCO's profits by participating in the energy market as active players in market interactions. The simulation results demonstrated the PDISCO can obtain more profit when it works under the strategic model rather than the non-strategic model. Moreover, the authors in [15] presented a stochastic framework for optimizing the operational decisions of PDISCOs in two stages. Minimizing the expected operation cost and load curtailments are considered as the main objectives for the DA and real-time (RT) operation stages. Analyzing the application of this framework concluded that the level of dependency on the RT declines, as the concern on the system risk proliferates. Despite proposing various techniques for reducing the risk of systems with massive uncertainties, the flexibility of such systems is still challenging. In this regard, other effective solutions have been offered for energy management aiming to increase the system's flexibility with a high penetration of stochastic producers. For this aim, demand response (DR) programs are introduced and widely used for increasing the reliability and flexibility of distribution networks. Indeed, PDISCOs will be more flexible under the availability of DR resources in the demand side [16]. For example, the incentive-based DR is presented in [17] to improve the system flexibility in maximizing the usage of clean energy for meeting different energy carriers by proposing a novel structure of the virtual energy plant. In [18], a multi-process generation program and DR policies are proposed for facilitating the integration of RSs into manufacturing systems with the aim of optimal operation of the power grid. The DR program is intended in [19] as a comparatively and realistic inexpensive solution for increasing RSs penetration into the bulk power grid by managing the amount of energy consumption on the demand side. A multi-stage stochastic DR model is developed in [20] using the advantages of the optimization-driven heuristic method for managing the energy consumption of a large manufacturer in co-optimizing energy and reserve markets. In [21], DR programs are integrated for accurately assessing the consumer behavior in the microgrid energy management, aiming to gain techno-economic benefits. Moreover, the authors in [22] examined the economic potential of the DR in the renewable exploitation as well as energy markets' effects on the large-scale DR deployment in the region.

In the distribution system, the PDISCO plays as a profit-driven company and active electricity producer that can be targeted for executing ambitious schemes to purchase excessive DR to sell in the RT aiming to upsurge its profit [23]. In this regard, DRs are typically allocated heterogeneously and dispersedly at a small scale, which has made their participation in the energy market interactions challenging [23]. To address this, the aggregators are appeared as a new business player to schedule and assemble the dispersed DR resources so that the PDISCO can trade with them instead of small-scale DRs in distribution networks to gain more economic benefit. Although valuable researches have been done regarding the PDISCO's profit maximization, a comprehensive model that can procure suitable conditions for its effective presence in the competitive environment has not been presented yet. Some recent literature has only used various techniques for maximizing the PDISCO's profit, and some others have only focused on modeling the uncertainties in the competitive market. However, a complete model that can include an effective approach for uncertainty modeling and employ a sustainable technology and method for increasing the reliability, resiliency, and flexibility of distribution networks is not provided simultaneously in the mentioned references. Additionally, energy trading as a critical way of establishing a dynamic energy balance is not intended and a suitable strategy is also not exerted for the PDISCO's profit maximization in distribution systems. In this respect, transactive energy is emerged as the market-based paradigm for integrating the numerous RSs by adopting appropriate energy trading mechanisms within the power grid [24,25]. This technology has recently been applied for controlling energy sharing between the interconnected microgrids (MGs) in the RSs penetrated network [26]. Also, the capability of transactive energy is effectively used in [27] for providing a satisfactory level of individual and collective benefits for community MGs in the cluster mode. Therefore, this article suggests a transactive energy approach for PDISCO's electricity exchanging strategy aiming to improve its profit along with establishing equality between the electricity supply and demand in a deregulated environment. Additionally, the capability of the DR program is also used by dividing the electricity demand into the inelastic and elastic loads to high usage of shiftable loads' potential in maximizing the flexibility of the distribution network.

In this research, solar and wind systems are widely used for carbon-free electricity production that makes the distribution system more uncertain. Hence, an appropriate uncertainty modeling method is needed for evaluating the stochastic behaviors of such systems with a large number of uncertainties. To this end, various methods are exerted in recent literature including chance-constrained programming [28], information gap decision theory [29], SP [30], distributionally robust optimization [31], just to name a few. Recent studies have developed such uncertainty quantification techniques for pursuing different goals in related mathematical problems. A robust optimization approach is employed in [32] to model stochastic volatilities in the cooling demand for achieving optimal robust chiller loading in the deregulated environment. In [33], the risk-constrained optimization model is proposed to effectively manage the risk of purchasing power at on-peak hours in the home energy management system. The Monte Carlo simulation method is exerted in [34] to perform the stochastic analysis for identifying the variables that mostly influence the obtained results as well as procuring probable ranges of life cycle related to the net energy ratio and greenhouse gas emissions. In [35], the authors developed an improved stochastic algorithm for properly dealing with uncertain variations of the electricity load in the short-term load forecasting of the electricity market. Moreover, a new possibilistic chance-constrained programming method is suggested in [36] for uncertainty modeling in scrutinizing the resiliency of the hybrid network in the co-optimization of gas and electricity grids. Although the mentioned methods are effective techniques in modeling uncertainties of the power grid, they are not suitable individually to model a variety of uncertain parameters in the system. Indeed, generating several scenarios in stochastic-based methods can be used for modeling different fluctuations of uncertain parameters such as wind velocity, but these techniques cannot make the system robust enough. Moreover, given the generation of numerous scenarios in SP, there are some other disadvantages related to this approach, including computational burden, running time, and complexity. On the other hand, different states of uncertain parameters occurrence using the robust-based techniques are not intended, which are suitable only for those parameters with lower fluctuation [37]. In this regard, a robust/stochastic hybrid method is applied for uncertainty modeling by using the advantages of both the SP and robust optimization (RO) methods in analyzing the fluctuations of the system [38]. This method has recently been applied for uncertainty modeling of RSs outputs with acceptable results [39]. For example, it is applied in [40] for minimizing the charging cost of the electric vehicle aggregator by adopting an appropriate bidding strategy in the DA market. In [41], the authors have developed a robust/stochastic hybrid method for capturing uncertainties associated with RSs, power prices, and load demand with the aim of determining optimal bidding and offering strategies for the industrial consumer. Moreover, the authors in [42] have employed this approach for minimizing the expected net cost. To sum up, the research gaps can be briefly expressed as follows:

- Developing a holistic model is ignored in recent literature for the PDISCO that not only procures suitable conditions for the PDISCO's successful participation in the energy market interactions but also effectively maximizes its techno-economic benefits.
- A sustainable energy sharing strategy is not developed yet to enable the PDISOC for effective usage of energy exchanging possibility for serving energy in the highly uncertain environment while allowing it to pursue its economic and technical objectives.
- A proper comprehensive technique is not developed for quantifying uncertainties in the PDISCO's profit maximization problem for realistic modeling stochasticities aiming to gain confident results.

1.3. Contributions and organization

The main goal of this paper stands on developing a transactive energy model for developing a sustainable energy sharing strategy that allows PDISCO to effectively participate in the energy market interactions with the aim of obtaining techno-economic benefits. To ensure the energy balance in the highly renewable-penetrated structure, the DR scheme is employed by using the elasticity property of the electricity demand. As uncertainty modeling is one of the useful steps for realistic modeling of the system with a high level of RSs, exerting an appropriate method is necessary for probabilistic analysis of the problem. In this work, a robust/stochastic hybrid method is taken into account for examining the stochasticities in the PDSICO's profit maximization problem. In this technique, the SP method is employed for modeling the fluctuations of solar radiation and wind speed by using the Latin Hyperbolic Sampling (LHS) and fast forward selection (FFS) approaches with the aim of scenario generation and reduction. Furthermore, the RO technique is exerted to assess the volatility of the RT balancing market price. The main contributions of this research are expressed as follows:

- Transactive energy application is developed for professionalizing the PDISCO's electricity sharing strategy in the energy marketplace and ensuring reliably creating time-to-time equality between the electricity supply and demand in the highly deregulated power grid.
- The application of the SP and RO is developed as a hybrid technique for uncertainty quantification, in which the SP benefits probabilistic scrutinizing whole sample space's elements using the LHS and effectively excerpting scenarios with a high occurrence chance by the FFS while the sufficient level of robustness is endowed for the high RSs penetrated system by the RO.

In the remainder of this article, Section 2 describes the key models of this work. Afterward, Section 3 elaborates on the problem formulation for this research. Section 4 provides a discussion and an assessment of simulation results. Finally, concluding remarks are explained in Section 5.

2. Key models

2.1. Uncertainty modeling

Uncertainties in the results of excessive operation of RSs are the perpetual challenges for the existing structure of the power grid [43]. To capture uncertainties associated with RSs, many approaches have been proposed in recent decades, among which an effective method is the SP [44]. In this work, this approach is applied for handling a large amount of uncertainties associated with the PV panel and wind turbine outputs as uncertain parameters. The LHS is employed to generate several scenarios considering various stochastic changes of uncertain parameters. In this technique, the generated scenarios are obtained by dividing the scale of cumulative probability (0 to 1) to the ψ (number of scenarios) intervals with the same length [45]. In the next step, a sample can be chosen randomly from each of mentioned intervals, or their midpoints can be considered as candidate scenarios. Then, the occurrence probability of generated scenarios should be determined to accurately intend the impact of each scenario on the studied problem. For example, by assuming the wind speed as the uncertainty parameter, its value can be computed using the LHS as follows:

$$\omega_s = CDF^{-1}\left(\frac{s-0.5}{\psi}\right) = \sqrt{\ln\left(\frac{1}{\left(1-\frac{s-0.5}{\psi}\right)^{2\beta^2}}\right)} \tag{1}$$

$$CDF(\omega) = \int_0^{\omega} \left(\frac{\omega}{\beta^2}\right)\left(e^{-\left(\frac{\omega}{\sqrt{2}\beta}\right)^2}\right) \tag{2}$$

where ω_s denotes the wind speed in scenario s^{th} and CDF is the cumulative distribution function. More details about the LHS method can be found in [46,47]. Because of the more computational burden and complexity of a large number of scenarios, scenario reduction methods have been presented for solving this challenge. To this end, the FFS approach is exerted in this paper to select effective scenarios with a high amount of occurrence probability. In this method, candidate scenarios are determined by considering their distance with other scenarios, among which those with minimum Kantorovich distance are used for the uncertainty modeling process. The detailed description of the FFS method can be obtained from [48].

Given the pattern of the changes of the energy price in the electricity market, the RO is employed for modeling its volatility in the marketplace [49]. This method imposes a low computational burden on the system than other uncertainty quantification methods [32] and intends the worst state of uncertain parameters to provide certain economic benefits for the PDISCO [50]. Indeed, the capability of the RO approach is used for guaranteeing the PDISCO's profit in the competitive energy trading market. In other words, the RO technique is targeted to provide a robust model with very conservative results [51] in terms of achieving a certain amount of profit for the PDISCO in renewable-based systems.

2.2. Demand response modeling

In this study, the electricity load comprises the elastic and inelastic loads, in which the curtailable and shiftable properties of elastic demands are intended in the DR program. The inelastic portion of the demand is the indispensable load, which cannot be shaved or shifted during a day [52]. Indeed, this portion of demand cannot help to improve the system flexibility and should be met over the scheduling horizon. On the other hand, another portion of the electricity demand, i.e., elastic loads, can be scheduled for enhancing the system flexibility and reliability, intending the shavable and shiftable features of the dispensable loads. In this respect, the elasticity limit of the RT energy consumption, ϖ, is used for controlling the amount of shifting or shaving loads during the time interval t. The main structure of this type of DR program can be accessed in [16]. Also, a similar model of the DR scheme is applied in [37] to assist the system in procuring a continuous electricity supply.

3. Problem formulation

One of the main objectives of the PDISCO is to maximize its profit in the new structure of the power network with a high penetration of RSs. In such networks, adopting an appropriate energy exchanging strategy can be more effective in reliably meeting the energy demand and maximizing the PDISCO's profit. Therefore, this paper benefits the transactive energy technology as a sustainable energy sharing strategy for managing the PDISCO's electricity sharing in the deregulated environment. Because the energy sharing possibility is considered for the PDISCO under the transactive energy paradigm, it can actively participate in the energy market trading floors. It is done by selling or purchasing the energy at each hour without requiring for storing energy with associated capital and operating expenses. A similar strategy for the PDISCO has also been adopted in some recent studies [23]. The objective function of this problem, along with operational constraints, is provided in the following sections.

3.1. Objective function

In this research, beside a high usage of RSs for pollutant-free electricity production, DGs are also exploited as backup systems to reliably supply the required energy to consumers. Moreover, the possibility of energy sharing with the upstream network and implementing the DR scheme as the other strategies are provided for the PDISCO energy meeting schemes. This assumption is considered that the PDISCO is the owner of the DERs in the distribution network [53,54]. Herein, the participation of the PDISCO only in the RT market is another assumption because it has several controllable devices (DGs), and it has the ability to regulate the amount of energy production, selling, and purchasing strategies to maximize its profit. The SP is exerted to model the intermittences associated with RSs, thereby, the objective function of this problem based on the SP model is given as:

$$Z = \sum_{s=1}^{N_s} \xi_s \left[\begin{array}{l} \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{B} (\gamma_t^{Sell}.P_{i,t}^{Load} - \gamma_t^{LSh}.P_{i,t,s}^{LSh}).\Delta t - \sum\limits_{t=1}^{T}\gamma_t^{RT}.P_{t,s}^{RT}.\Delta t \\ - \sum\limits_{i=1}^{\Omega^{DG}}\sum\limits_{t=1}^{T}\left(Co_{i,t,s}^{DG}.U_{i,t}^{DG} + Co_{i,t}^{SU}.U_{i,t}^{SU} + Co_{i,t}^{SD}.U_{i,t}^{SD}\right).\Delta t \end{array} \right] \tag{3}$$

where Z is the objective function of PDICSO, which is targeted to maximize in this research. $P_{t,s}^{RT}$ is the amount of energy traded in the RT energy exchanging process. The magnitude of $P_{t,s}^{RT}$ can be positive when PDISCO is scheduled to purchase energy from the RT energy market for meeting its energy demand, and it is negative when PDISCO sells energy to the main grid. In addition, Ω^{DG} presents the buses including DG units. In (3), the first term states the revenue of selling energy to consumers minus the cost of load shedding in the emergency conditions. The second term indicates the revenue (cost) of power selling (purchasing) to (from) the power network from (by) PDISCO. Finally, the third term states the electricity production cost by DG units, in which $Co_{i,t,s}^{DG}$ is modeled using the quadratic polynomial function and can be calculated as follows:

$$Co_{i,t,s}^{DG} = \varsigma_{1,i}^{DG} + \varsigma_{2,i}^{DG}.P_{i,t,s}^{DG} + \varsigma_{3,i}^{DG}.(P_{i,t,s}^{DG})^2 \forall i \in \Omega^{DG}, \forall t, \forall s \tag{4}$$

In this research, solar radiation, energy price at the RT market, and wind speed play the role of uncertain parameters. Several effective methods are proposed for uncertainty modeling in problems with stochastic parameters, all of which, however, have some advantages and disadvantages. As such, the selection of a suitable approach for modeling the system directly depends on the type of the problem and uncertain parameters. In this regard, one of the effective approaches for uncertainty modeling accompanying with guaranteeing a certain amount of economic benefits is a robust/stochastic hybrid method. This technique not only has a lower computational burden than other approaches by applying a proper scenario reduction method but also intends the worst occurrence state of an uncertain parameter to guarantee a special profit for the system owner. In this paper, the volatility of the RT market price is modeled by the RO. Thereby, the second term in (3) is replaced with auxiliary variable W for simply robust modeling of the system. After this assumption, the objective function can be rewritten as:

$$\max Z = -W + \sum_{t=1}^{T}\sum_{i=1}^{B}(\gamma_t^{Sell}.P_{i,t}^{Load} - \gamma_t^{LSh}.P_{i,t}^{LSh}).\Delta t - \sum_{i=1}^{\Omega^{DG}}\sum_{t=1}^{T}\left(Co_{i,t}^{DG}.U_{i,t}^{DG} + Co_{i,t}^{SU}.U_{i,t}^{SU} + Co_{i,t}^{SD}.U_{i,t}^{SD}\right).\Delta t \tag{5}$$

$$s.t.\quad \sum_{t=1}^{T}\gamma_t^{RT}.P_t^{RT}.\Delta t \geq W \tag{6}$$

In (5), γ_t^{RT} presents the actual amount of the RT price, which is the sum of the predicted price and its deviation according to the following equation.

$$\gamma_t^{RT} = \gamma_t^{RT,p} + \gamma_t^{RT,+} - \gamma_t^{RT,-} \tag{7}$$

where, up and down deviations from the forecasted RT price $\gamma_t^{RT,p}$ are indicated with $\gamma_t^{RT,+}$ and $\gamma_t^{RT,-}$, respectively.

Typically, the worst state of an uncertain parameter is intended in the robust analysis of the studied system. Due to this, the worst state of the RT electricity price in both selling and purchasing states can be formulated as:

$$\gamma_t^{RT} = \begin{cases} \gamma_t^{RT,p} - \gamma_t^{RT,-}, P_t^{RT} \leq 0 \\ \gamma_t^{RT,p} + \gamma_t^{RT,+}, P_t^{RT} \geq 0 \end{cases} \tag{8}$$

After applying mentioned models on Eqs. (5) and (6), the robust-based mathematical problem is as follows:

$$\begin{cases} \left[\left(\sum_{t=1}^{T}\gamma_t^{RT,p}.P_t^{RT}.\Delta t\right) - \max_{\zeta_t}\left(\sum_{t=1}^{T}\zeta_t.\gamma_t^{RT,-}.P_t^{RT}.\Delta t\right)\right] \geq W \\ , P_t^{RT} \leq 0 \\ \left[\left(\sum_{t=1}^{T}\gamma_t^{RT,p}.P_t^{RT}.\Delta t\right) - \max_{\zeta_t}\left(\sum_{t=1}^{T}\zeta_t.\gamma_t^{RT,+}.P_t^{RT}.\Delta t\right)\right] \geq W \\ , P_t^{RT} \geq 0 \end{cases} \tag{9}$$

$$0 \leq \zeta_t \leq 1, \forall t : \psi_t \tag{10}$$

$$0 \leq \sum_{t=1}^{T}\zeta_t \leq \Gamma : \phi \tag{11}$$

where, ζ_t is the auxiliary binary variable in the RO problem and Γ is the budget of uncertainty, which is used for limiting the overall deviation of the electricity price. Based on the decision maker's degree of conservativeness, this parameter can be set during an optimization process [55]. The present structure of the problem is a bi-level one due to applying the RO technique. In this research, duality theory is applied for transmuting the bi-level into a single problem. After this conversion, the single-level problem is given as:

$$\max Z = -W + \sum_{t=1}^{T}\sum_{i=1}^{B}(\gamma_t^{Sell}.P_{i,t}^{Load} - \gamma_t^{LSh}.P_{i,t}^{LSh}).\Delta t - \sum_{i=1}^{\Omega^{DG}}\sum_{t=1}^{T}\left(Co_{i,t}^{DG}.U_{i,t}^{DG} + Co_{i,t}^{SU}.U_{i,t}^{SU} + Co_{i,t}^{SD}.U_{i,t}^{SD}\right).\Delta t \quad s.t. \tag{12}$$

$$\begin{cases} \left[\left(\sum_{t=1}^{T}\gamma_t^{RT,p}.P_t^{RT}.\Delta t\right) - \min_{\phi,\psi_t}\left(\phi\Gamma + \sum_{t=1}^{T}\psi_t\right)\right] \geq W \\ , P_t^{RT} \leq 0 \\ \left[-\sum_{t=1}^{T}\gamma_t^{RT,p}.P_t^{RT}.\Delta t - \min_{\phi,\psi_t}\left(\phi\Gamma + \sum_{t=1}^{T}\psi_t\right)\right] \geq W \\ , P_t^{RT} \geq 0 \end{cases} \tag{13}$$

$$\begin{cases} \psi + \vartheta_t \geq \gamma_t^{RT,-}.P_t^{RT}, P_t^{RT} \leq 0 \\ \psi + \vartheta_t \geq \gamma_t^{RT,+}.P_t^{RT}, P_t^{RT} \geq 0 \end{cases} \tag{14}$$

+ Allconstraintsintheproblem(constraints(15)to(36))

Additionally, the complete constraints of the PDISCO's profit maximization problem are listed as follows.

3.2. Constraints

3.2.1. Electricity balance constraint

$$\sum_{i\in\Omega^{DG}} P_{i,t}^{DG} + \sum_{i\in\Omega^{W}} P_{i,t}^{Wind} + \sum_{i\in\Omega^{PV}} P_{i,t}^{PV} + \sum_{i=1}^{T} P_t^{RT} = \sum_{i=1}^{B}(P_{i,t}^{Load} - P_{i,t}^{LSh}) + Ploss_t \forall t \tag{15}$$

where, Ω^W and Ω^{PV} are the sets of wind turbines and PV panels, respectively.

3.2.2. DG constraints

$$U_{i,t}^{DG}.P_{i,t}^{DG,LB} \leq P_{i,t}^{DG} \leq U_{i,t}^{DG}.P_{i,t}^{DG,UB} \forall t, \forall i \in \Omega^{DG} \tag{16}$$

$$P_{i,t}^{DG,UB} \leq P_{i,t}^{DG,Gas}.HR_{Gas}^{DG}.\Delta t \tag{17}$$

$$P_{i,t}^{DG} - P_{i,t-1}^{DG} \leq Rup_i^{DG}, \text{if } P_{i,t}^{DG} \geq P_{i,t-1}^{DG} \tag{18}$$

$$P_{i,t-1}^{DG} - P_{i,t}^{DG} \leq Rdown_i^{DG}, \text{if } P_{i,t-1}^{DG} \geq P_{i,t}^{DG} \tag{19}$$

$$(\Upsilon_{i,t-1}^{DG,on} - MUT_i^{DG}).(U_{i,t-1}^{DG} - U_{i,t}^{DG}) \geq 0 \tag{20}$$

$$(\Upsilon_{i,t-1}^{DG,off} - MDT_i^{DG}).(U_{i,t-1}^{DG} - U_{i,t}^{DG}) \geq 0 \tag{21}$$

$$U_{i,t}^{DG} - U_{i,t-1}^{DG} \leq U_{i,t}^{SU} \tag{22}$$

$$U_{i,t-1}^{DG} - U_{i,t}^{DG} \leq U_{i,t}^{SD} \tag{23}$$

$$U_{i,t}^{DG} - U_{i,t-1}^{DG} \leq U_{i,t}^{SU} - U_{i,t}^{SD} \tag{24}$$

Eq. (16) limits the power generation by DGs in the allowable range. Eq. (17) intends the fuel limitation for DGs. Eqs. (18) and (19) model the ramp-up and ramp-down limitations of DGs. Eqs. (20) and (21) formulate the minimum up and down limitations for DGs. Eqs. (22)–(24) model the startup and shut down statuses of DGs.

3.2.3. Wind power constraint

$$P_{i,t}^{Wind} = \begin{cases} 0\omega_t < \omega_i^{Cin}, \omega_t > \omega_i^{Cout} \\ \bar{P}_i^{Wind} \times \left(\frac{\omega_{t,s} - \omega_i^{Cin}}{\omega_i^{Rat} - \omega_i^{Cin}}\right)^3 \omega_i^{Cin} \leq \omega_t \leq \omega_i^{Rat} \\ \bar{P}_i^{Wind}\omega_i^{Rat} \leq \omega_t \leq \omega_i^{Cout} \end{cases} \tag{25}$$

Eq. (25) models the wind power generation based on the cut-out, cut-in, and rated wind speed.

3.2.4. Demand response constraints

$$0 \leq x_{i,t} + y_{i,t} \leq \varpi \forall t, i \tag{26}$$

$$P_{i,t}^{Load} = P_{i,t}^{RTI} + x_{i,t}P_{i,t}^{RTE} \forall t, i \tag{27}$$

Eqs. (26) and (27) are used for modeling the elastic and inelastic loads in the demand-side energy management scheme.

3.2.5. Load scheduling constraints

$$\underline{P}_{i,t}^{LSh} \le P_{i,t}^{LSh} \le \bar{P}_{i,t}^{LSh} \forall t, \forall i \tag{28}$$

$$\underline{P}_{i,t}^{Load} \le P_{i,t}^{Load} - P_{i,t}^{LSh} \le \bar{P}_{i,t}^{Load} \tag{29}$$

Eqs. (28) and (29) are used for limiting the amount of load shedding in the permissible range.

3.2.6. PV panel constraint

$$P_{i,t}^{PV} \le PV_i^{Size}.PV_t^{SR}.PV^{\eta} \forall t, \forall i \tag{30}$$

Eq. (30) models the PV panels output using the solar radiation, efficiency, and size of the PV panels.

3.2.7. Electricity network constraints

$$P_{i,t}^{Gen} + y_{i,t}P_{i,t}^{RTE} - P_{i,t}^{Load} = \sum_{j=1}^{B} V_{i,t}.V_{j,t}.Y_{ij}.\mathrm{Cos}(\delta_{i,j} + \theta_{j,t} - \theta_{i,t}) \tag{31}$$

$$Q_{i,t}^{Gen} + Q_{i,t}^{C} - Q_{i,t}^{Load} = -\sum_{j=1}^{B} V_{i,t}.V_{j,t}.Y_{ij}.\mathrm{Sin}(\delta_{i,j} + \theta_{j,t} - \theta_{i,t}) \tag{32}$$

$$\underline{S}_{i,j} \le S_{i,j,t} \le \bar{S}_{i,j} \forall t, i, j \tag{33}$$

$$\underline{V}_{i} \le V_{i,t} \le \bar{V}_i \forall t, i \tag{34}$$

$$\underline{\theta}_{i} \le \theta_{i,t} \le \bar{\theta}_i \forall t, i \tag{35}$$

$$\underline{Q}_{i,t}^{C} \le Q_{i,t}^{C} \le \bar{Q}_{i,t}^{C} \forall t, i \tag{36}$$

Eqs. (31) and (32) model the power flow for the active and reactive powers in the grid. Eqs. (33)–(36) respectively denote the permissible variations of the complex power, voltage magnitude, phase angle, and shunt compensator.

3.2.8. Energy trading constraints

$$\underline{P}_{t}^{RT} \le P_{t}^{RT} \le \bar{P}_{t}^{RT} \forall t \tag{37}$$

$$U_t^{TE,I} + U_t^{TE,O} \le 1 \forall t \tag{38}$$

$$P_t^{TE,I} \le \Psi^{TE}.U_t^{TE,I} \forall t \tag{39}$$

$$P_t^{TE,O} \le \Psi^{TE}.U_t^{TE,O} \forall t \tag{40}$$

$$\sum_t P_t^{TE,I} = \sum_t P_t^{TE,O} \forall t \tag{41}$$

Eq. (37) limits electricity trading in the RT energy market. Eq. (38) indicates the input/output status of electricity trading in the local energy transaction market. Eqs. (39) and (40) constraint the input and output power in the local transaction market. Eq. (41) states the power balance.

4. Simulation results

For the PDISCO problem, the IEEE 33-bus case study is recognized as one of the suitable test systems and is widely used to evaluate the PDISCO's challenges from various viewpoints in recent studies [23,56]. Therefore, in this study, a modified IEEE 33-bus distribution system is utilized for validating extracted results and indicating the capability of the proposed strategy for the PDISCO. The schematic of this test system integrated with the wind turbines, PV panels, and DG units is illustrated in Fig. 1. The required information of this test system, such as line and bus data, can be fully accessed in [57,58].

The information about the RT energy trading price, load shedding price, and energy selling price can be obtained from [59]. The solar and wind units are used as environmentally friendly electricity production resources, for which the complete required parameters can be found in [60,61,51], respectively. Moreover, DGs are used as the backup devices for RSs aiming to enhance the reliability of a dynamic electricity supply in the system [62]. Herein, a methodology flowchart is demonstrated in Fig. 2.

The problem is solved in two cases for effectively validating the simulation results. Case 1 solves the optimization problem without uncertainty modeling, while Case 2 is targeted for modeling uncertainties using the developed approach. According to the research framework indicated in Fig. 2, the base model of the investigated problem (Case 1) is formulated in the first step. In the base model, the deterministic version of the problem is considered without uncertainty quantification. Then, in Case 2, uncertainty modeling is started by conducting the scenario generation and reduction processes for wind velocity and solar radiation while building the uncertainty set for the energy price using the RO method. Afterward, the main structure of the PDISCO problem is formulated based on the robust/stochastic hybrid technique. The PDISCO's profit maximization problem is a mixed-integer nonlinear problem (MINLP) due to the existence of nonlinear equations such as power flow formulation and binary variables of DGs. Therefore, the General Algebraic Modeling System (GAMS) is applied to solve the MINLP problem using its SBB [63] and DICOPT [64] solvers. Solving the problem using two different solvers eventuated the same results that indicate the acceptable optimality range of the obtained results. Indeed, this is

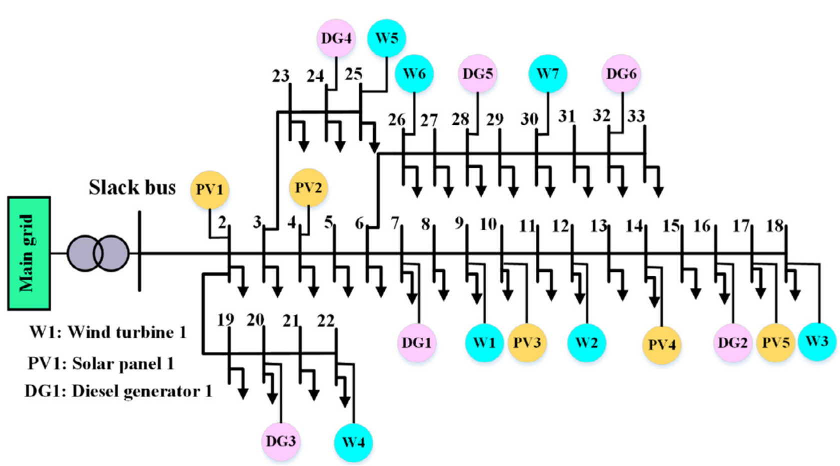

Fig. 1. The modified structure of the IEEE 33-bus case study.

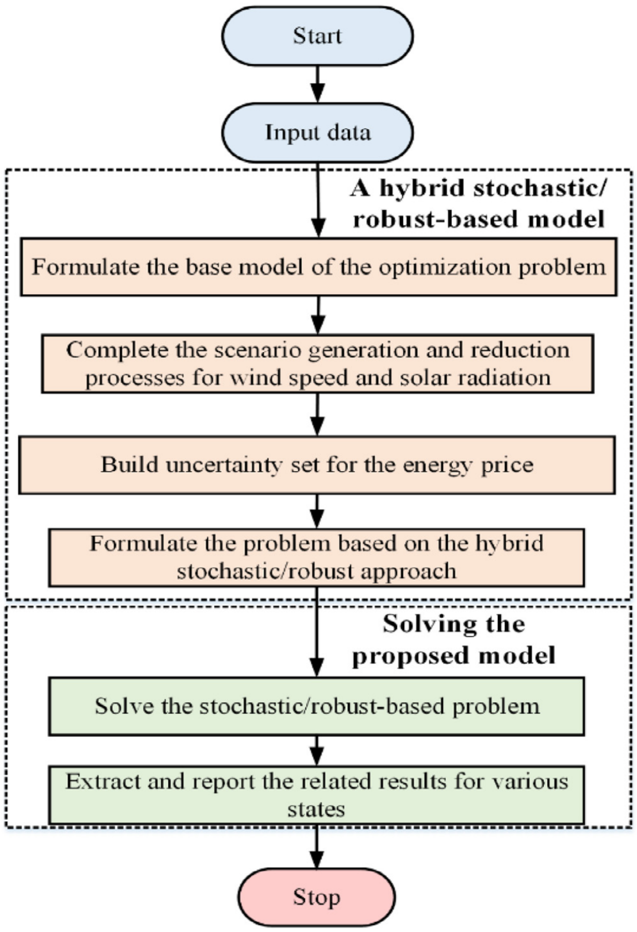

Fig. 2. A methodology flowchart of the problem.

done to ensure the quality of the solution. After problem solving, the value of PDISCO's profit is equal to $15396.595. The total cost and revenue of the PDISCO are illustrated in Fig. 3.

Given Fig. 3, the cost of PDISCO in the early morning (1–6 am) is lower than its revenue due to lower energy consumption and selling extra energy generation of wind units in the RT balancing market. However, the amount of energy consumption is increasing by moving towards the peak hours (10–12 am and 1–7 pm), leading to the operation of DGs at the highest level with more fuel costs. Moreover, the high energy price at the mentioned hours has also led to maximize the PDISCO revenue by selling energy to consumers. At night, the energy cost of PDISCO is increased due to a high amount of energy purchased from the energy network. In addition, diminishing the power consumption at night hours has reduced the volume of power-sharing for the PDISCO subsequently resulting in decreasing its profit. In this regard, the output level of wind turbines and electricity sharing in the RT energy exchanging market are depicted in Fig. 4.

As shown in this figure, the production level of wind turbines is high in the early morning and at noontime due to suitable wind blowing at the mentioned times of the studied area. A portion of the wind power is dedicated to meeting the energy load and the surplus of it is sold to the main grid aiming to maximize the PDISCO's profit. On the other hand, the amount of selling electricity to the power network is increased in the early morning due to lower electrical load and a high output of wind turbines in these hours. From 5 to 10 am, diminishing in the wind speed has been led to the reduction in the wind turbines output and the level of power generation in the system is substantially reduced. Subsequently, the amount of purchasing electricity from the power grid is started to increase in the morning with the aim of serving the electricity demand of the peak hours. In addition to the usage of power exchanging potential for meeting the peak demand, the maximum clean produced power by the wind turbines are also utilized for balancing power in the grid. The effective potential of energy exchanging is also used at night for energy supply to consumers due to the lower outputs of wind units at these times. As the power generation by the wind systems is at the lowest level in the last hours of the day, the exploitation of controllable units is necessary for supporting the system in an uninterrupted power supply. In order to enhance the reliability of continuous electricity supply, DGs are also operated as the backup units, and their energy production and PV panels' output during a day are shown in Fig. 5. In addition, load shedding as the costly and last option is also intended for balancing of the system, the scheduling of which is indicated in Fig. 5.

In Fig. 5, DG units have maximum electricity production in the early morning and at peak times for supporting the system to meet the consumers' energy demand. In the early morning, an appropriate opportunity of the lower fuel price is used by DG units for high energy production with the aim of selling to the power grid for maximizing revenue. However, the maximum energy production of DG units is realized at peak hours to assist the system in meeting the high energy consumption of these times. This is while the system is scheduled for the lowest level of DGs operation at night when the power consumption is significantly reduced and only a lower portion of DGs potential is used for balancing energy. The solar panel as another clean energy production unit is employed throughout the distribution network. As seen in Fig. 5, the power generation of the PV panel is zero at 1–5 am and 7–12 pm when the amount of solar radiation is zero in the studied area. However, its output is at the maximum amount at peak hours with the highest intensity of sunlight. This behavior of PV panels has provided a significant opportunity for the power grid to meet a high portion of the energy load at peak hours using the PV panels' potential. Because of the large energy costs for the load shedding, this option is intended only at some hours of peak times with a minimum amount to help the establishment of a continuous electricity balance in the system. In the renewable-based structure, DR programs are one of the affordable ways for managing power consumption that allow the system to be more flexible in balancing power generation and consumption. To this end, the DR program is investigated for demand-side energy management. In this respect, the electrical load is divided into the inelastic and elastic demands to provide suitable conditions for appropriate usage of the shavable and shiftable properties of the elastic loads. The impacts of the DR program on the interrupted load (IL) cost and profit of the PDISCO are demonstrated in Fig. 6.

As seen in Fig. 6, by increasing the amount of elasticity limit, the amount of load shedding is reduced over the scheduling horizon, resulting in the reduction of the IL cost. This is because increasing the elasticity limit has led to providing the possibility of shifting a high amount of elastic loads from peak times to the other hours with low energy consumption, which avoids the probable load shedding and extra costs. On the other hand, this issue has led to the lower energy demand at peak hours that the high-level operation of DG units is not needed for meeting the electricity load. Thereby, reducing the working level of DG units along with load shedding in the system has led to an increase of the PDISCO's profit. As uncertainties are one of the main dominant factors that affect the optimal scheduling of the system, a capable technique needs to be developed for quantifying uncertainties with the aim of reaching accurate outputs. In this study, the RO method is exerted to model the uncertainty of the RT energy price. In this regard, the impacts of deviations on the energy price and budget of uncertainty on the profit of the PDISCO are portrayed in Fig. 7.

According to Fig. 7, the amount of PDISCO's profit is diminished by raising the deviation of the energy price from its predicted amount. This is because when the fluctuation of the energy price rises in the RT balancing market, the risk of participating in the energy market interactions increases for maximizing profit. Moreover, increasing the budget of uncertainty results in decline in PDISCO's profit. Indeed, increasing

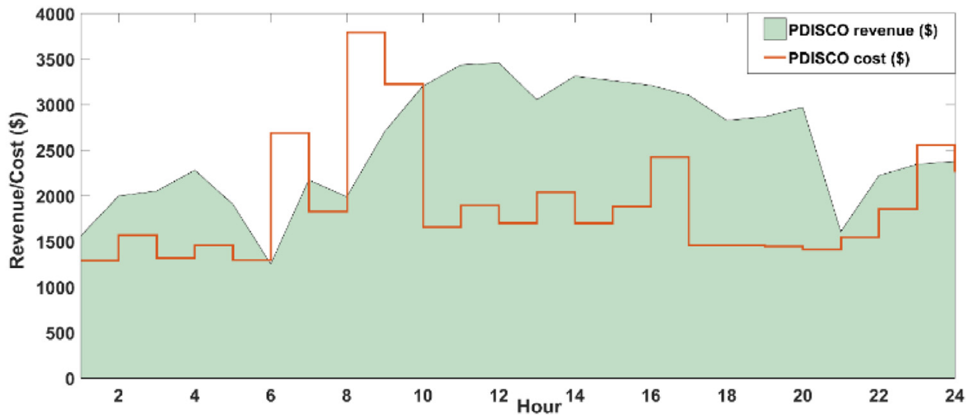

Fig. 3. Total cost and revenue of the PDISCO during a day.

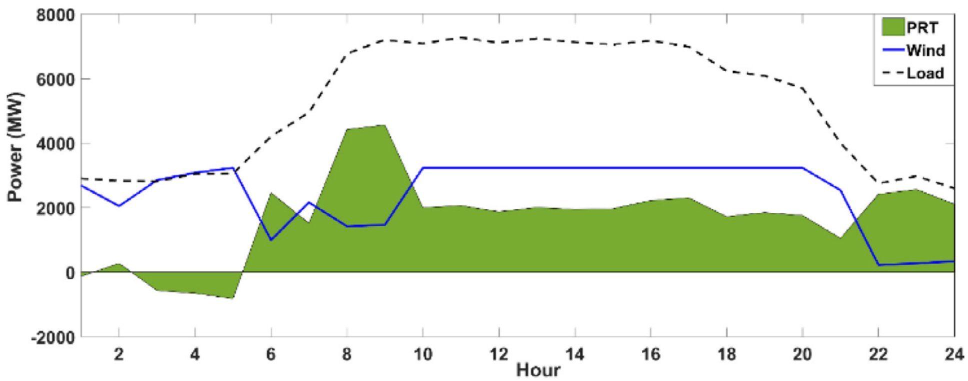

Fig. 4. Outputs of the wind turbines and energy trading in the RT balancing market for 24 h.

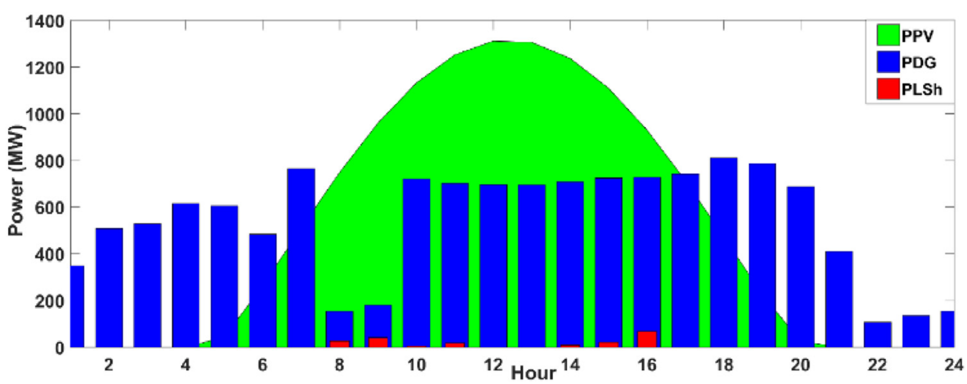

Fig. 5. Scheduling of DG units, load shedding, and PV panels.

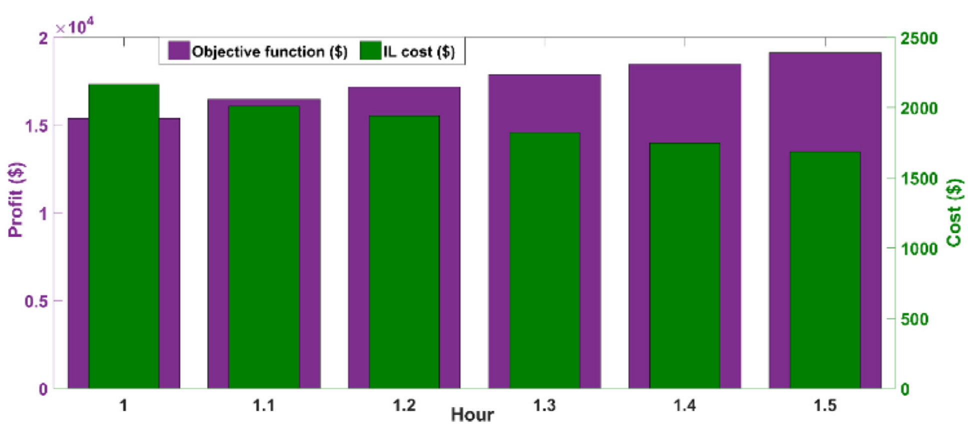

Fig. 6. Impacts of the DR program on the IL cost and objective function.

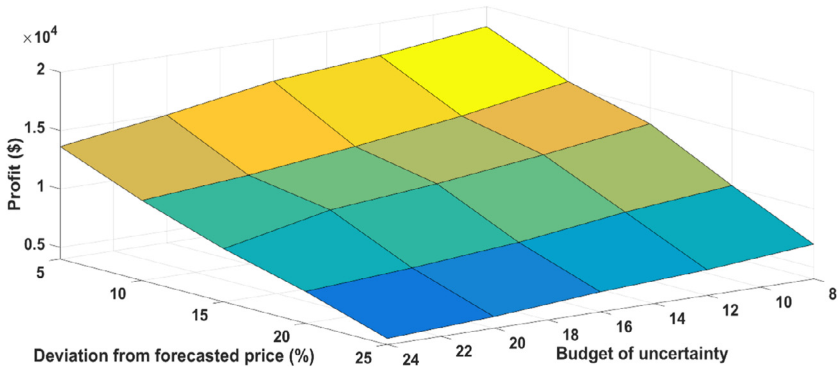

Fig. 7. Impacts of deviations in the energy price and budget of uncertainty on the PDISCO's profit.

the budget of uncertainty has concluded an enhancement in the system robustness by intending the worst state of an uncertain parameter in more hours. Therefore, although a large number of the budget of uncertainty can increase the robustness of the system and guarantee the achieving of a certain profit, a lower profit is reached for the PDISCO due to take the worst state of the system into account in more hours.

In this work, a transactive energy model is proposed for the PDISCO aiming to maximize its profit in the power market interactions. The main achievements of this work are: (1) Creating affordable conditions for maximizing the PDISCO's profit by proposing the transactive energy-based strategy for the PDISCO's active participation in the power interactions that enable it to effectively pursue its economic and technical objectives. (2) Achieving more flexibility for the system by employing the DR scheme for the demand-side power management in the presence of a high contribution of RSs. (3) Providing a proper degree of robustness for the renewable-based system and gaining confident results by realistic modeling of the grid by developing the hybrid uncertainty quantification technique. Although this work achieves the aforementioned advantages for the PDISCO, it also includes some limitations including the geographical limitations in operating a high level of RSs, the lack of a comprehensive method for reaching the global optimal results in the presence of nonlinear equations, and ignoring the effects of other distribution companies related to different carriers of energy as well as the interactions between them.

5. Conclusion

In this study, transactive energy technology was suggested as the special electricity trading strategy for effectively involving the PDISCO in the electricity market interactions with the aim of maximizing its profit. RSs were used as cost-effective and pollutant-free electricity resources for providing a high portion of the energy load over the scheduling horizon. Moreover, DGs were also employed as backup devices for enhancing the reliability of the uninterrupted electricity supply. Due to the exploitation of renewable-based systems, the uncertainty modeling was done using a robust/stochastic hybrid method. For this aim, LHS and FFS advantages in scenario generation and reduction were used in the SP process, considering the solar radiation and wind speed as uncertain parameters. Moreover, the RO technique was also employed to intend the worst state of the RT market price fluctuations. The capability of the DR program was investigated for managing the demand side by categorizing the electricity load into the inelastic and elastic portions. A modified IEEE 33-bus case study was designated for validating simulation results. The obtained results indicated the capabilities of the proposed transactive energy-based strategy for the optimal operation of the PDISCO. Indeed, the transactive energy-based strategy enabled the PDISCO to effectively participate in the power trading market to not only meet its technical goals but also maximize its economic achievements. Given the results, employing the DR program enhanced the PDISCO ability in dynamic power balancing and increased the flexibility of the system with a high level of RSs penetration. On the other hand, as applying transactive energy strategy and DR program provided affordable conditions for optimal operation of the PDISCO, more energy costs were imposed on the system for achieving the appropriate level of robustness in the presence of RSs. In this regard, considering the robustness of the system along with guaranteeing a special level of profit for the PDISCO was led to a 23.197% reduction in its profit than the base case without the uncertainty modeling under a large number of uncertainties.

In energy structures with a high contribution of RSs, providing a confident condition for energy supply is taken into account as one of the remarkable challenges. In this respect, energy trading mechanisms are recognized as effective tools for creating a continuous electricity balance in renewable-based systems. However, an appropriate structure is a basic requirement for realizing the effectiveness of these mechanisms in the power grid. Thus, developing local energy trading markets can provide a significant opportunity for the aforementioned mechanisms to be used in the energy marketplace. On the other hand, different objectives such as economic or environmental goals can be intended in this development aiming to provide satisfactory conditions for various participants in the energy markets. All of these challenges can be evaluated as future works for this research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] D.S. Kirschen, G. Strbac, Fundamentals of Power System Economics, Wiley Online Library, 2004.
[2] M.C. Cerbantes, R. Fernández-Blanco, M.A. Ortega-Vazquez, J.R.S. Mantovani, Short-term operation of a distribution company: a pseudo-dynamic tabu search-based optimisation, IET Gener. Trans. Distrib. 12 (12) (2018) 2995–3004.
[3] M. Daneshvar, B. Mohammadi-Ivatloo, A. Anvari-Moghaddam, Optimal energy trading strategy for proactive DISCO considering demand response programs in the distribution networks, in: Proceedings of the CIGRE Symposium, 2019, CIGRE (International Council on Large Electric Systems, 2019, pp. 1–10.
[4] N. Akbari, D. Jones, F. Arabikhan, Goal programming models with interval coefficients for the sustainable selection of marine renewable energy projects in the UK, Eur. J. Op. Res. 293 (2) (2021) 748–760.
[5] M. Santamouris, K. Vasilakopoulou, Present and future energy consumption of buildings: challenges and opportunities towards decarbonisation, E-Prime 1 (2021) 100002.
[6] T. Tapia, Á. Lorca, D. Olivares, M. Negrete-Pincetic, A robust decision-support method based on optimization and simulation for wildfire resilience in highly renewable power systems, Eur. J. Op. Res. (2021).
[7] M. Daneshvar, B. Mohammadi-ivatloo, K. Zare, S. Asadi, A. Anvari-Moghaddam, A novel operational model for interconnected microgrids participation in transactive energy market: a hybrid IGDT/stochastic approach, IEEE Trans. Ind. Inf. 17 (6) (2021) 4025–4035.
[8] S. Bahramara, M. Yazdani-Damavandi, J. Contreras, M. Shafie-Khah, J.P. Catalão, Modeling the strategic behavior of a distribution company in wholesale energy and reserve markets, IEEE Trans. Smart Grid 9 (4) (2018) 3857–3870.

[9] H. Li, Y. Li, Z. Li, A multiperiod energy acquisition model for a distribution company with distributed generation and interruptible load, IEEE Trans. Power Syst. 22 (2) (2007) 588–596.
[10] H. Haghighat, S.W. Kennedy, A bilevel approach to operational decision making of a distribution company in competitive environments, IEEE Trans. Power Syst. 27 (4) (2012) 1797–1807.
[11] R. Palma-Behnke, L.S. Vargas, A. Jofré, A distribution company energy acquisition market model with integration of distributed generation and load curtailment options, IEEE Trans. Power Syst. 20 (4) (2005) 1718–1727.
[12] H. Khazaei, B. Vahidi, S.H. Hosseinian, H. Rastegar, Two-level decision-making model for a distribution company in day-ahead market, IET Gener. Transm. Distrib. 9 (12) (2015) 1308–1315.
[13] A. Ameli, M. Farrokhifard, A. Ahmadifar, M.R. Haghifam, Distributed generation planning based on the distribution company's and the DG owner's profit maximization, Int. Trans. Electr. Energy Syst. 25 (2) (2015) 216–232.
[14] Y. Cai, J. Lin, C. Wan, Y. Song, Stochastic bi-level trading model for an active distribution company with DGs and interruptible loads, IET Renew. Power Gener. 11 (2) (2016) 278–288.
[15] A. Safdarian, M. Fotuhi-Firuzabad, M. Lehtonen, A stochastic framework for short--term operation of a distribution company, IEEE Trans. Power Syst. 28 (4) (2013) 4712–4721.
[16] C. Zhang, Q. Wang, J. Wang, P. Pinson, J.M. Morales, J. Østergaard, Real-time procurement strategies of a proactive distribution company with aggregator-based demand response, IEEE Trans. Smart Grid 9 (2) (2018) 766–776.
[17] L. Ju, P. Li, Z. Tan, W. Wang, A dynamic risk aversion model for virtual energy plant considering uncertainties and demand response, Int. J. Energy Res. 43 (3) (2019) 1272–1293.
[18] J.L.R. Duarte, N. Fan, T. Jin, Multi-process production scheduling with variable renewable integration and demand response, Eur. J. Op. Res. 281 (1) (2020) 186–200.
[19] W.A. Wattoo, D. Feng, M. Yousif, S. Tahir, M.T. Anwar, M. Numan, Optimal asset allocation of wind energy units in conjunction with demand response for a large-scale electric grid, Int. J. Energy Res. 43 (10) (2019) 5447–5459.
[20] M. Habibian, A. Downward, G. Zakeri, Multistage stochastic demand-side management for price-making major consumers of electricity in a co-optimized energy and reserve market, Eur. J. Op. Res. 280 (2) (2020) 671–688.
[21] L.P. Raghav, R.S. Kumar, D.K. Raju, A.R. Singh, Analytic hierarchy process (AHP)–Swarm intelligence based flexible demand response management of grid–connected microgrid, Appl. Energy 306 (2022) 118058.
[22] J. Kirkerud, N.O. Nagel, T. Bolkesjø, The role of demand response in the future renewable northern European energy system, Energy 235 (2021) 121336.
[23] C. Zhang, Q. Wang, J. Wang, P. Pinson, J.M. Morales, J. Østergaard, Real-time procurement strategies of a proactive distribution company with aggregator-based demand response, IEEE Trans. Smart Grid 9 (2) (2016) 766–776.
[24] M. Daneshvar, et al., Chance-constrained models for transactive energy management of interconnected microgrid clusters, J. Clean. Prod. 271 (2020) 122177.
[25] N. Good, E.A.M. Ceseña, C. Heltorp, P. Mancarella, A transactive energy modelling and assessment framework for demand response business cases in smart distributed multi-energy systems, Energy 184 (2019) 165–179.
[26] M. Daneshvar, B. Mohammadi-Ivatloo, M. Abapour, S. Asadi, R. Khanjani, Distributionally robust chance constrained transactive energy framework for coupled electrical and gas microgrids, IEEE Trans. Ind. Electron. 68 (1) (2021) 347–357.
[27] M. Daneshvar, B. Mohammadi-ivatloo, S. Asadi, S. Galvani, Short term optimal hydro-thermal scheduling of the transmission system equipped with pumped storage in the competitive environment, Majlesi J. Electr. Eng. 14 (1) (2020) 77–84.
[28] L.F. Escudero, M.A. Garín, J.F. Monge, A. Unzueta, Some matheuristic algorithms for multistage stochastic optimization models with endogenous uncertainty and risk management, Eur. J. Op. Res. 285 (3) (2020) 988–1001.
[29] M. Khajehvand, A. Fakharian, M. Sedighizadeh, A hybrid approach based on IGDT–MOCMA-ES method for optimal operation of smart distribution network under severe uncertainties, Int. J. Energy Res. 45 (6) (2021) 9463–9491.
[30] K. Bülbül, N. Noyan, H. Erol, Multi-stage stochastic programming models for provisioning cloud computing resources, Eur. J. Op. Res. 288 (3) (2021) 886–901.
[31] K. Zhao, T.S. Ng, C.H. Tan, C.K. Pang, An almost robust model for minimizing disruption exposures in supply systems, Eur. J. Op. Res. 295 (2) (2021) 547–559.
[32] M. Saeedi, M. Moradi, M. Hosseini, A. Emamifar, N. Ghadimi, Robust optimization based optimal chiller loading under cooling demand uncertainty, Appl. Therm. Eng. 148 (2019) 1081–1091.
[33] M.S. Javadi, et al., Conditional value-at-risk model for smart home energy management systems, E-Prime 1 (2021) 100006.
[34] M.M. Rahman, E. Gemechu, A.O. Oni, A. Kumar, Energy and environmental footprints of flywheels for utility-scale energy storage applications, E-Prime 1 (2021) 100020.
[35] N. Ghadimi, A. Akbarimajd, H. Shayeghi, O. Abedinia, Two stage forecast engine with feature selection technique and improved meta-heuristic algorithm for electricity load forecasting, Energy 161 (2018) 130–142.
[36] V. Shabazbegian, H. Ameli, M.T. Ameli, G. Strbac, M. Qadrdan, Co-optimization of resilient gas and electricity networks; a novel possibilistic chance-constrained programming approach, Appl. Energy 284 (2021) 116284.
[37] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, S. Asadi, Two-stage robust stochastic scheduling model for transactive energy based renewable microgrids, IEEE Trans. Ind. Inf. 16 (11) (2020) 6857–6867.
[38] W. Cai, R. Mohammaditab, G. Fathi, K. Wakil, A.G. Ebadi, N. Ghadimi, Optimal bidding and offering strategies of compressed air energy storage: a hybrid robust-stochastic approach, Renew. Energy 143 (2019) 1–8.
[39] S.Z. Moghaddam, T. Akbari, Network-constrained optimal bidding strategy of a plug-in electric vehicle aggregator: a stochastic/robust game theoretic approach, Energy 151 (2018) 478–489.
[40] L. Baringo, R.S. Amaro, A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator, Electr. Power Syst. Res. 146 (2017) 362–370.
[41] O. Abedinia, M. Zareinejad, M.H. Doranehgard, G. Fathi, N. Ghadimi, Optimal offering and bidding strategies of renewable energy based large consumer using a novel hybrid robust-stochastic approach, J. Clean. Prod. 215 (2019) 878–889.
[42] G. Liu, Y. Xu, K. Tomsovic, Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization, IEEE Trans. Smart Grid 7 (1) (2015) 227–237.
[43] A. Hermann, T.V. Jensen, J. Østergaard, J. Kazempour, A complementarity model for electric power transmission-distribution coordination under uncertainty, Eur. J. Op. Res. 16 (2021).
[44] R. Mínguez, W. van Ackooij, R. García-Bertrand, Constraint generation for risk averse two-stage stochastic programs, Eur. J. Op. Res. 288 (1) (2021) 194–206.
[45] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, M. Abapour, S. Asadi, A. Anvari–Moghaddam, Chance-constrained scheduling of hybrid microgrids under transactive energy control, Int. J. Energy Res. 45 (7) (2021) 10173–10190.
[46] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, S. Asadi, Transactive energy management for optimal scheduling of interconnected microgrids with hydrogen energy storage, Int. J. Hydrog. Energy 30 (2020) 16267–16278.
[47] A. Gupta, A. Kumar, ATC calculation including wind: a probabilistic study and a comparison of MCS and LHS, in: Proceedings of the IEEE 6th International Conference on Power Systems (ICPS), IEEE, 2016, pp. 1–6.
[48] Y. Wang, Y. Liu, D.S. Kirschen, Scenario reduction with submodular optimization, IEEE Trans. Power Syst. 32 (3) (2017) 2479–2480.
[49] B. Fanzeres, A. Street, L.A. Barroso, Contracting strategies for renewable generators: a hybrid stochastic and robust optimization approach, IEEE Trans. Power Syst. 30 (4) (2014) 1825–1837.
[50] E. Kuznetsova, C. Ruiz, Y.F. Li, E. Zio, Analysis of robust optimization for decentralized microgrid energy management under uncertainty, Int. J. Electr. Power Energy Syst. 64 (2015) 815–832.
[51] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, Two-stage optimal robust scheduling of hybrid energy system considering the demand response programs, J. Clean. Prod. 248 (2020) 119267.
[52] M. Daneshvar, H. Eskandari, A.B. Sirous, R. Esmaeilzadeh, A novel techno-economic risk-averse strategy for optimal scheduling of renewable-based industrial microgrid, Sustain. Cities Soc. 70 (2021) 102879.
[53] B. Jeddi, V. Vahidinasab, P. Ramezanpour, J. Aghaei, M. Shafie-khah, J.P. Catalão, Robust optimization framework for dynamic distributed energy resources planning in distribution networks, Int. J. Electr. Power Energy Syst. 110 (2019) 419–433.
[54] M. Sadeghi, M. Kalantar, Multi types DG expansion dynamic planning in distribution system under stochastic conditions using covariance matrix adaptation evolutionary strategy and Monte-Carlo simulation, Energy Convers. Manag. 87 (2014) 455–471.
[55] A. Soroudi, Robust optimization based self scheduling of hydro-thermal Genco in smart grids, Energy 61 (2013) 262–271.
[56] C. Zhang, Q. Wang, J. Wang, P. Pinson, J. Østergaard, Real-time trading strategies of proactive DISCO with heterogeneous DG owners, IEEE Trans. Smart Grid 9 (3) (2016) 1688–1697.
[57] M. Daneshvar, E. Babaei, Exchange market algorithm for multiple DG placement and sizing in a radial distribution system, J. Energy Manag. Technol. 2 (1) (2018) 54–65.
[58] M. Daneshvar, B. Mohammadi-Ivatloo, S. Asadi, M. Abapour, A. Anvari-Moghaddam, A transactive energy management framework for regional network of microgrids, in: Proceedings of the International Conference on Smart Energy Systems and Technologies (SEST), IEEE, 2019, pp. 1–6.
[59] C. Zhang, Q. Wang, J. Wang, P. Pinson, J. Østergaard, Real-time trading strategies of proactive DISCO with heterogeneous DG owners, IEEE Trans. Smart Grid 9 (3) (2018) 1688–1697.
[60] M. Daneshvar, B. Mohammadi-Ivatloo, M. Abapour, S. Asadi, Energy exchange control in multiple microgrids with transactive energy management, J. Mod. Power Syst. Clean Energy 8 (4) (2020) 719–726.
[61] M. Daneshvar, B. Mohammadi-ivatloo, K. Zare, Integration of distributed energy resources under the transactive energy structure in the future smart distribution networks, in: Operation of Distributed Energy Resources in Smart Distribution Networks, Elsevier, 2018, pp. 349–379.
[62] J. Qiu, J. Zhao, H. Yang, Z.Y. Dong, Optimal scheduling for prosumers in coupled transactive power and gas systems, IEEE Trans. Power Syst. 33 (2) (2018) 1970–1980.
[63] M.R. Bussieck and A. Drud, "SBB: a new solver for mixed integer nonlinear programming," Talk, Available online (accessed Sep. 2021): https://www.gams.com/archives/presentations/present_sbb.pdf, OR, 2001.
[64] I.E. Grossmann, J. Viswanathan, A. Vecchietti, R. Raman, E. Kalvelagen, in: GAMS/DICOPT: A Discrete Continuous Optimization Package, 37, GAMS Corporation Inc, 2002, p. 55.