IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 18, 2020, accepted June 18, 2020, date of publication June 26, 2020, date of current version July 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3005294

Two-Stage Robust-Stochastic Electricity Market Clearing Considering Mobile Energy Storage in Rail Transportation

MOHAMMAD AMIN MIRZAEI[1], MOHAMMAD HEMMATI[1], KAZEM ZARE[1], BEHNAM MOHAMMADI-IVATLOO[1,2], (Senior Member, IEEE), MEHDI ABAPOUR[1], MOUSA MARZBAND[3,4], (Senior Member, IEEE), AND ALI FARZAMNIA[5], (Senior Member, IEEE)

[1]Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz 5166616471, Iran
[2]Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam
[3]Department of Mathematics, Physics and Electrical Engineering, Northumbria University, Newcastle upon Tyne NE1 8QH, U.K.
[4]Center of Research Excellence in Renewable Energy and Power Systems, King Abdulaziz University, Jeddah 21589, Saudi Arabia
[5]Faculty of Engineering, Universiti Malaysia Sabah, Kota Kinabalu 88400, Malaysia

Corresponding authors: Ali Farzamnia (ali-farzamnia@ieee.org) and Kazem Zare (kazem.zare@tabrizu.ac.ir)

This work was supported by Research and Innovation Management Center (PPPI) and Faculty of Engineering, Universiti Malaysia Sabah (UMS).

ABSTRACT This paper proposes a two-stage robust-stochastic framework to evaluate the effect of the battery-based energy storage transport (BEST) system in a day-ahead market-clearing model. The model integrates the energy market-clearing process with a train routing problem, where a time-space network is used to describe the limitations of the rail transport network (RTN). Likewise, a price-sensitive shiftable (PSS) demand bidding approach is applied to increase the flexibility of the power grid operation and reduce carbon emissions in the system. The main objective of the proposed model is to determine the optimal hourly location, charge/discharge scheduling of the BEST system, power dispatch of thermal units, flexible loads scheduling as well as finding the locational marginal price (LMP) considering the daily carbon emission limit of thermal units. The proposed two-stage framework allows the market operator to differentiate between the risk level of all existing uncertainties and achieve a more flexible decision-making model. The operator can modify the conservatism degree of the market-clearing using a non-probabilistic method based on info-gap decision theory (IGDT), to reduce the effect of wind power fluctuations in real-time. In contrast, a risk-neutral-based stochastic technique is used to meet power demand uncertainty. The results of the proposed mixed-integer linear programming (MILP) problem, confirm the potential of BEST and PSS demand in decreasing the LMP, line congestion, carbon emission, and daily operation cost.

INDEX TERMS Battery-based energy storage transport, demand side-management, rail transport network, day-ahead market clearing, hybrid optimization technique, wind energy.

NOMENCLATURE

Index

bl	Index of demand blocks
b, b'	Index of buses
i	Index of thermal units
j	Index of loads
k, n	Index of train station
m	Index for generation blocks
t	Index of times
ts	Index of time-spaces
tr	Index of trains
wp	Index of wind turbine
w	Index of scenarios

Constant

BL	Number of demand blocks
M	Number of generation blocks
N	Number of thermal units
T	Number of time intervals
W	Number of scenarios
TR	Number of trains

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Massaro.

TS	Number of time-spaces
U	Number of thermal units
WP	Number of wind turbine
TR	Number of trains
J	Number of electrical loads
A	Set of arcs related to time-space in RTN
A_k^-	Set of arcs in a time-space network which end at station k.
A_k^+	Set of arcs in a time-space network which start from station k.
C_{tr}	The transport cost of train tr
C_{tr}^{ch}	Operation cost of trains during charging mode
C_{tr}^{dis}	Operation cost of trains during charging mode
$voll_{j,t}$	Value of loss load j at time t
$P_{i,m}^{\min}/P_{i,m}^{\max}$	Minimum/ maximum power generated by unit i
MDT_i/MUT_i	Minimum down/ up time of thermal unit i
C_i^{SU}/C_i^{SD}	Startup/shutdown cost of thermal unit i
R_i^{down}/R_i^{up}	Ramp down/ up of thermal unit i
$P_{tr}^{ch,\min}/P_{tr}^{ch,\max}$	Minimum/ maximum power charged by train tr
$P_{tr}^{dis,\min}/P_{tr}^{dis,\max}$	Minimum/ maximum power discharged by train tr
$\eta_{tr}^{ch}/\eta_{tr}^{dis}$	Charging/ discharging efficiency of train tr
$E_{tr}^{\min}/E_{tr}^{\max}$	Minimum/ maximum energy capacity in train tr
$E_{tr,0}$	Initial energy capacity of train tr
$D_{j,t}$	Load demand j at time t
$dr_{bl,j}^{\max}$	Maximum demand block
$FL_{j,t}$	Value of flexible load demand j at time t
$Bid_{bl,j}$	Bid price of load j at block bl
d_j^{down}/d_j^{up}	Ramp down/up rate for demand at consecutive time intervals
$X_{b,b'}$	Line reactance between buses b and b'
$PX_{Line}^{\max}$	Maximum power capacity of transmission line
$\hat{P}_{wp,t}$	The forecasted wind power
EC	Maximum allowable daily emission pollution
$MC_{i,t}$	Minimum marginal cost of thermal unit i
γ	Load factor participation in DR
Variable SF	Social welfare
$dr_{bl,j,t}$	Demand block bl for load j at time t
$P_{i,t}$	Power generated by unit i at time t
$P_{i,t,w}$	Power generated by unit i at time t and scenario w
$P_{tr,t}^{ch}/P_{tr,t}^{dis}$	Value of power charged/ discharged by train tr at time t
π_w	Probability of scenario w
$Lsh_{j,t,w}$	Load shedding value for load j at t time and scenario w
$TU_{i,u}/TD_{i,u}$	Number of successive ON/ OFF hours of unit i
$P_{tr,t}^{ch}/P_{tr,t}^{dis}$	Power charged/ discharged by train tr at time t
$E_{tr,t}$	Energy capacity of train tr at time t
$DR_{j,t}$	Supplied demand of load j at time t after implementation of DR
$PX_{b,b',t}$	Power flow value crossing transmission line between buses b and b' at time t
$F^E(P_{i,t})$	Emission function of thermal unit i
$\delta_{b,t}/\delta_{b',t}$	Angle magnitude of bus b and b' at time t
$\Delta dr_{bl,j,t,w}$	Adjusted demand of load j at time t and scenario w
$\Delta P_{i,t,m,w}$	Adjusted power of unit i in real-time dispatch at time t and scenario w
$\Delta P_{tr,t,w}^{ch}$	Adjusted charge power of BEST at time t and scenario w
$\Delta P_{tr,t,w}^{dis}$	Adjusted discharge power of BEST at time t and scenario w
$\Theta_{j,t,w}$	Value of variable $\Theta \in \{D, DR, FL\}$ in second stage
$\Theta_{tr,t,w}$	Value of variable $\Theta \in \{E, P^{ch}, P^{dis}\}$ in second stage
$\Theta_{i,t,w}$	Value of variable $\Theta \in \{P\}$ in second stage
$\Theta_{b,t,w}$	Value of variable $\Theta \in \{PX, \delta\}$ in second stage

Binary variable

$Y_{i,t}/Z_{i,t}$	Binary variable for shutdown/startup i at time t
$I_{i,t}$	Binary variable to denote the status of unit i at time t
$I_{k,n,ts}$	Status of routes k n of train tr at time span ts.
$I_{tr,t}^{ch}/I_{tr,t}^{dis}$	Binary variable for charging/ discharging mode of train tr at time t

I. INTRODUCTION

A. OVERVIEW

The total global capacity from onshore wind energy is projected to reach 1787 GW by 2030 [1]. The fast-growing installation of fluctuating wind energy with the aim of coping with global warming has introduced new challenges like as energy imbalance, reliability and system security issues. In addition to the power fluctuations, one of the significant obstacles of renewable energy source (RES) development, especially wind energy, is the transfer of produced energy from wind farms to load centers through transmission lines. This issue, in addition to causing high costs, also results in the congestion of transmission lines. A suitable solution to overcome such challenges is to employ fast-response and flexible technologies in the power system. Energy storage systems (ESS) attracted much attention to compensate for

the fluctuation of wind energy [2]. Among all energy storage facilities, battery energy storage systems (BESS) with high efficiency, high power density, faster response, as well as no specific geographic requirements can be integrated with the high penetration of wind energy. One of the most important features of BESS is the mobility potential to move easily from place to place. The mobility of BESS through rail transport networks (RTN), while facilitating the participation of BESS in the energy markets, also is a suitable option for overcoming the issues related to the transmission of wind energy from wind farms to load centers, thereby saving the cost of installing new or expanding the existing power transmission lines [3]. Furthermore, battery mobility via RTN and giving out energy in buses with relatively low congestion can impose the scheduling of expensive highly polluting thermal units.

Restructuring the power system and the power market has gained new emergence, which consistently provides a competitive environment for both consumers and producers. RES and BESS owned by the different entities started to take part in the energy markets [4]. Besides, there are enormous interests in utilizing demand response (DR) for responsible loads as another flexible alternative that enables consumer participation in competitive markets [5]. Although the emergence of flexible resources as new market players leads to numerous economic and environmental benefits, it severely imposes on the security and reliability of power systems, including thermal units operation and unit commitment, power flow calculation, line congestion, locational marginal prices, and etc. Furthermore, integrating the RTN with the power system as a suitable solution to ease the challenges of renewable-based systems should thoroughly be investigated. However, the development of an appropriate optimization approach to more realistic modeling of such integrated systems incorporating emerging flexible sources from technical, economic, and environmental perspectives while tackling the unknown uncertainties, including wind power production and load demand, has been rarely studied in previous works and requires further investigations.

B. LITERATURE REVIEW

The fluctuation in wind power output could impose adverse effects on the reliability and security of power systems. There are several studies in the literature that focuses on the integration of high penetration of wind energy into the power systems via multiple flexible resources. A two-stage framework to assess the capability of bulk energy storage (BES) integrated with wind energy was presented in [6]. First, the stochastic unit commitment (UC) problem considering wind uncertainty was formulated. Then, the solution from the UC problem is implemented to derive the optimal scheduling of energy storage in economic dispatch. A stochastic day-ahead market-clearing model coordinated with BES, DR, and plug-in electric vehicles (PEVs) to cover the inflexibility gap due to the variability of wind energy was developed by [5]. The comprehensive proposed model reveals the benefits of incorporating flexible sources from the independent system operator (ISO) point of view to manage both reserve and energy markets. Authors of [7] have developed a day-ahead market-clearing model incorporated with emerging flexible resources including BESS, DR, and PEV to offer a flexible ramp, energy and reserve scheduling in the presence of wind energy. In [8], a security-constraint unit commitment (SCUC) problem integrated with large-scale BESS, RES (wind and solar) considering load uncertainty and degradation cost of BESS based on the MILP model was investigated. The techno-economic flexibility criterion is to provide high-level flexibility of conventional generation capturing two emerging resources, including BES and DR was developed in [9], where a new flexibility index was studied in the day-ahead market clearing problem. A multi-objective problem incorporating flexible sources such as DR, compressed air energy storage system, and PEV was developed in [10], where a two-stage stochastic framework was implemented to deal with the uncertainty of wind energy. The authors in [11], concentrated on the evaluation of ESS as a price-maker entity in the competitive market. The proposed problem was formulated as a mix-min problem to evaluate the effect of ESS from the ISO point of view based on the bi-level optimization framework. In [12], a novel BESS operational cost for participation in energy and reserve markets, as well as locational marginal cost (LMP) was developed. This literature illustrated that the independently owned BESS could submit bids/offers to participate in the energy and spinning reserve markets during both charging and discharging cycles. The market-based DR and the comprehensive evaluation of DR's roles in the future electricity markets to mitigate the variability nature of wind energy aiming to maximize system security, and reduce the total operational cost was presented in [13].

In the mentioned literature above, ESS has been introduced as a fixed resource in optimal scheduling of wind-based power systems, while a major obstacle of wind energy is the long distance between wind farms and load centers, which results in an increase in wind power curtailment due to line congestion. The mobility of BESS provides a suitable solution for transporting the produced wind energy from generation sides to load centers all over different areas in the system. To improve the resilience of the power system, a SCUC model integrated with BESS transportation via the railway system considering power and transportation systems restrictions was proposed in [14]. The proposed model evaluates the effects of battery-based energy storage transport (BEST) on the hourly behavior of thermal units (power generation, ON/OFF states) while the system uncertainties have been neglected. Authors in [15], revealed the potential of BEST via shipping, trunks, and train for managing the lines congestion. Therefore, an hourly SCUC model integrated with BEST for optimal calculation of batteries charging/discharging schemes, as well as power exchange with the power system, was developed in this paper. The proposed model considers all the power and transportation systems constraints, regardless of the system uncertainties.

The potential of BEST for optimal operation of power system integrated with wind energy was developed in [16], where the wind power, load demand, and outages of both power and railway transportation systems components are considered as uncertain parameters. In [17], the joint post-disaster restoration schedule of the distribution network contains multiple microgrids (MGs) integrated with the mobile transportable energy storage system (TESS) was developed. Distribution network can be separated into multiple islanded MGs via reconfiguration in an emergency condition, while TESS travels among all MGs and dispatches to prevent area blackout or consumer's interruptions. Electrical vehicles (EVs) act as mobile storage/demand has the appropriate potential to integrate RES. Authors of [18], concentrated on EVs fleet on transmission-constraints in the system operation to facilitate the wind energy integration. The effects of EV's batteries charging/discharging schemes, and the behavior of drivers on hourly UC considering transmission-constraint were evaluated in this literature. The coordinated large-scale PEV fleet as mobile storage and demand in the stochastic UC model considering wind energy, hourly demand, and behavior of EV's drivers uncertainty was developed in [19]. In [20], a stochastic UC model integrated with the traffic assignment of large-scale EVs with the high penetration of wind energy was proposed. The traffic network was modeled by EVs travels. The effects of optimal charging/discharging schemes, and departure time of EVs on transmission networks, and thermal units scheduling has been investigated in this paper.

However, the growing interest in the utilization of hybrid optimization methods allows the system operator to benefit from all advantages of methods simultaneously in the face of existing uncertainties The hybrid robust/stochastic optimization framework to deal with uncertainty in day-ahead scheduling of active distribution network imposed by the unpredictable load and solar energy was developed by [21]. In [22], a hybrid stochastic/interval/information gap decision theory (IGDT) framework was developed to evaluate the optimal operation of the integrated energy hub system incorporated with the DR concept. A novel hybrid IGDT/stochastic co-optimization strategy for coordinated power and gas grids in the presence of electrical and gas demands, as well as wind energy uncertainties, was developed by [23]. In [24], a multi-energy microgrid operation incorporated with high penetration of RES was optimized via a hybrid stochastic/interval framework exposed by multi-energy demands and RES power output variation. An optimal bidding strategy of compressed air energy storage system with the aim of profit maximization under a hybrid robust/stochastic approach was developed by [25]. The market price uncertainty was modeled by a set of scenarios, while the maximum capacity of CAES cavern is handled by a robust strategy. A novel hybrid stochastic/IGDT approach is used for decision-making of EVs aggregator in the presence of high-level uncertainty including initial state of charge, arrival and departure times of EVs into the parking lot, as well as market price, has been investigated by [26]. The IGDT-based robust optimization was applied to handle price uncertainty, while a scenario-based stochastic approach was used to address other random variables.

C. CONTRIBUTIONS

To the best of the authors' knowledge, the reviewed works have not extensively investigated the economic, technical, and environmental advantages of battery-based energy storage mobility in an LMP-based two-stage market-clearing framework. Moreover, the effect of the coordinated scheduling of demand-side resources and the BEST system on the result of energy market clearing was ignored in the literature. The significant gaps in the studied works are as follows:

- In [5-13], BESSs was applied as fixed resources into energy market-clearing mechanism, and mobility of BESSs in reducing line congestion and maximizing social welfare was neglected.
- In [14-20], although the authors have investigated the mobility of battery-based energy storage into network-constrained unit commitment, they have not extensively focused on environmental issues, the flexibility of demand-side resources, and market-clearing process.
- In [5-20], the authors mainly have utilized deterministic, stochastic and robust-based optimization approaches to solve the problem, while the operator at times preferred to differentiate between the risk levels of the existing uncertainties and manage them depending on the different optimization techniques
- In [21-26], the authors have not applied a hybrid optimization approach in the market-clearing process, while these kinds of techniques can provide major benefits for the market operator to handle uncertainties in real-time dispatch.

Hence, this paper applies a new two-stage robust-stochastic framework into energy market-clearing constrained to the power grid, environmental issues, and rail transport network (RTN) to achieve high-efficiency scheduling of ESS and handle the uncertainties associated with demand and wind power generation. Power demand and wind power generation uncertainties are addressed in the real-time dispatch by a scenario-based stochastic model and an info-gap-based robust technique, respectively. The time-space network has also been considered to study the effects of constraints and flexibility of RTN on the market-clearing outputs and social welfare. Additionally, a demand-side management technique coordinated with the vehicle routing problem (VRP) is adopted to properly manage the fluctuating nature of renewable energy sources, reduce line congestion and carbon emissions. The main contributions of the paper can be summarized as follows:

- The mobility of BESS is evaluated from an economic, environmental, and technical perspective by proposing a market-clearing approach constrained to environmental issues, rail transport, and power networks, in which a

time-space network is applied to model constraints and flexibility of RTN.

- A demand-side management model coordinated with VRP is presented into the proposed market-clearing framework for high-efficiency scheduling of the price-sensitive shiftable (PSS) demand.
- A new two-stage robust-stochastic framework is adopted to model the uncertainties related to demand and wind power production. The proposed model increases the flexibility of the operator's decision-making when facing uncertainties, since the operator might differentiate between the risk levels of system uncertainties.

D. PAPER ORGANIZATION

The remainder of the paper is organized as follows. In Section II, the problem description contains BEST, PSS load, and market-clearing models are represented. Section III represents two-stage robust-stochastic market-clearing formulation, including objective function and corresponding restrictions. Numerical results are reported and discussed in Section IV. Finally, Section V concludes the paper.

II. PROBLEM DESCRIPTION

A. BEST MODEL

RTNs are an important part of the transportation systems worldwide. In addition to daily passenger transportation, which requires an optimal schedule of trains by the classic VRP, the mobility capability of BESS offers an appropriate opportunity for RTN to transport BESS from one region to another. However, the BEST model via RTN requires a realistic model, considering all railway restrictions. In this paper, the time-span network as [14], is applied to model railway lines and stations with VRP. Let us consider small RTN with three stations and railroads crossing, as depicted in Fig. 1, there are three stations {1, 2, 3} that are connected by lines between any two neighboring stations. In addition, the distance time between any to neighboring stations offered as time span is shown at the top of each railroad. For example, distance-time between stations 1 and 3 is twice the distance-time between any two neighboring stations, equals to a 2-time span. To simplify the modeling of the RTN framework, a virtual station (station number 4) is considered between station numbers 1 and 3. Hence, distance-time between any two neighboring stations in Fig. 1 is a 1-time span.

The time-space network for the RTN with 4 stations is depicted in Fig. 2. According to Fig. 2, all possible hourly connections for the actual and virtual station is shown. The vertical axis in Fig. 2 applied to denote the railway station, and the hourly scheduling horizon is exhibited by a horizontal axis. Railway stations are represented by nodes, while connections line between each neighboring stations are represented by arcs. There are two types of arcs in the time-space network shown in Fig. 2: grid connecting arcs and transporting arc. Grid connecting arcs are horizontal solid

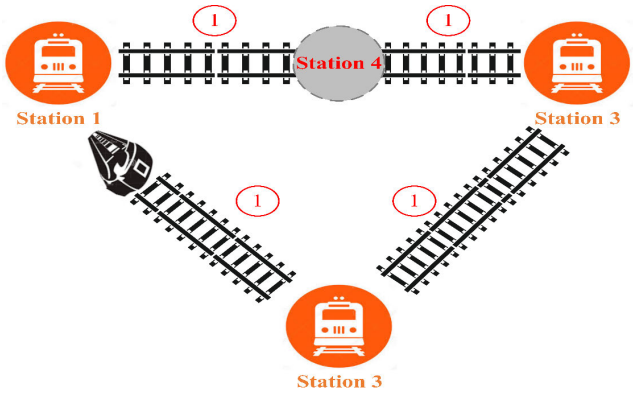

FIGURE 1. Simple RTN configuration.

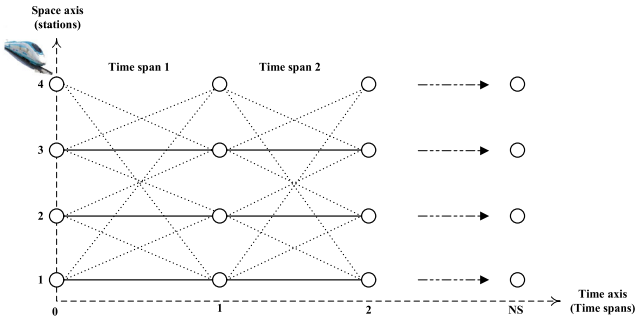

FIGURE 2. Time-space network for a simple RTN configuration.

arc in a time-space network, represent the BESS stop in any station that is connected to the upstream grid for power exchange. Another type, transporting arcs are sloped dotted arcs in a time-space network express the BEST system statues between neighboring stations at any given period of time horizon. It should be noted that the actual station (station 1, 2, and 3 in Fig. 1) can be connected to both grid connecting and transporting arcs, while virtual station (station number 4 in Fig. 1) can only be connected to second types of arcs. Obviously, the BEST cannot be connected to the upstream network in such a virtual station due to a lack of charging/ discharging equipment. All mathematical formulation related to the RTN will be presented in the next sections.

B. PSS DEMAND BIDDING MODEL

Demand bidding program (DBP) is one type of DR program that has been recently adopted by different electrical companies such as PG&E, encourages large energy consumption to reduce their energy demand by setting their own target [27]. The bidding strategy in DR programs has the same concepts as in real-time and day-ahead markets. In the day-ahead market, market players in the DR program, submit their bid package contains the amount of energy reduction in the preceding day. If suggested bids are accepted, consumers are obliged to diminish their daily energy consumption according to the contract. Otherwise, they will be subjected to heavy penalties on a monthly charge. In DBP, participants determine

how much and at what price they would want to reduce or shift their load demand. Hence, a novel modeling strategy for DBP is presented in this paper. In fact, in this strategy, participants submit their bids, including the desired purchase price and demand to be met by the market operator. In other words, if the market price is less or equals to the submitted price bid, the desired load demand is served; otherwise, the market operator has the authority to curtail or shift demand to times with lower electricity prices. Accordingly, the market operator will decide how much demand should be met. Figure 3 describes the proposed PSS demand bidding model to the market operator.

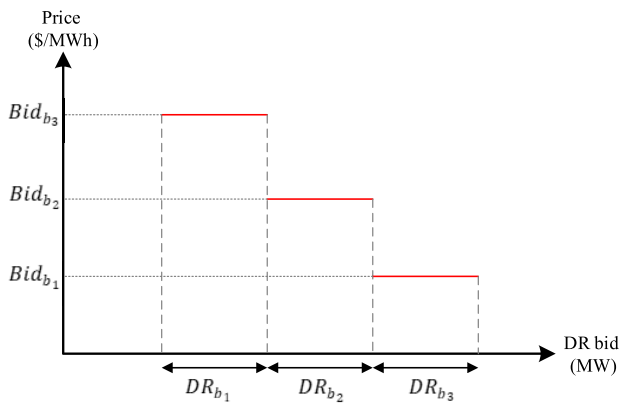

FIGURE 3. Price-sensitive shiftable demand bidding model.

C. MARKET CLEARING STRUCTURE

Under the proposed framework, the market operator takes offers and bids from different market players before clearing the day-ahead market. The market operator has the potential to apply both generation-side and demand-side resources to achieve more cost-effective generation dispatch in energy markets. The BEST systems and PSS demands as flexible options can be used as a generation or consume power according to the market operator's requirements. On this basis, consumers consisting of fixed demand and PSS demands send energy purchase bids, and conventional generation units submit energy selling offers. The BEST system also presents discharging offers and charging bids to provide energy. Technical and cost parameters related to market players consisting of conventional units, wind power plants, BEST systems, and PSS demand are the main inputs of the proposed model. For example, the offered package of conventional generating units not only contains their price-quantity offers for supplying energy but also consists of their technical and environmental features such as minimum up/down-times, carbon emission, ramp rates, minimum/maximum power generation limits, etc. The offer and bid packages considered for BEST systems and PSS demand also include their own technical parameters. Since the market-clearing process is integrated with VRP, the operator solves a market-clearing problem constrained to power and rail transport networks to maximize social welfare. Therefore, the market operator should have access to data related to the power network and RTN to achieve a high-efficiency scheduling model in which such data are considered as input parameters in the proposed model. In addition, to handle the uncertainties related to wind power and demand in real-time dispatch, the market operator might apply a two-stage market-clearing mechanism, which is described in Fig. 4 in more detail.

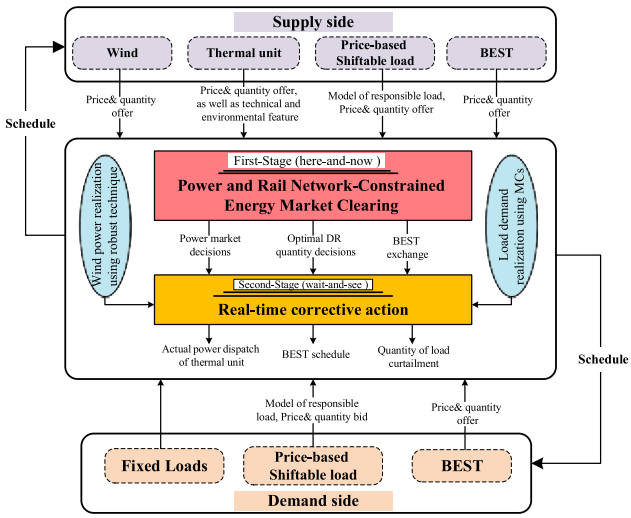

FIGURE 4. An overall perspective of the proposed model.

III. PROBLEM FORMULATION

Based on the proposed framework, the market operator solves a two-stage robust-stochastic energy market clearing problem integrated with VRP, where the constraints associated with the power grid, RTN, and environmental issues are considered in the clearing process. The market operator during the day-ahead market clearing faces some significant challenges due to the resource uncertainties that might appear in real-time. On the other hand, the market operator tends to be able to differentiate between the level of risk of system uncertainties due to the intensity of uncertainty of such resources. Hence, in this paper, the operator applies a scenario-based stochastic model to manage the power demand in real-time dispatch, while employing an info-gap based robust optimization technique to handle the wind power uncertainty due to its severe uncertain nature. The introduced model aims to maximize social welfare while obtaining the optimal hourly location, charge/discharge schedule of the BEST system, power dispatch of thermal units, optimal management of PSS demand, and LMP in each bus. In conclusion, the two-stage stochastic approach is considered to investigate the electricity demand uncertainty in the market clearing process. Then, the robust optimization technique will be integrated into the two-stage market-clearing framework for facing the uncertainty of wind power in real-time dispatch.

A. TWO-STAGE STOCHASTIC MARKET-CLEARING

The main objective of the proposed model is to maximize social welfare, which is formulated as a two-stage stochastic

mixed-integer linear programming (MILP) problem. The objective function (1) includes six terms. The first term is the consumer's surplus in the first stage. The second term is the operation cost of thermal units, which includes minimum generation cost (no-load cost), startup/shutdown cost, and the cost of providing energy in the first stage. The third term is the operation cost of the BEST system, which consists of transport cost and charge/discharge cost in the first stage. The fourth, fifth, and sixth terms are the consumer's surplus, the power production cost of thermal units, the charge/discharge cost of the BEST system, and the load shedding cost in the second stage, respectively.

$$\begin{aligned} SF = \max & \sum_{bl=1}^{BL}\sum_{j=1}^{J}\sum_{t=1}^{T} Bid_{bl,j} dr_{bl,j,t} \\ & - \sum_{t=1}^{T}\sum_{i=1}^{U}\left[\begin{array}{l} MC_{i,t}I_{i,t} + SU_{i,t} + SD_{i,t} \\ + \sum_{m=1}^{M} C^{E}_{i,t,m} P_{i,t,m} \end{array}\right] \\ & - \sum_{tr=1}^{TR}\left[\sum_{(k,n)\in A}\sum_{ts=1}^{TS} C_{tr} I_{tr,k,n,ts} \right. \\ & \left. + \sum_{t=1}^{T}\left[C^{ch}_{tr} P^{ch}_{tr,t} + C^{dis}_{tr} P^{dis}_{tr,t}\right]\right] \\ & + \sum_{t=1}^{T}\sum_{w=1}^{W} \pi_w \left[\begin{array}{l} \sum_{bl=1}^{BL}\sum_{n=1}^{N} Bid_{bl,j}\Delta dr_{bl,j,t,w} \\ - \sum_{i=1}^{U}\sum_{m=1}^{M} C^{E}_{i,t,m}\Delta P_{i,t,m,w} \\ - \sum_{tr=1}^{TR} C^{ch}_{tr}\Delta P^{ch}_{tr,t,w} + C^{dis}_{tr}\Delta P^{dis}_{tr,t,w} \\ - \sum_{j=1}^{J} voll_{j,t}\, Lsh_{j,t,w} \end{array}\right] \end{aligned} \tag{1}$$

1) FIRST STAGE CONSTRAINTS

In this section, the constraints associated with "*here and now*" variables are defined. The constraints of thermal units in the first stage are stated as (2)-(12). The power generated by the thermal unit is limited by upper and lower levels as expressed by (2) and (3). The ramp-up and ramp-down constraints for continuous hours are respectively indicated by (4)-(7). Constraints (8)-(11) represent minimum up and down time limits that bind the thermal unit to be turned on and off for a certain time before starting-up and shutting-down. The startup and shutdown costs are expressed by (12) and (13), respectively.

$$P^{\min}_{i,m} I_{i,t} \le P_{i,t,m} \le P^{\max}_{i,m} I_{i,t} \tag{2}$$

$$P_{i,t} = \sum_{m=1}^{M} P_{i,t,m} \tag{3}$$

$$P_{i,t} - P_{i,t-1} \le (1 - Y_{i,t}) R^{up}_i + Y_{i,t} P^{\min}_i \tag{4}$$

$$P_{i,t-1} - P_{i,t} \le (1 - Z_{i,t}) R^{dn}_i + Z_{i,t} P^{\min}_i \tag{5}$$

$$Y_{i,t} - Z_{i,t} = I_{i,t} - I_{i,t-1} \tag{6}$$

$$Y_{i,t} + Z_{i,t} \ge 1 \tag{7}$$

$$I_{i,t} - I_{i,t-1} \le I_{i,t+TU_{i,u}} \tag{8}$$

$$TU_{i,u} = \begin{cases} u & u \le MUT_i \\ 0 & u > MUT_i \end{cases} \tag{9}$$

$$I_{i,t-1} - I_{i,t} \le 1 - I_{i,t+TD_{i,u}} \tag{10}$$

$$TD_{i,u} = \begin{cases} u & u \le MDT_i \\ 0 & u > MDT_i \end{cases} \tag{11}$$

$$\begin{aligned} & SU_{i,t} \ge C^{SU}_i (I_{i,t} - I_{i,t-1}) \\ & SU_{i,t} \ge 0 \end{aligned} \tag{12}$$

$$\begin{aligned} & SD_{i,t} \ge C^{SD}_i (I_{i,t-1} - I_{i,t}) \\ & SD_{i,t} \ge 0 \end{aligned} \tag{13}$$

The constraints related to the BEST system in the first stage are defined as (14)-(23). The limitation related to the location state of the BEST system is determined by (14). In a specific time span, each train can only be on one route. Movement limits of the BEST system are given in (15)-(17). If the BEST system in time span s has been in one of the routes ending in the node k, in the next time span s + 1, it will be in one of the routes that start from the node k, which is formulated by (15). The constraints related to the initial and final states of the BEST system location are described by (16) and (17), respectively. The BEST system can be in one of the states of charge or discharge when it is connected to the grid, which is formulated by (18). The charge/discharge limitations of the BEST system can be specified by (19)-(20). The state of charge of the BEST system in each hour is shown by (21). The capacity limit of the BEST system is defined as (22). The initial and final state of charge of the BEST system is limited to (23).

$$\sum_{(k,n)\in A} I_{k,n,ts} = 1 \tag{14}$$

$$\sum_{(k,n)\in A^{+}_i} I_{tr,k,n,ts+1} = \sum_{(k,n)\in A^{-}_i} I_{tr,k,n,ts} \tag{15}$$

$$\sum_{(k,n)\in A^{+}_i} I_{tr,k,n,1} = I_{tr,k,n,0} \tag{16}$$

$$\sum_{(k,n)\in A^{-}_i} I_{tr,k,n,TR} = I_{tr,k,n,TR} \tag{17}$$

$$I^{ch}_{tr,t} + I^{dis}_{tr,t} \le I^{ch}_{tr,k,k,ts} \tag{18}$$

$$P^{ch,\min}_{tr} I^{ch}_{tr,t} \le P^{ch}_{tr,t} \le P^{ch,\max}_{tr} I^{ch}_{tr,t} \tag{19}$$

$$P^{dis,\min}_{tr} I^{dis}_{tr,t} \le P^{dis}_{tr,t} \le P^{dis,\max}_{tr} I^{dis}_{tr,t} \tag{20}$$

$$E_{tr,t} = E_{tr,t-1} + \eta^{ch}_{tr} P^{ch}_{tr,t} - \frac{P^{dis}_{tr,t}}{\eta^{dis}_{tr}} \tag{21}$$

$$E^{\min}_{tr} \le E_{tr,t} \le E^{\max}_{tr} \tag{22}$$

$$E_{tr,0} = E_{tr,T} \tag{23}$$

The constraints of PSS demand in the first stage are described by (24)-(30). The relationship between demand

blocks and the total load considering adjustable demand are given by (24) and (25). In addition, the limit on the demand block is mentioned by (26). The constraint of the adjustable demand is presented by (27). The ramp rates for demand at consecutive time intervals are limited by (28) and (29). The total shifted load during the scheduling can be stated as (30).

$$DR_{j,t} = D_{j,t} - FL_{j,t} \tag{24}$$

$$\sum_{bl=1}^{BL} dr_{bl,j,t} = DR_{j,t} \tag{25}$$

$$0 \le dr_{bl,j,t} \le dr_{bl,j}^{\max} \tag{26}$$

$$\begin{cases} 0 \le FL_{j,t} \le \gamma D_{j,t}, & if\ FL_{j,t} \ge 0 \\ FL_{j,t} \ge D_{j,t} - (1+\gamma)D_{j,t}, & else \end{cases} \tag{27}$$

$$DR_{j,t} - DR_{j,t-1} \le d_j^{up} \tag{28}$$

$$DR_{j,t-1} - DR_{j,t} \le d_j^{down} \tag{29}$$

$$\sum_{t=1}^{T} FL_{j,t} = 0 \tag{30}$$

The constraints associated with the power grid can be represented by (31)-(34). Constraint (31) defines the load balance at each bus incorporating DR. The DC-power flow, model, is applied to calculate the value of power crossing each transmission line as represented by (32). The power flow in each line is restricted by the maximum allowable line power capacity expressed by (33).

$$\sum_{i=1}^{U_b} P_{i,t} + \sum_{wp=1}^{WP_b} P_{wp,t} + \sum_{tr=1}^{TR_b} \left[P_{tr,t}^{dis} - P_{tr,t}^{ch}\right] - \sum_{j=1}^{J_b} DR_{j,t} = \sum_{i=1}^{U_b} PX_{b,b',t} \tag{31}$$

$$PX_{b,b',t} = \frac{\delta_{b,t} - \delta_{b',t}}{X_{b,b'}} \tag{32}$$

$$-PX_{Line}^{\max} \le PX_{b,b',t} \le PX_{Line}^{\max} \tag{33}$$

The constraint (34) limits the allowable amount of daily pollution emissions.

$$\sum_{t=1}^{T}\sum_{i=1}^{U} F^E(P_{i,t}) \le EC \tag{34}$$

2) SECOND STAGE CONSTRAINTS

In this section, the constraints related to "*wait and see*" variables are discussed. The related constraints with the thermal units in the second stage can be expressed by (35)-(39), which includes the produced power and ramp rate limits. The constraints of the BEST system in the second stage are defined by (40)-(46). The limitations on the scheduled load by the market operator in the second stage are described by (47)-(53). Finally, the limits of DC power flow and carbon emission are shown by (54)-(57).

$$P_{i,t,w} = P_{i,t,w} + \Delta P_{i,t,w} \tag{35}$$

$$P_{i,m}^{\min} I_{i,t} \le P_{i,t,m,w} \le P_{i,m}^{\max} I_{i,t} \tag{36}$$

$$P_{i,t,w} = \sum_{m=1}^{M} P_{i,t,m,w} \tag{37}$$

$$P_{i,t,w} - P_{i,t-1,w} \le (1 - Y_{i,t})R_i^{up} + Y_{i,t}P_i^{\min} \tag{38}$$

$$P_{i,t-1,w} - P_{i,t,w} \le (1 - Z_{i,t})R_i^{dn} + Z_{i,t}P_i^{\min} \tag{39}$$

$$P_{tr,t,w}^{ch} = P_{tr,t}^{ch} + \Delta P_{tr,t,w}^{ch} \tag{40}$$

$$P_{tr,t,w}^{dis} = P_{tr,t}^{dis} + \Delta P_{tr,t,w}^{dis} \tag{41}$$

$$P_{tr}^{ch,\min} I_{tr,t}^{ch} \le P_{tr,t,w}^{ch} \le P_{tr}^{ch,\max} I_{tr,t}^{ch} \tag{42}$$

$$P_{tr}^{dis,\min} I_{tr,t}^{dis} \le P_{tr,t,w}^{dis} \le P_{tr}^{dis,\max} I_{tr,t}^{dis} \tag{43}$$

$$E_{tr,t,w} = E_{tr,t-1,w} + \eta_{tr}^{ch} P_{tr,t,w}^{ch} - \frac{P_{tr,t,w}^{dis}}{\eta_{tr}^{dis}} \tag{44}$$

$$E_{tr}^{\min} \le E_{tr,t,w} \le E_{tr}^{\max} \tag{45}$$

$$E_{tr,0,w} = E_{tr,T,w} \tag{46}$$

$$DR_{j,t,w} = D_{j,t,w} - FL_{j,t,w} \tag{47}$$

$$\sum_{bl=1}^{BL} dr_{bl,j,t} + \sum_{bl=1}^{BL} \Delta dr_{bl,j,t,w} = DR_{j,t,w} \tag{48}$$

$$0 \le dr_{bl,j,t} + \Delta dr_{bl,j,t,w} \le dr_{bl,j}^{\max} \tag{49}$$

$$\begin{cases} 0 \le FL_{j,t,w} \le \gamma D_{j,t,w}, & if\ FL_{j,t,w} \ge 0 \\ FL_{j,t,w} \ge D_{j,t,w} - (1+\gamma)D_{j,t,w}, & else \end{cases} \tag{50}$$

$$DR_{j,t,w} - DR_{j,t-1,w} \le d_j^{up} \tag{51}$$

$$DR_{j,t-1,w} - DR_{j,t,w} \le d_j^{down} \tag{52}$$

$$\sum_{t=1}^{NT} FL_{j,t,w} = 0 \tag{53}$$

$$\sum_{i=1}^{U_b} P_{i,t,w} + \sum_{wp=1}^{WP_b} P_{wp,t} + \sum_{tr=1}^{TR_b} \left[P_{tr,t,w}^{dis} - P_{tr,t,w}^{ch}\right] - \sum_{j=1}^{J_b} \left[DR_{j,t,w} - Lsh_{j,t,w}\right] = \sum_{b=1}^{B} PX_{b,b',t,w} \tag{54}$$

$$PX_{b,b',t,w} = \frac{\delta_{b,t,w} - \delta_{b',t,w}}{X_{b,b'}} \tag{55}$$

$$-PX_{Line}^{\max} \le PX_{b,b',t,w} \le PX_{Line}^{\max} \tag{56}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{U} F^E(P_{i,t,w}) \le EC \tag{57}$$

B. TWO-STAGE ROBUST-STOCHASTIC MARKET-CLEARING

In this section, the proposed two-stage robust-stochastic model is applied to clear the energy market involving the uncertainties associated with electrical load and wind power. In the hybrid approach, the operator can use the advantages of both methods simultaneously to deal with the existing uncertainties. Additionally, the operator can differentiate between the risk level of the uncertainties. Since the uncertainty of wind power is more severe than the electrical load, the operator prefers to apply a risk-based approach to manage wind

power, while the fluctuations of electrical load are managed using Monte-Carlo simulation (MCs). In this regard, an info-gap-based robust optimization model is applied to manage the risk-based wind power production. This technique does not need extra information like probability distribution function and a fuzzy membership set of uncertain parameters [27]. More details about the IGDT method can be studied in [28]. The mathematical description of the info-gap-based two-stage hybrid model is as follows:

$$\alpha_r = \max \alpha \tag{58}$$

$$\Delta_C = (1-\beta_r)\, SF_b \tag{59}$$

$$\begin{aligned}
&\min \sum_{bl=1}^{BL}\sum_{j=1}^{J}\sum_{t=1}^{T} Bid_{bl,j} dr_{bl,j,t} \\
&- \sum_{t=1}^{T}\sum_{i=1}^{U}\left[\begin{array}{l} MC_{i,t} I_{i,t} + SU_{i,t} + SD_{i,t} \\ + \sum_{m=1}^{M} C^{E}_{i,t,m} P_{i,t,m} \end{array}\right] \\
&- \sum_{tr=1}^{TR}\left[\sum_{(k,n)\in A}\sum_{ts=1}^{TS} C_{tr} I_{tr,k,n,ts} \right. \\
&\left. + \sum_{t=1}^{T}\left[C^{ch}_{tr} P^{ch}_{tr,t} + C^{dis}_{tr} P^{dis}_{tr,t}\right]\right]
\end{aligned} \tag{60}$$

$$+ \sum_{t=1}^{T}\sum_{w=1}^{W} \pi_w \left[\begin{array}{l} \sum_{bl=1}^{BL}\sum_{n=1}^{N} Bid_{bl,j} \Delta dr_{bl,j,t,w} \\ - \sum_{i=1}^{U}\sum_{m=1}^{M} C^{E}_{i,t,m} \Delta P_{i,t,m,w} \\ - \sum_{tr=1}^{TR} C^{ch}_{tr} \Delta P^{ch}_{tr,t,w} + C^{dis}_{tr} \Delta P^{dis}_{tr,t,w} \\ - \sum_{j=1}^{J} voll_{j,t}\, Lsh_{j,t,w} \end{array}\right] \geq \Delta_C$$

$$(1-\alpha)\hat{P}_{wp,t} \leq P_{wp,t} \leq (1+\alpha)\hat{P}_{wp,t}$$

$$\text{Eqs. (2)} - \text{(57)} \tag{61}$$

where α is the maximum deviation of wind power from the forecasted value in real-time dispatch. Δ_C is the acceptable level of social welfare, which the operator can determine it by changing the robustness parameter β_r. SF_b is the value of the social welfare calculated by the operator under conditions in which the produced wind power in real-time dispatch ($P_{wp,t}$) is the same as the forecasted wind power ($\hat{P}_{wp,t}$). So, SF_b is determined by solving the problem (1)-(57) without considering the uncertainty of wind power.

The defined mathematical model above is a bi-level optimization problem so that in the upper level, the operator tends to maximize the radius of wind power forecasting error. In contrast, in the lower level, a two-stage stochastic model is solved by the operator to maximize social welfare. In the risk-based strategy, the generated wind power in real-time dispatch has an undesirable influence on social welfare. On the other hand, a reduction in wind power in real-time dispatch leads to a decrease in social welfare. So, the proposed model can be converted into a single-level problem as follows:

$$\alpha_r = \max \alpha \tag{62}$$

$$\Delta_C = (1-\beta_r)\, SF_b \tag{63}$$

$$\begin{aligned}
&\sum_{bl=1}^{BL}\sum_{j=1}^{J}\sum_{t=1}^{T} Bid_{bl,j} dr_{bl,j,t} \\
&- \sum_{t=1}^{T}\sum_{i=1}^{U}\left[\begin{array}{l} MC_{i,t} I_{i,t} + SU_{i,t} + SD_{i,t} \\ + \sum_{m=1}^{M} C^{E}_{i,t,m} P_{i,t,m} \end{array}\right] \\
&- \sum_{tr=1}^{TR}\left[\sum_{(k,n)\in A}\sum_{ts=1}^{TS} C_{tr} I_{tr,k,n,ts} \right. \\
&\left. + \sum_{t=1}^{T}\left[C^{ch}_{tr} P^{ch}_{tr,t} + C^{dis}_{tr} P^{dis}_{tr,t}\right]\right]
\end{aligned} \tag{64}$$

$$+ \sum_{t=1}^{T}\sum_{w=1}^{W} \pi_w \left[\begin{array}{l} \sum_{bl=1}^{BL}\sum_{n=1}^{N} Bid_{bl,j} \Delta dr_{bl,j,t,w} \\ - \sum_{i=1}^{U}\sum_{m=1}^{M} C^{E}_{i,t,m} \Delta P_{i,t,m,w} \\ - \sum_{tr=1}^{TR} C^{ch}_{tr} \Delta P^{ch}_{tr,t,w} + C^{dis}_{tr} \Delta P^{dis}_{tr,t,w} \\ - \sum_{j=1}^{J} voll_{j,t}\, Lsh_{j,t,w} \end{array}\right] \geq \Delta_C$$

$$\sum_{i=1}^{U_b} P_{i,t,w} + \sum_{wp=1}^{WP_b} (1-\alpha)\hat{P}_{wp,t} + \sum_{tr=1}^{TR_b}\left[P^{dis}_{tr,t,w} - P^{ch}_{tr,t,w}\right] \tag{65}$$

$$- \sum_{j=1}^{J_b} DR_{j,t,w} = \sum_{b=1}^{B} PX_{b,b',t,w}$$

$$\text{Eqs. (2)} - \text{(53) and (55)} - \text{(57)} \tag{66}$$

The flowchart of the proposed problem-solving process is represented in Fig 5.

IV. CASE STUDY AND SIMULATION RESULTS

In this study, an integrated electricity and rail transport network is introduced to evaluate the advantages of the proposed model, which is shown in Fig. 6. Specifications associated with the electricity and transportation network are given by [14]. The predicted values related to wind power production and demand are shown in Fig. 7. Also, the carbon emission coefficients of thermal units have been taken from [29]. In this study, it is assumed that the sodium-sulfur (NaS) battery technology is employed in the BEST system, while any different types of batteries can be used. The employed batteries have energy and power densities of 200 W/kg and 50 W/Kg, respectively. Besides, it is assumed that a standard railway wagon of 50-feet can handle 100 tons of cargo; so each wagon carries NaS batteries with a capacity of $100 \times 10^3 \times 200 \times 10^{-6} = 20$ MWh and a specific power of $100 \times 10^3 \times 50 \times 10^{-6} = 5$MW. The BEST system involves one locomotive and six railway wagon. Consequently, the energy and power of the BEST system are 120 MWh

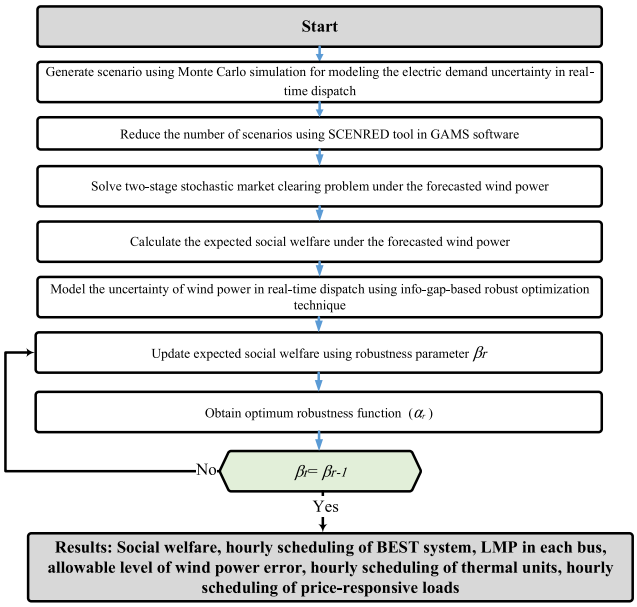

FIGURE 5. The proposed hybrid problem-solving process.

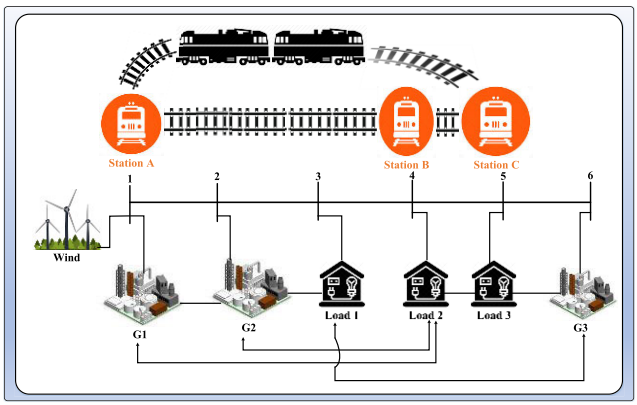

FIGURE 6. The integrated power and rail transport networks.

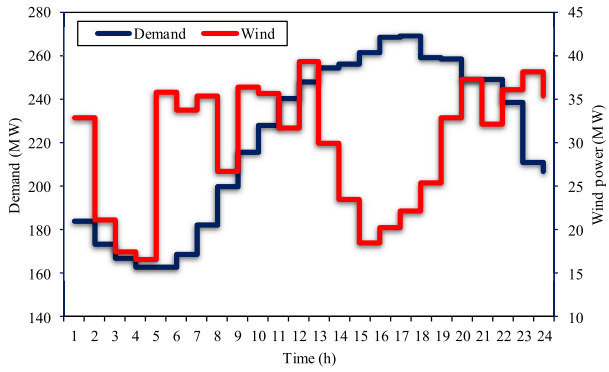

FIGURE 7. The forecasted demand and wind power.

and 30 MW, respectively. In addition, the travel time between the two stations is assumed to be 2 hours, so a 2-hour time span is selected. The cost of charge and discharge power of the BEST system is assumed to be 1$/MWh [14]. The marginal benefit of consumers is also assumed to be 45$/MWh [30].

The power demand forecasting error follows a normal distribution function with a mean of zero and a standard deviation of 10%. The 1000 scenarios are generated by MCs, which is reduced to 10 scenarios using the SCENRED tool in GAMS software. The proposed model is a MILP problem, which is solved by CPLEX solver in GAMS software. Three case studies are considered to investigate the benefits of the proposed model, which are summarized as follows:

Case 1: In this case, the effect of the BEST system on social welfare, power dispatch of thermal units, line congestion, LMP, and carbon emission is evaluated under the two-stage stochastic approach. In addition, a comparison between the BEST system and fixed BESS is provided in this case to specify the model effectiveness. In this case, wind power uncertainty is not considered.

Case 2: In this case, the benefits of shiftable demand along with the BEST system on the social welfare, power dispatch of thermal units, line congestion, LMP, and carbon emission are evaluated under the two-stage stochastic approach. Besides, the effect of DR on hourly optimal location and scheduling of the BEST system is investigated to show the benefits of demand-side management coordinated with VRP. In this case, wind power uncertainty is also ignored.

Case 3: In this case, instead of the two-stage stochastic approach, a two-stage robust-stochastic technique is preferred to manage the wind power uncertainty under the risk-averse approach. In this case, DR and the BEST system are considered.

TABLE 1. Location and state of BEST system without considering the transport cost.

Social welfare= $161831.05				
Time span (h)	**0-2**	**2-4**	**4-6**	**6-8**
Location of BEST	A-C	C-C	C-B	B-B
State of BEST	Transport	Charge	Transport	Charge
Time span (h)	**8-10**	**10-12**	**12-14**	**14-16**
Location of BEST	B-B	B-B	B-B	B-B
State of BEST	Charge	Charge	Discharge	Discharge
Time span (h)	**16-18**	**18-20**	**20-22**	**22-24**
Location of BEST	B-C	C-C	C-C	C-A
State of BEST	Transport	Discharge	Charge	Transport

The studied cases are discussed in detail as follows:

Case 1: The optimal location and state of the BEST system are shown in Table 1. It is assumed that the BEST system is located initially at station A and the transport cost is zero. It can be seen that the BEST system is moved from station A to station C in the first time span. In the second time span, the BEST system is located in station C (fifth bus) and is operated in charge mode. Then in the third time span it is moved from station C to station B. From the fourth to the eighth time span, the BEST system stays at station B (fourth bus) and it is employed in charge and discharge modes, respectively. In the ninth time span, the BEST system is returned to Station C. In the tenth and eleventh time span, the BEST system is used in the discharge and charge mode, and in the last time span, it is returned to the station A.

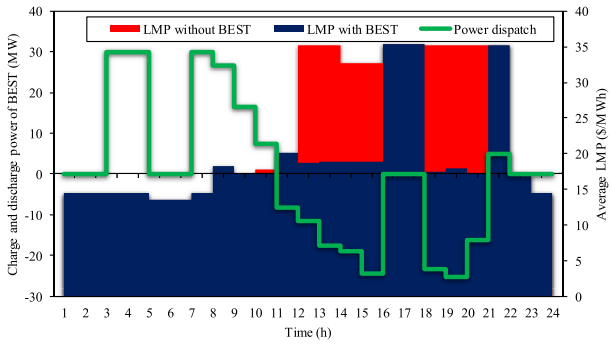

FIGURE 8. The impact of optimal hourly scheduling of the BEST system on LMP.

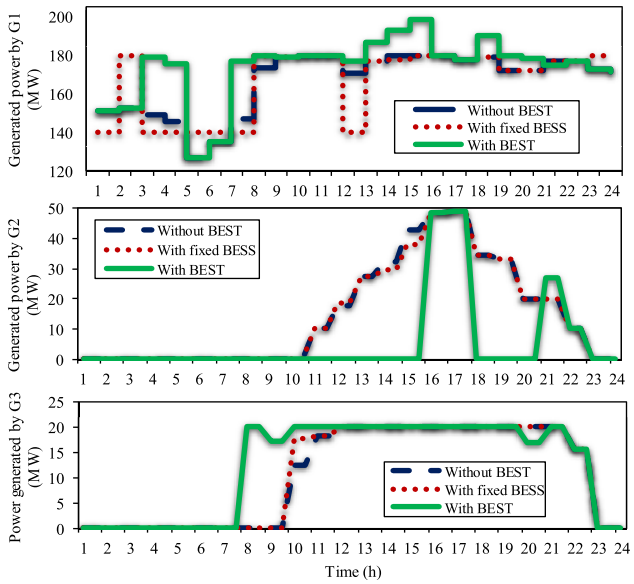

FIGURE 9. The effect of the BEST system on the optimal scheduling of the thermal units.

The effect of charge and discharge scheduling of the BEST system on the average LMP is shown in Fig. 8. It can be seen that in the hours when the average LMP is low (between $t = 1$ and $t = 11$), the BEST system is used in the charge mode. Then it is operated in the discharge mode in the hours between $t = 11$ and $t = 21$, which causes a decrease in average LMP during peak hours. The main reason for the power prices reduction during peak hours is the power dispatch increase of unit G1 (The cheapest unit), which results in reducing the power dispatch of unit G2 in the mentioned periods. Fig. 9 shows the effect of the BEST system on the optimal operation of the generation units. It was observed that the BEST system during peak hours increases effectively whilst the power dispatch of unit G1 reduces the power dispatch of unit G2 compared to the fixed BESS and without the presence of BEST. In fact, the obtained results confirm that the BEST system effectively reduces line congestion during peak hours and increases the power dispatch of unit G1. As a result, social welfare is increased to $16,1831.05 with the BEST system, which is $2,895.43 and $3,487.78 more than the fixed BESS and without BESS, respectively.

TABLE 2. Location and state of BEST system considering the transport cost and without carbon emission limit.

Social welfare= $160656.42				
Time span (h)	**0-2**	**2-4**	**4-6**	**6-8**
Location of BEST	A-B	B-B	B-B	B-B
State of BEST	Transport	Charge	Charge	Charge
Time span (h)	**8-10**	**10-12**	**12-14**	**14-16**
Location of BEST	B-B	B-B	B-B	B-B
State of BEST	-	Discharge	Discharge	Charge/-
Time span (h)	**16-18**	**18-20**	**20-22**	**22-24**
Location of BEST	B-B	B-B	B-B	B-A
State of BEST	-	Charge	Charge/-	Transport

TABLE 3. The impact of the BEST system and carbon emission limit on the total dispatched power.

	G1	G2	G3
Total power without BEST	4,006.22	345.64	246.46
Total power with fixed BESS	4,007.64	338.79	251.88
Total power with BEST	4,165.19	184.99	248.14
Total power with BEST and emission constraint (MWh)	4,106.92	372.58	118.81

TABLE 4. The impact of the BEST system on social welfare considering carbon emission limit.

	-	Fixed BESS	BEST
Social welfare without emission constraint ($)	158,343.27	158,935.62	160,656.42
Social welfare with emission constraint ($)	155,727.25	156,402.65	158,612.22

Table 2 shows the effect of transport costs on the BEST system scheduling. Transport cost is estimated to be $200 [14]. It can be seen that considering the cost of transport, the operator prefers to employ the BEST system in less time span in transport mode, which shows the dependence between the transport cost and optimal scheduling of the BEST system. Under these conditions, social welfare is equal to $160,656.42, which is less than it without considering the cost of transport. Table 3 shows the effect of the BEST system, and the carbon emission limits on the total dispatched power taking into account the cost of transport. It can be observed that with the BEST system, the power generation of unit G1 is increased compared to the fixed BESS and without BESS, which leads to a decrease in the power production of more expensive units like G2 and G3. In fact, the BEST system acts as a viable option to reduce the effect of line congestion on power dispatch of unit G1, which results in increasing social welfare. Besides, with consideration of the carbon emission constraint, the operator's willingness to use the unit G2 increases due to the lower carbon emission of this unit compared to other generation units. Table 4 also shows the overall effect of the BEST system on social welfare under different conditions. It can be seen that social welfare increases from $155,727.25 without the BEST system compared to $158,612.22 with the BEST considering the carbon emission constraint. It should be noted that the carbon emission constraint is estimated at 3,000 lbs/day.

Case 2: The effect of shiftable load on the hourly demand considering the carbon emission limit is shown in Fig. 10. The shiftable load participation factor in the DR program is

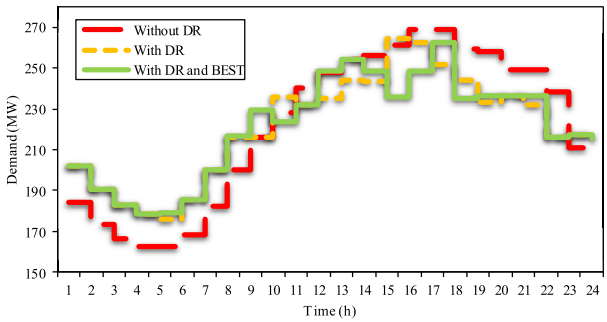

FIGURE 10. The effect of shiftable load on the hourly demand considering the carbon emission limit.

TABLE 5. Location and state of BEST system considering the transport cost, carbon emission limit and without DR.

Social welfare= $158,612.22				
Time span (h)	**0-2**	**2-4**	**4-6**	**6-8**
Location of BEST	A-B	B-B	B-B	B-B
State of BEST	Transport	Charge	Charge	Charge
Time span (h)	**8-10**	**10-12**	**12-14**	**14-16**
Location of BEST	B-B	B-B	B-B	B-B
State of BEST	-/Discharge	Discharge	Discharge	Charge
Time span (h)	**16-18**	**18-20**	**20-22**	**22-24**
Location of BEST	B-B	B-B	B-A	A-A
State of BEST	Discharge	Discharge	Transport	-

assumed to be 10%. It can be seen that by implementing the DR program, the load is shifted from peak hours to non-peak hours, which results in a reduction in the participation of expensive units and decreasing LMP during peak hours. Besides, it can be seen that by considering the BEST system, the pattern of shiftable load scheduling changes, which shows the dependence between the BEST system and responsive-load scheduling. So, to meet high-efficiency demand-side management, the operator must integrate the BEST system routing problem with the demand-side management problem. Tables 5 and 6 also show the effect of DR on the scheduling of the BEST system, taking into account the carbon emission constraint. It can be observed that with the implementation of the DR program, the optimal location, charge and discharge state of the BEST system changes entirely from the ninth to the twelfth time span, which shows the importance of integrated management. The effect of coordinated scheduling of the BEST system and DR on the average LMP is also shown in Fig. 11. although with DR and BEST increases the LMP during non-peak hours, it also decreases significantly during peak hours. Also, Fig. 12 confirms the benefit of the integrated scheduling of demand response of the BEST system to reduce the line congestion. under the coordinated method, the power produced by unit G1 increases by 197.4 MWh during peak hours, which results in decreasing the hourly commitment of the unit G2, reduction of LMP, and increasing social welfare. In this case, social welfare is equal to $163,378.54, which is viewed as an increase of 2.9% in social welfare in comparison without DR.

Case 3: In order to handle the uncertainty of wind power generation under the IGDT-based robust strategy, the

TABLE 6. Location and state of BEST system considering the transport cost, carbon emission limit and DR.

Social welfare= $163,378.54				
Time span (h)	**0-2**	**2-4**	**4-6**	**6-8**
Location of BEST	A-B	B-B	B-B	B-B
State of BEST	Transport	Charge	Charge	Charge/-
Time span (h)	**8-10**	**10-12**	**12-14**	**14-16**
Location of BEST	B-B	B-B	B-B	B-B
State of BEST	Discharge	-/Discharge	Discharge	Transport
Time span (h)	**16-18**	**18-20**	**20-22**	**22-24**
Location of BEST	A-A	A-A	A-A	A-A
State of BEST	-/Charge	Discharge/-	Charge/-	-

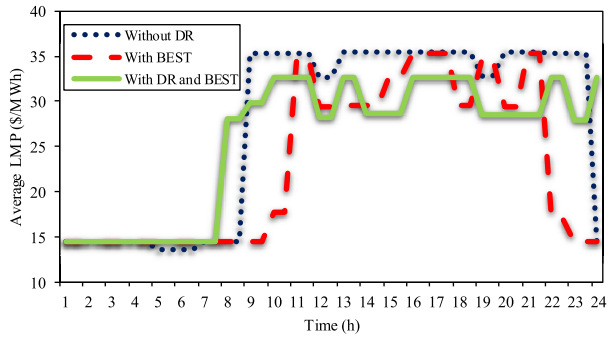

FIGURE 11. The effect of coordinated scheduling of the DR and the BEST on the LMP.

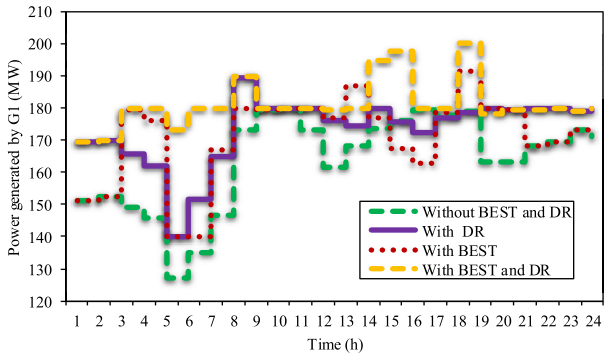

FIGURE 12. The effect of coordinated scheduling of the DR and the BEST system on the hourly dispatch of unit G1.

robustness parameter β_r is increased by steps 0.01 from 0.01 to 0.04. The initial amount of social welfare is estimated at $163,378.54, which is obtained by solving the optimization problem (1)-(57) under the predicted wind power. The carbon emission constraint is estimated at 3,000 lbs/day. Figure 13 shows the effect of variations of the robustness parameter β_r on the optimal robustness function α_r and social welfare. It is observed that by increasing the robustness parameter β_r, the optimal robustness function α_r increases, and social welfare decreases, which means that by increasing the robustness parameter β_r, the market operator can handle a wider range of wind power forecast errors. However, this increase in the range of wind power forecast errors leads to a decrease in social welfare. In fact, by increasing β_r, the market operator adopts a more robust approach with less social welfare against the uncertainty of wind power.

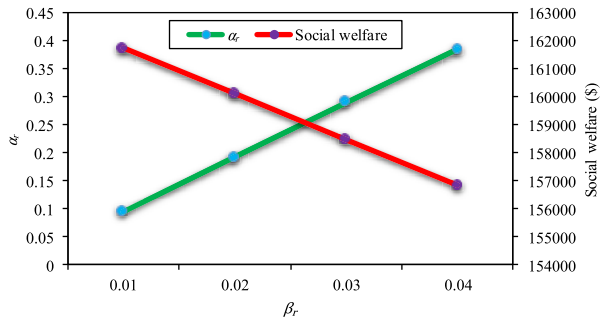

FIGURE 13. The effect of variations of the robustness parameter β_r on the optimal robustness function α_r and social welfare.

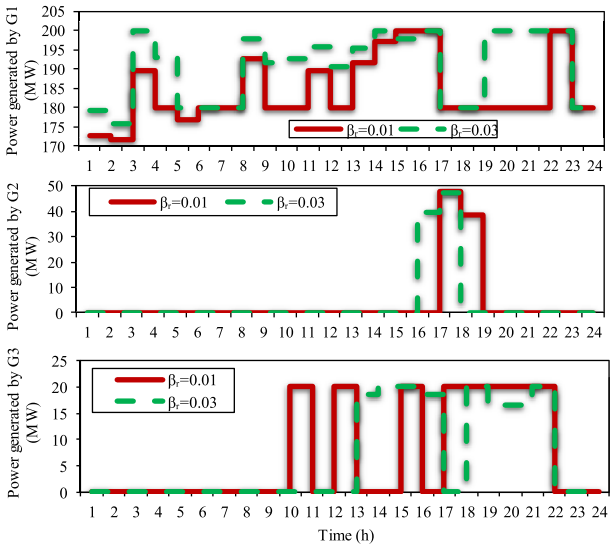

FIGURE 14. The effect of variations of the robustness parameter β_r on the hourly dispatch of units.

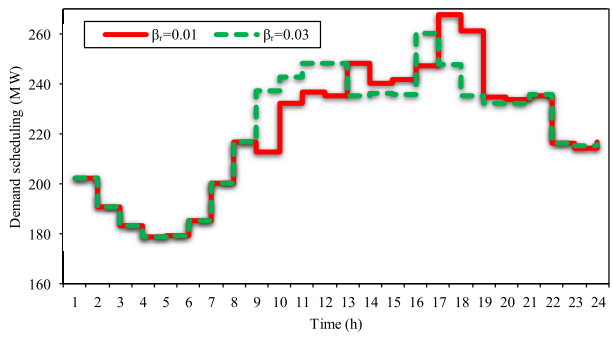

FIGURE 15. The effect of variations of the robustness parameter β_r on the hourly scheduling of price-responsive load.

For instance, for β_r =0.01 and 0.03, social welfare is calculated as \$161,744.8 and \$158,477.2, respectively. Therefore, these social welfare values for the market operator are guaranteed under the condition that at no time, the error of forecasting wind power production in real-time is more than 9.6% and 29.1%, respectively.

Fig. 14 shows the effect of variations of the robustness parameter β_r on the optimal scheduling of power generation units. It can be seen that by increasing parameter β_r, the produced power by unit G1 increases, which is due to the decrease in generated wind power in bus 1 in real-time dispatch. Due to the direct relationship between the reduction of wind-produced power and the carbon emission increase of thermal units, the optimal scheduling of units G2 and G3 also change with increasing the robustness parameter β_r in a way that maximizes social welfare and satisfies the constraint of daily carbon emission. Fig. 15 and 16 also show the optimal scheduling of price-responsive load and the BEST system for different values β_r. It can be seen that the optimal scheduling of these resources depends on the level of moderation that the market operator adopts.

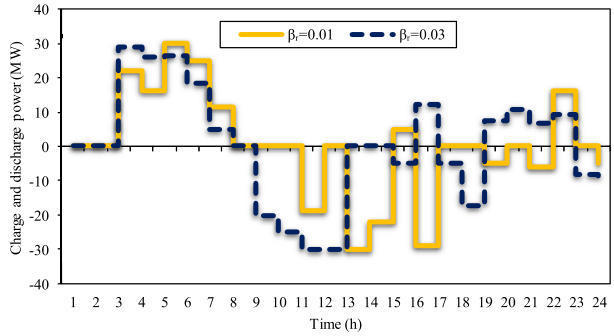

FIGURE 16. The effect of variations of the robustness parameter β_r on the hourly scheduling of the BEST system.

V. CONCLUSION

This paper evaluated the economic, technical, and environmental effects of BESS mobility and price-based DR program under coordinated scheduling in the day-ahead market-clearing. A time-space network was also utilized to model the constraints of the rail transport network and couple the market-clearing process with the vehicle routing problem. In addition, a two-stage robust-stochastic approach was proposed to manage the uncertainties associated with electric demand and wind power generation in the real-time. The proposed model obtained the optimal hourly location, charge/discharge scheduling of the BEST system, power generation of thermal units, price-responsive loads scheduling, and the LMP considering the daily carbon emission limit of thermal units. The obtained results can be summarized as follows:

- Applying the BEST system in the energy market-clearing process constrained to the power grid could increase social welfare by 1.3% and 1.8%, respectively, in comparison with the fixed BESS and without BESS. Additionally, it could decrease the line congestion during peak hours by 9.3% compared to the fixed BESS.
- The transport cost had a significant effect on the optimal hourly location, charge and discharge scheduling of the BEST system. It decreased social welfare by 0.7% in comparison without the transport cost.

- Coordinated scheduling of the price-responsive loads and the BEST system could enhance social welfare by about 2.9% compared to the non-coordinated scheduling. Besides, the line congestion during peak-hours was reduced by 4.5% in comparison with non-integrated management.
- The proposed two-stage hybrid framework enabled the market operator to differentiate between the risk level of the existing uncertainties and achieve a more flexible decision-making model. The operator could adjust the robustness level of the day-ahead scheduling using info-gap-based robust optimization to cover the uncertainty of wind power in real-time, while electric demand uncertainty was handled using a risk-neutral-based stochastic technique.

We will extend the proposed model in our future research, where the efficiency of battery charging/discharging in renewable energy integration will be completely considered. Moreover, when the proposed model is employed in larger-scale power and transport systems, the model could be over complicated to be solved as a single MILP problem. The proposed model will be improved by considering the application of decomposition technologies such as Benders decomposition and Lagrangian relaxation in our future works.

ACKNOWLEDGMENT

The authors appreciate those who contributed to make this research successful.

REFERENCES

[1] (Oct. 2019). *IRENA*. [Online]. Available: https://www.irena.org/publications/2019/Oct/Future-of-wind

[2] H. Xie, X. Teng, Y. Xu, and Y. Wang, "Optimal energy storage sizing for networked microgrids considering reliability and resilience," *IEEE Access*, vol. 7, pp. 86336–86348, 2019.

[3] N. Shaukat, B. Khan, S. M. Ali, C. A. Mehmood, J. Khan, U. Farid, M. Majid, S. M. Anwar, M. Jawad, and Z. Ullah, "A survey on electric vehicle transportation within smart grid system," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1329–1349, Jan. 2018.

[4] M. A. Mirzaei, A. S. Yazdankhah, B. Mohammadi-Ivatloo, M. Marzband, M. Shafie-Khah, and J. P. S. Catalão, "Stochastic network-constrained co-optimization of energy and reserve products in renewable energy integrated power and gas networks with energy storage system," *J. Cleaner Prod.*, vol. 223, pp. 747–758, Jun. 2019.

[5] E. Heydarian-Forushani, M. E. H. Golshan, and P. Siano, "Evaluating the benefits of coordinated emerging flexible resources in electricity markets," *Appl. Energy*, vol. 199, pp. 142–154, Aug. 2017.

[6] N. Li, C. Uckun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible operation of batteries in power system scheduling with renewable energy," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 685–696, Apr. 2016.

[7] E. Heydarian-Forushani, M. E. H. Golshan, M. Shafie-Khah, and P. Siano, "Optimal operation of emerging flexible resources considering sub-hourly flexible ramp product," *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 916–929, Apr. 2018.

[8] A. Ahmadi, A. E. Nezhad, and B. Hredzak, "Security-constrained unit commitment in presence of lithium-ion battery storage units using information-gap decision theory," *IEEE Trans. Ind. Informat.*, vol. 15, no. 1, pp. 148–157, Jan. 2019.

[9] E. Heydarian-Forushani, M. E. H. Golshan, and P. Siano, "Evaluating the operational flexibility of generation mixture with an innovative techno-economic measure," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2205–2218, Mar. 2018.

[10] Z. Soltani, M. Ghaljehei, G. B. Gharehpetian, and H. A. Aalami, "Integration of smart grid technologies in stochastic multi-objective unit commitment: An economic emission analysis," *Int. J. Electr. Power Energy Syst.*, vol. 100, pp. 565–590, Sep. 2018.

[11] H. Chabok, M. Roustaei, M. Sheikh, and A. Kavousi-Fard, "On the assessment of the impact of a price-maker energy storage unit on the operation of power system: The ISO point of view," *Energy*, vol. 190, Jan. 2020, Art. no. 116224.

[12] N. Padmanabhan, M. Ahmed, and K. Bhattacharya, "Battery energy storage systems in energy and reserve markets," *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 215–226, Jan. 2020.

[13] N. Hajibandeh, M. Shafie-Khah, S. Talari, S. Dehghan, N. Amjady, S. J. P. S. Mariano, and J. P. S. Catalao, "Demand response-based operation model in electricity markets with high wind power penetration," *IEEE Trans. Sustain. Energy*, vol. 10, no. 2, pp. 918–930, Apr. 2019.

[14] Y. Sun, Z. Li, M. Shahidehpour, and B. Ai, "Battery-based energy storage transportation for enhancing power system economics and security," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2395–2402, Sep. 2015.

[15] Y. Sun, Z. Li, W. Tian, and M. Shahidehpour, "A lagrangian decomposition approach to energy storage transportation scheduling in power systems," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4348–4356, Nov. 2016.

[16] Y. Sun, J. Zhong, Z. Li, W. Tian, and M. Shahidehpour, "Stochastic scheduling of battery-based energy storage transportation system with the penetration of wind power," *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 135–144, Jan. 2017.

[17] S. Yao, P. Wang, and T. Zhao, "Transportable energy storage for more resilient distribution systems with multiple microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3331–3341, May 2019.

[18] M. E. Khodayar, L. Wu, and M. Shahidehpour, "Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1271–1279, Sep. 2012.

[19] M. E. Khodayar, L. Wu, and Z. Li, "Electric vehicle mobility in transmission-constrained hourly power generation scheduling," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 779–788, Jun. 2013.

[20] Y. Sun, Z. Chen, Z. Li, W. Tian, and M. Shahidehpour, "EV charging schedule in coupled constrained networks of transportation and power system," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 4706–4716, Sep. 2019.

[21] A. Baharvandi, J. Aghaei, A. Nikoobakht, T. Niknam, V. Vahidinasab, D. Giaouris, and P. Taylor, "Linearized hybrid stochastic/robust scheduling of active distribution networks encompassing PVs," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 357–367, Jan. 2020.

[22] M. Majidi and K. Zare, "Integration of smart energy hubs in distribution networks under uncertainties and demand response concept," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 566–574, Jan. 2019.

[23] M. A. Mirzaei, M. Nazari-Heris, B. Mohammadi-Ivatloo, K. Zare, M. Marzband, and A. Anvari-Moghaddam, "A novel hybrid framework for co-optimization of power and natural gas networks integrated with emerging technologies," *IEEE Syst. J.*, early access, Mar. 20, 2020, doi: 10.1109/JSYST.2020.2975090.

[24] Y. Jiang, C. Wan, C. Chen, M. Shahidehpour, and Y. Song, "A hybrid stochastic-interval operation strategy for multi-energy microgrids," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 440–456, Jan. 2020.

[25] W. Cai, R. Mohammaditab, G. Fathi, K. Wakil, A. G. Ebadi, and N. Ghadimi, "Optimal bidding and offering strategies of compressed air energy storage: A hybrid robust-stochastic approach," *Renew. Energy*, vol. 143, pp. 1–8, Dec. 2019.

[26] P. Aliasghari, B. Mohammadi-Ivatloo, and M. Abapour, "Risk-based scheduling strategy for electric vehicle aggregator using hybrid Stochastic/IGDT approach," *J. Cleaner Prod.*, vol. 248, Mar. 2020, Art. no. 119270.

[27] H. Hui, Y. Ding, Q. Shi, F. Li, Y. Song, and J. Yan, "5G network-based Internet of Things for demand response in smart grid: A survey on application potential," *Appl. Energy*, vol. 257, Jan. 2020, Art. no. 113972.

[28] M. Majidi, B. Mohammadi-Ivatloo, and A. Soroudi, "Application of information gap decision theory in practical energy problems: A comprehensive review," *Appl. Energy*, vol. 249, pp. 157–165, Sep. 2019.

[29] A. Alabdulwahab, A. Abusorrah, X. Zhang, and M. Shahidehpour, "Coordination of interdependent natural gas and electricity infrastructures for firming the variability of wind energy in stochastic day-ahead scheduling," *IEEE Trans. Sustain. Energy*, vol. 6, no. 2, pp. 606–615, Apr. 2015.

[30] H. Wu, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, "Thermal generation flexibility with ramping costs and hourly demand response in stochastic security-constrained scheduling of variable energy sources," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 2955–2964, Nov. 2015.

MOHAMMAD AMIN MIRZAEI received the B.Sc. degree in electrical engineering from Ilam University, Ilam, Iran, in 2015, and the M.Sc. degree in electrical engineering from the Sahand University of Technology, Tabriz, Iran, in 2018. He is currently a Research Assistant at the University of Tabriz, Tabriz. His research interests include energy market-clearing, risk-based energy management, emerging energy storage technologies, demand response, and integrated energy systems.

MOHAMMAD HEMMATI received the B.Sc. degree (Hons.) in electrical power engineering from the Sahand University of Technology, Tabriz, Iran, in 2014, and the M.Sc. degree (Hons.) from the Faculty of Electrical and Computer Engineering, University of Tabriz, in 2017, where he is currently pursuing the Ph.D. degree. His research interests include scheduling and operation of reconfigurable microgrid, stochastic programming, multi-carrier energy systems, energy storage systems, and risk management.

KAZEM ZARE received the B.Sc. and M.Sc. degrees in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2000 and 2003, respectively, and the Ph.D. degree from Tarbiat Modares University, Tehran, Iran, in 2009. He is currently a Professor at the Faculty of Electrical and Computer Engineering, University of Tabriz. His research interests include power system economics, distribution networks, microgrid, energy management, smart building, demand response, and power system optimization.

BEHNAM MOHAMMADI-IVATLOO (Senior Member, IEEE) received the B.Sc. degree (Hons.) in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2006, and the M.Sc. and Ph.D. degrees (Hons.) from the Sharif University of Technology, Tehran, Iran, in 2008. He is currently an Associate Professor at the Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz. His research interests include economics, operation, and planning of intelligent energy systems in a competitive market environment.

MEHDI ABAPOUR received the B.Sc. and M.Sc. degrees in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2005 and 2007, respectively, and the Ph.D. degree from Tarbiat Modares University, in 2012. He is currently an Assistant Professor at the Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz. His research interests include planning of power systems, power market, reliability assessment, multi-level inverter, and energy management.

MOUSA MARZBAND (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from the Department of Electrical Engineering, Polytechnic University of Catalonia, Barcelona, Spain, in 2014. After his Ph.D. degree, he joined The University of Manchester, Manchester, U.K., as a Postdoctoral Research Fellow, and then joined the University College Cork, Cork, Ireland, as a Senior Researcher. He is currently a Senior Lecturer at the Department of Mathematics, Physics, and Electrical Engineering, Northumbria University, Newcastle upon Tyne, U.K. His research interests include operation and control strategies in DGs, mathematical modeling and control of optimal energy management system within multi-energy carrier systems, and cooperative and non-cooperative game theory applications in energy market.

ALI FARZAMNIA (Senior Member, IEEE) received the B.Eng. degree in electrical engineering telecommunication engineering from Islamic Azad University of Urmia, Iran, in 2005, the M.Sc. degree in electrical engineering telecommunication engineering from the University of Tabriz, in 2008, and the Ph.D. degree in electrical engineering (telecommunication engineering) from Universiti Teknologi Malaysia (UTM), in 2014. He is appointed as a Senior Lecturer (Assistant Professor) with the Electrical and Electronic Engineering Program, Faculty of Engineering, Universiti Malaysia Sabah (UMS), in 2014. His research interests include wireless communication, signal processing, network coding, information theory, and bio-medical signal processing. He is a Chartered Engineer (U.K.) (CEng) and a member of IET.