Two-Stage Stochastic Optimization of Sodium-Sulfur Energy Storage Technology in Hybrid Renewable Power Systems

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ABSTRACT Energy storage systems (ESS) are considered among the key elements for mitigating the impact of renewable intermittency and improving the economics for establishing a sustainable power grid. The high cost combined with the need for optimal capacity and allocation of ESS proves to be pertinent to maintain the power quality as well as the economic and operational viability of a renewable integrated power grid. In case of ESS sizing in terms of optimized power (kW) and energy (kWh) capacity, an oversized ESS results in high capital investment and in some cases increases the system losses. Conversely, an undersized ESS significantly impacts the reliability and availability of the power network. In this paper, a two-stage stochastic optimization strategy is presented for sodium-sulfur (NaS) battery considering the output power uncertainties of wind and solar energy sources. The objective aims at minimizing the total cost of NaS-ESS incorporation while maintaining acceptable system operation using AC optimal power flow. Many scenarios from the historical data are considered for the development of the system stochasticity on a 24-bus reliability test system (RTS) that is incorporated with a hybrid renewable energy system (HRES), namely solar and wind. Moreover, to demonstrate the efficacy of the proposed stochastic optimization framework a comparative analysis is performed with a deterministic optimization technique based on several reliability indices.

INDEX TERMS Energy storage, hybrid renewable energy, renewable uncertainty, sodium sulfur battery, two-stage stochastic optimization.

I. INTRODUCTION

Renewable energy resources (RES) are nowadays widely preferred for electric power generation to satisfy the ever increasing load demand. Wind and solar resources are among the most preferred RES technologies. Nevertheless, most RESs impose various challenges to settle their characteristics with diesel generator's characteristics [1], [2]. Usually generators have different kind of variability levels [3], which are regulated to sustain the grid operation. However, RES imposes a greater degree of challenge and difficultly in terms of availability, predictability, and controllability that are pertinent to

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ensure grid stability. Many researchers and developers have extensively invested to produce various techniques to increase the overall controllability over RESs for numerous different applications [4]–[6]. Among the novel solutions, the mitigation of RES fluctuations and its associated challenges can be multifariously solved by using the concept of renewable integrated microgrid (MG) systems [7]–[9].

A MG mainly consists of distributed generation (DG) units, loads, and energy storage systems (ESS). MG has the potential to link various technologies of DG units along with distributed ESS into the power network [10]. MG based renewable integration in a power network comparatively enhances the system reliability and security with overall improved efficiency [11]–[13]. However, controlling the MG

Y. M. Al-Humaid *et al.*: Two-Stage Stochastic Optimization of NaS kWh Storage Technology in Hybrid Renewable kW Systems

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with various types of DGs, different loads, and ESSs is very complicated especially when it comes to higher level of RES integration. This can be controlled by using maximum peak power tracking algorithms [14]. In recent years, ESS systems have been used frequently in MGs to manage and optimize the variability of renewable resources and to control the peak load [15]. Furthermore, in [16], an economic model of the distributed system is presented using on a novel dissipativity based prediction control theory. This enables the users of the MG to optimize their economic gain and concurrently maintain the system stability and ensure appropriate performance of the MG for residential scale application.

ESS is an important dispatchable energy source in the MG. It ensures power quality as well as continuity of supply to the power network in both islanded and grid-connected modes while maintaining the economical significance of the MG components. The study in [17], demonstrates the incorporation of ESS that aims to smooth the unstable generation of hybrid renewable energy sources (HRES) comprising of solar and wind energy sources. The ESS maintains a smooth output power profile that inherently improves the reliability and security of the power network [18]. Albeit, an optimal size is pertinent considering the high cost of the available ESS technologies. Optimal sizing of energy storage system not only ensures system stability and optimal power flow (OPF) but is identified to maintain a viable total cost of operation and investment [19].

Similarly, identification and selection of suitable ESS technology in accordance with the grid power quality requirements considering renewable integration proves to be a multi-faced challenge. While different ESS technologies can be considered to provide energy buffering operation and overcome the technical challenges associated with renewable integration, intensive attention is also needed to maintain the economical and operational viability of ESSs. Before large-scale ESS installation, several technological, economic, and operational constraints needs to be considered [20]–[22]. For instance, the relatively low power density and slow dynamic response of the popularly preferred lithium-ion battery leads to over-sizing and pre-mature replacements that leads to high capital cost in long-term large scale utility applications [23].

Ideally, ESS should possess high energy and power density for optimal operation that can be facilitated by sodium-sulfur (NaS) batteries that are among the most prominent storage technologies with relatively high energy density, high power density, moderate cost, safety, temperature stability, and low self-discharge rate [24]. Considering the countries with high renewable potential along with extreme climatic conditions such as Saudi Arabia, the selection of ESS considering its technical characteristics is pertinent to not only regulate demand-generation mismatch but also to enable a feasible long-term energy solution [25]. Therefore, apart from pumped hydro and compressed air energy storage system that are limited by topographically dependency, NaS based ESS technology proves to be suitable due to its

technological maturity, mobility, environmental applicability, and long-term storage solutions [26]–[28]. Presently, technological development are made to mitigate the potential drawbacks of NaS ESS that mainly includes high operating temperature ($\sim 350°C$) that negatively impacts its efficiency exacting higher cost of implementation that hinders their commercialized deployment [28].

Accordingly, numerous uncertainty analyses have been presented based on distinct optimal power flow (OPF) strategies to outline the impact of RESs [29]. The study in [30], presented a combination of stochastic problem studies of an OPF problem that is formulated based on a convex model considering the DC model of the power network. This study confers the unpredictably of the renewables and their impact on the system power quality. Therefore, large data analysis and accurate prediction of RES are necessary to address different possible scenarios for enabling the grid operators to overcome these challenges considering the worst case scenarios [31]. In this front, a model is proposed in [32], which presents a spectral analysis technique for hybrid RES by gathering daily load figures. This model is utilized on an off-grid system where the ESS is estimated for various level of mean load. The ESS is developed for one day horizon on an hourly basis (24-h) taking into account the worst case scenario and the unserved energy that determines the ESS size. In [33], an optimal ESS capacity optimization is presented to maintain the power balance for various RES fluctuations. This study utilizes discrete fourier transform to resolve the required balancing power over different time according to a variable periodic component that is utilized to determine the ESS capacity for various types of energy storage technologies.

The uncertainty in a renewable integrated power grid is mainly due to integration of variable RESs as typically load forecasting has a lower degree of errors (< 2 %). With the integration of bulk or systematic increment of RESs at distinct locations, the power grid is subsequently exposed to larger uncertainties in the form of aggregated forecast errors [34] that contribute to demand-generation mismatch. Therefore, the inclusion of non-dispatchable RESs into the existing power grid will have consequences on system operation and future expansions due to distinctive time and scale of variability of RESs combined with the probability of forecasting errors [35]. Hence, a probabilistic approach is pertinent to comprehend these variabilities to obviate additional operational cost, penalty costs, and load shedding [36].

In [37], the authors proposed a chance-constrained programming methodology for optimal ESS sizing considering the uncertainties of renewables. The methodology is based on genetic algorithm technique joint with Monte-Carlo simulation. To solve the optimization problem that is targeted to gain the optimum energy cost while guaranteeing balance between the output power difference with the wind energy source, ESS, and a predefined load profile. Similarly, optimal energy storage operation during specified period based on the cost optimization and forecasting the stochastic nature of system
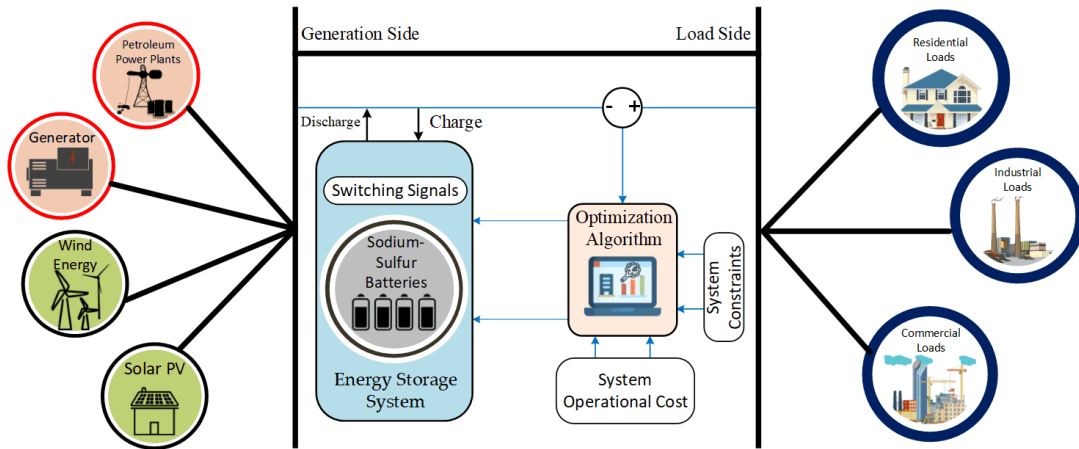
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Y. M. Al-Humaid *et al.*: Two-Stage Stochastic Optimization of NaS kWh Storage Technology in Hybrid Renewable kW Systems

FIGURE 1. A schematic diagram of hybrid renewable energy system.

is studied in [38]. The study in [39], aims to maximize the utilization of wind power while the operation and investment costs are minimized. In this study, the stochastic behaviour of wind power are modelled by the Monte–Carlo simulation to optimally determine the capacity and location of BESS. A novel battery operation cost model is presented in [36], which utilizes a battery as an equivalent fuel-run generator to make it feasible in accordance with the unit commitment problem. The constraint is used as a probabilistic approach to combine it with the uncertainties data of RESs as well as the load demand to formulate an economic dispatch and unit commitment problem.

In this paper, a stochastic cost optimization methodology is presented to formulate a strategic planning framework for designing a hybrid renewable energy system. The objective is to derive the optimal capacity and allocation of NaS ESS under AC-OPF problem with the uncertainty of RES (Fig. 1). The novelty and contribution of this paper includes the development of the solar and wind stochasticity using historical data sets while optimizing the ESS capacity and allocation problem. The major advantage of this planning framework is its robustness towards high nonlinearity of the system model that obviates the need of developing meticulous solar and wind energy models with faster convergence and few simulations. Therefore, ten random scenarios of solar, wind, thermal, and load demand profiles are considered based on historical seasonal uncertainty data over a 24-hour time interval that are used to develop the stochastic model. The planning framework is tested on a day-ahead data deriving the optimal allocation as well as capacity size in term of power (kW) and energy (kWh) of the NaS ESS. Accordingly, the proposed methodology is further compared with the deterministic method to in terms of ESS cost and reliability indices to highlight the relative efficacy.

The remainder of this paper is organized as follows: Section II presents the problem statement and the description of the equation used for identifying the optimal size and location of ESS. Modelling and system constraints that are used to design the power network are presented in Section III. Section IV illustrates case study and presents the results and discussion followed by the conclusion in Section V.

II. PROBLEM DESCRIPTION
A. TWO STAGE STOCHASTIC OPTIMIZATION TECHNIQUE
The uncertainties of the solar and wind energy sources are modeled and introduced in the optimization problem with the probabilities being distributed to all the scenarios. Each scenarios are multiplied with these probabilities and the uncertainty is modeled using the probability density function (PDF). Therefore, in the stochastic optimization problem, some or all the parameters are probabilistic and it is divided into two-stages of optimization. The first stage decisions have to be made before the specific values of the random variables are known, while the second stage decisions are made after the specific values are known. The associated formulation of two stage stochastic strategy are expressed as [40], [41]:

$$\min_{x} c^T x + E_w Q(x, w)$$
$$Ax = b$$
$$x \leq 0 \tag{1}$$
$$Q(x, w) = \min_{y} d_w^T y$$
$$T_w x + W_w y = h_w$$
$$y \geq 0 \tag{2}$$

where, E_w is the expected scenario, w is the possible outcome with respect to the defined probability (Ω, p). The first stage variables are denoted with variable x, which is determined before the result of the stochastic variable ω is spotted. The variables y are the second-stage variables that are identified and computed after ω value is concluded. Further, considering only discrete distributions p, the formulation is derived as:

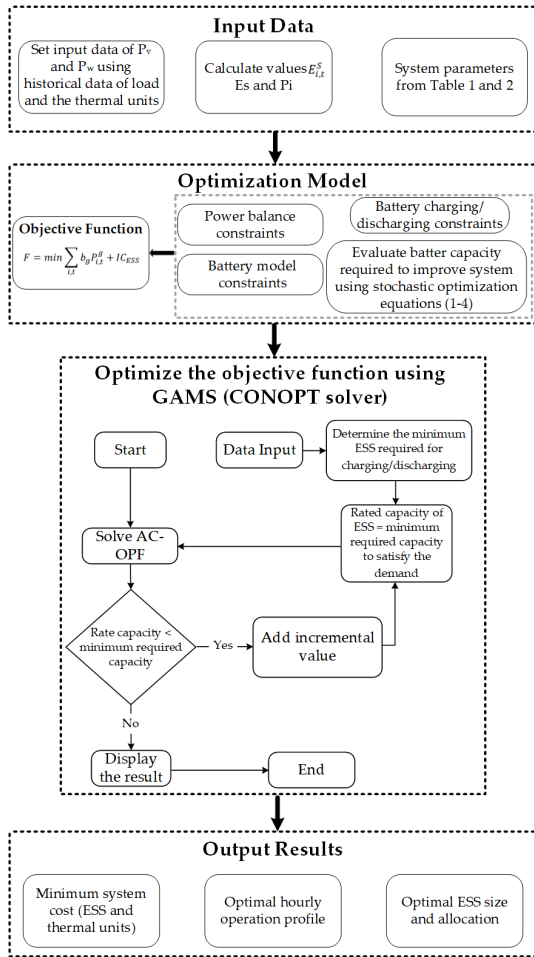$$E_w Q(x, \omega) = \sum_{w \in \Omega} p(w) Q(x, \omega) \tag{3}$$

FIGURE 2. Flowchart for the proposed stochastic programming based optimization technique.

Therefore, a huge linear programming (LP) can be formulated that forms the deterministic equivalent problem as:

$$\min c^T x + \sum_w p(w) d_w^T y_w$$
$$Ax = b$$
$$T_w x + W_w y_w = h_w \quad \forall \omega$$
$$x \geq 0, \quad y_w \geq 0 \tag{4}$$

The sequence of conditions in this model are stated as the followings: Firstly, first stage decision x is made by the decision maker. Secondly, the outcome ($w \in \Omega$) is determined by subjecting the random process (Ω, p) to the system. Finally, the second stage decision y is implemented by the decision maker.

B. OPTIMAL SIZING AND ALLOCATION OF STORAGE SYSTEM

The optimal operational schedule of the power network is dispatched using the AC-OPF. The optimization framework is depicted in Fig. 2. In accordance with the load requirement the generation and the storage units are utilized considering their physical bounds and constraints under and optimized

cost function of the generation units. Stochastic technique is applied in this study based on two stage stochastic optimization technique, which has been utilized to optimally allocate and size the ESS corresponding to the uncertainties of the integrated renewable sources and employing AC-OPF to sustain the system's power quality. The objective function (Obj_F) is postulated as follows:

$$Obj_F = min \sum_{i,t} b_g P_{i,t}^g + IC_{ESS} \tag{5}$$

where, $P_{i,t}^g$ denotes the generated active power from the thermal unit g located on bus i for the time interval t. The line susceptance between branch i and j is represented using b_g in p.u. The fixed cost of the thermal generation unit as well as its variable costs along with the ESS investment costs are incorporated in the objective function. IC_{ESS} is the cost of capital investment for ESS that is further defined as:

$$IC_{ESS} = PC_{ESS} P_{ESS}^R + EC_{ESS} E_{ESS}^R \tag{6}$$

The rated power and of ESS are denoted by P_{ESS}^R and E_{ESS}^R, respectively. Accordingly, the power and energy cost of the ESS are represented using PC_{ESS} and EC_{ESS}. The active power flow ($P_{ij,t}$) in the power network is calculated as:

$$\sum_{j \in \Omega_\ell^i} P_{ij,t} = P_{i,t}^g + P_{i,t}^{PV} + P_{i,t}^w - P_{i,t}^L + P_{i,t}^S \tag{7}$$

where, $P_{i,t}^w$ and $P_{i,t}^{PV}$ are the active power generated by wind turbine and the solar PV connected respectively, connected at bus i (in MW), and $P_{i,t}^L$ is the active power component of the load demand. The charging ($P_{i,t}^c$) and discharging ($P_{i,t}^d$) characteristics for the active power component of the ESS ($P_{i,t}^S$) is further computed using:

$$P_{i,t}^S = P_{i,t}^d - P_{i,t}^c \tag{8}$$

Similarly, the reactive power flow ($Q_{ij,t}$) in the network in the network is calculated using the following equation:

$$\sum_{j \in \Omega_\ell^i} Q_{ij,t} = Q_{i,t}^g + Q_{i,t}^{PV} + Q_{i,t}^w - Q_{i,t}^L + Q_{i,t}^S \tag{9}$$

where, $Q_{i,t}^{PV}$ and $Q_{i,t}^w$ are the generated reactive power from the solar PV and wind turbine, respectively. $Q_{i,t}^L$ is the reactive power component of the load demand. The charging ($Q_{i,t}^c$) and discharging ($Q_{i,t}^d$) characteristics for the reactive component of ESS ($Q_{i,t}^S$) is calculated as:

$$Q_{i,t}^S = Q_{i,t}^d - Q_{i,t}^c \tag{10}$$

Finally, the total apparent power flow ($S_{ij,t}$) in the power network is based on the complex conjugate of the current between the corresponding branch and the voltage profile that is formulated as:

$$S_{ij,t} = (V_{i,t} \angle \delta_{i,t}) I_{i,t}^* \tag{11}$$

$$I_{ij,t} = \frac{V_{i,t} \angle \delta_{i,t} - V_{j,t} \angle \delta_{j,t}}{Z_{ij} \angle \theta_{ij}} + \frac{b V_{i,t}}{2} \angle (\delta_{i,t} + \frac{\pi}{2}) \tag{12}$$

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Y. M. Al-Humaid *et al.*: Two-Stage Stochastic Optimization of NaS kWh Storage Technology in Hybrid Renewable kW Systems
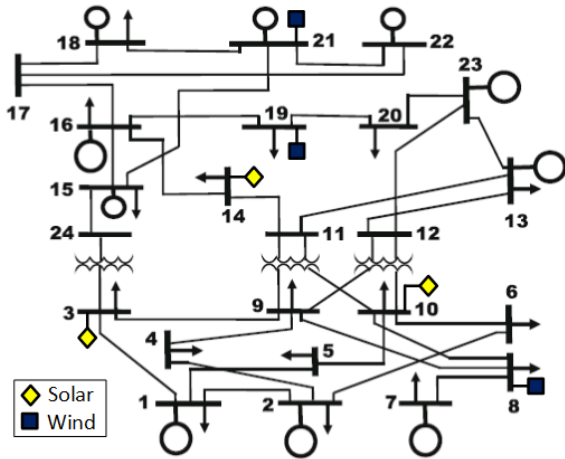
FIGURE 3. 24 bus IEEE reliability test system with renewable energy integration.

TABLE 1. Capacities and placement of wind and solar RESs in the 24-bus RTS.

Type of RES	Bus Location	Capacity Rating (MW)
Wind	21	100
Wind	19	150
Solar	14	60
Solar	10	60
Wind	8	200
Solar	3	60

where, $I_{ij,t}$, b (p.u.), and Z_{ij} are the current flow, line susceptance, and line impedance respectively, between branch i and j. The voltage magnitude (p.u.) of bus i is represented by $V_{i,t}$, $\delta_{i,t}$ is voltage angle (rad), and θ_{ij} is the difference between the phases of the voltage and the current in buses ij. The active ($P_{ij,t}$) and reactive power flow ($Q_{ij,t}$) is represented as:

$$P_{ij,t} = \frac{V_{i,t}^2}{Z_{ij}}cos(\theta_{ij}) - \frac{V_{i,t}V_{j,t}}{Z_{ij}}cos(\delta_{i,t} - \delta_{i,t} + \theta_{ij}) \quad (13)$$

$$Q_{ij,t} = \frac{V_{i,t}^2}{Z_{ij}}sin(\theta_{ij}) - \frac{V_{i,t}V_{j,t}}{Z_{ij}}sin(\delta_{i,t} - \delta_{i,t} + \theta_{ij}) - \frac{bV_{i,t}}{2} \quad (14)$$

where, θ_{ij} indicates the angle between real power and reactive power at buses ij at time t, and $sin(\theta_{ij})$ is the angle between reactive power and apparent power of buses ij at time t.

III. MODELING OF THE TEST SYSTEM

The system under consideration consists of a renewable integrated (RI) IEEE 24 bus reliability test system (RTS) [42]. The system is examined using the proposed optimal strategy under the uncertainties of the wind and solar energy sources. Therefore, the IEEE 24 bus RI-RTS consists of eight distributed renewable based generators as shown in Fig. 3. The bus allocation, capacity, and the type of the deployed renewable energy source are tabulated in Table 1.

TABLE 2. Weibull parameters of Riyadh based on monthly wind speed distribution.

Month	k	c
JAN	1.90	3.55
FEB	1.85	3.89
MAR	2.00	4.31
APR	1.95	3.93
MAY	2.00	3.86
JUN	2.00	4.42
JUL	2.05	4.56
AUG	1.85	3.87
SEP	1.90	3.12
OCT	1.75	2.56
NOV	1.72	2.85
DEC	1.83	3.24

The modelling of the solar and wind energy sources are modelled using Wiebull distribution technique. Weibull distribution density function can be used to determine the frequency of wind speed for certain values (15). This allows formulation of accurate data set patterns for synthetic time series based on historical data [43]. The wind speed frequency curve is utilized to define the Weibull distribution of the wind speed (v) in m/sec. The three parameters of wind speed probability function can be defined as:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1}exp\left(-\left(\frac{v}{c}\right)^k\right) \quad (15)$$

where, k is the shape factor which identifies the peaked value of the wind distribution, c is the scale parameter, and v denotes the mean wind speed. The energy conversion representation of the solar irradiance (G) to electrical energy is expressed using:

$$P_{S_{t,s}} = \begin{cases} P_{sr}\left(\frac{G^2}{G_{std}R_c}\right), & 0 < G < R_c \\ P_{sr}\left(\frac{G^2}{G_{std}}\right), & G \geq R_c \end{cases} \quad (16)$$

where, G_{std} it is denotes the solar irradiance in the normal standard set as $800 \ w/m^2$. R_c is a determined irradiance point set as $120 \ W/m^2$. P_{sr} is the rated output power of the solar PV unit.

To analyze the availability of the wind and solar, this study utilizes the Weibull distribution technique for the selected city (Riyadh) in Saudi Arabia. Besides, this technique allows the generation of wind speed scenarios by scale and shape factor. Hence, these parameters are approximated from the historical data (Table 2), using the scale parameter (c) and shape factor (k) [44]. Nevertheless, due to uncertainty of the considered renewable resources, the time series profile for different wind and solar profile cannot be accurately predicted. Consequently, various scenarios are needed to overcome the shortcoming of forecasting errors, handling of the stochastic optimization's randomness, and avoid potential system failures.

A. SYSTEM CONSTRAINTS

The operation of the system is maintained using the equality constraints. This constraint postulates that the total generation by all the power sources (namely, the HREs, ESSs, and the thermal generation units) should be equal to the total demand load as well as the system losses, at all times. The power balance equality constraint is formulated as:

$$\sum_{s=1}^{Ns}\left\{\sum_{i=1}^{NI} P_{i,t,s} + P_{i,t,s}^{S} + (P_{W_{t,s}} + P_{PV_{t,s}}) + P_{ij,t,s}\right\} = P_{L,t}$$

(17)

here, NI is the number of units, Ns is number of scenarios under consideration, $P_{S_{t,s}}$ represents the power discharged or stored at hour t under scenario s, $P_{W_{t,s}}$ is the power wind at time t under scenario s, $P_{PV_{t,s}}$ power of solar energy at time t in scenario s, $P_{L,t}$ load demand at time t, in power storage system P_S the system which is either to produce or to store energy, the sign in this matter is alternating depending on the operation. Furthermore, the transmission line capacity limits the power exchange between the grid and ESS. The power imported by the grid is denoted by a positive sign while a negative sign is denoted when ESS power is discharged. The transmission line constraint is expressed as:

$$-S_{ij}^{max} \leq S_{ij,t,s} \leq S_{ij}^{max}$$

(18)

where, S_{ij}^{max} represents the maximum transmission line capacity that allows the export/import of power to/from the main grid. The generation capacity constraint limits their active and reactive power generation that is based on the following equations:

$$P_i^{g,min} \leq P_{i,t,s}^g \leq P_i^{g,max}$$

(19)

$$Q_i^{g,min} \leq Q_{i,t,s}^g \leq Q_i^{g,max}$$

(20)

where, $P_i^{g,min}$, and $P_i^{g,max}$ are the minimum and maximum real power, and $Q_i^{g,min}$, and $Q_i^{g,max}$ denote the minimum and maximum reactive powers of the generation unit i. Furthermore, each generation unit consists of ramp up/down rates in accordance with their capacity and technology that are formulated as:

$$RU_i \geq P_{i,t}^g - P_{i,t-1,s}^g$$

(21)

$$RD_i \geq P_{i,t-1,s}^g - P_{i,t,s}^g$$

(22)

where, RD_g is the ramp down rating, and RU_g is the ramp up rating. In accordance with this constraint, the unit remains at their respective state for a certain time interval before their incremental or decremental transition to the second state.

The electrical power generated by the wind turbine is determined by the power curve, where the established connection between the power delivered and wind speed is expressed by the following [45]:

$$P_{W_{t,s}} = \begin{cases} 0, & v_{t,s} < v_{CI}, v_{t,s} \geq v_{CO} \\ P_W^{max}\dfrac{v_{t,s} - v_{CI}}{V_R - v_{CI}}, & v_{CI} \leq v_{t,s} < v_R \\ P_W^{max}, & v_R \leq v_{t,s} < v_{CO} \end{cases}$$
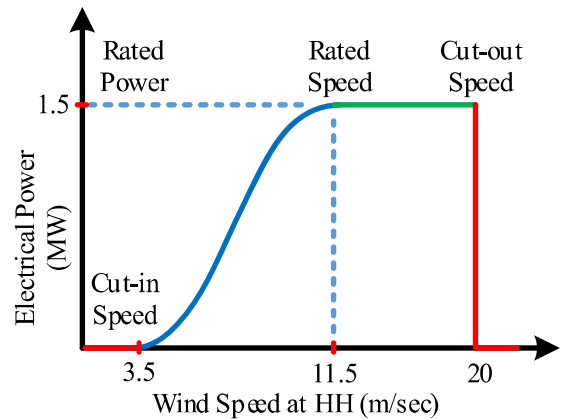
(23)

FIGURE 4. Wind power curve.

where, $P_{W_{t,s}}$ is electrical wind power at time (t) in scenario (s); v_{CI} is cut in wind speed; v_R is rated wind speed; v_{CO} is cut out wind speed; P_W^{max} is rated wind power. Fig. 4 [46], shows the relationship between wind speed and wind power [47]. In this study, v_{CI}, v_R, and v_{CO} are respectively taken as 2 m/s, 5 m/s, and 10 m/s. Wind power is identified as the development of air in the atmosphere to control and balance the mismatch in the heat that is brought by unequal heating of air by the master energy source, which is the Sun. This irregular heating provides kinetic energy which is changed to mechanical energy by wind energy conversion system (WECS). Therefore, wind power is the average of the alteration of the kinetic energy and can be computed with (15) and the formation of the output power is expressed as:

$$P_W = \frac{1}{2}\rho Av^3 = \frac{1}{2}\rho\pi R^2 v^3$$

(24)

where, R is radius of rotor blades (m) and ρ is the density of the air (kg/m^3). It can be observed that a minor difference in wind speed could shape major effect on output of wind turbine as wind power is basically subjected to the cube of wind speed. Hence, a precise knowledge of the wind speed values is very important for an effective utilization of the wind energy source from a specific location [48].

The charging/discharging capability of ESS is subjected to the limit imposed by the power rating of the ESS (P_{ESS}^R), which is lower than or equal to the rated power of the ESS (25). In this respect, ESS operates as a load and as a generation unit during its charging and discharging process, respectively. In this study, discharging power has positive sign, whereas charging power has negative sign. Accordingly, in accordance with the rated energy (E_{ESS}^R), the energy stored will always be greater than zero but less than or equal to the rated energy (26) and the rated power (27).

$$-P_{ESS}^R \leq P_{ESS_{t,s}} \leq P_{ESS}^R \quad \forall t \in T$$

(25)

$$0 \leq E_{ESS_{t,s}} \leq E_{ESS}^R \quad \forall t \in T$$

(26)

$$E_{ESS_{t,s}} \leq E_{ESS_{t,s}} \leq P_{ESS_{t,s}} \quad \forall t \in T$$

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Y. M. Al-Humaid *et al.*: Two-Stage Stochastic Optimization of NaS kWh Storage Technology in Hybrid Renewable kW Systems
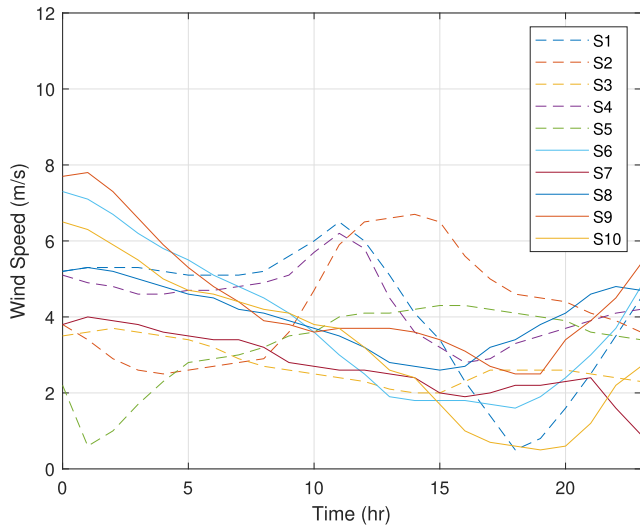

FIGURE 5. Hourly wind speed for ten scenarios considered in summer and winter season.
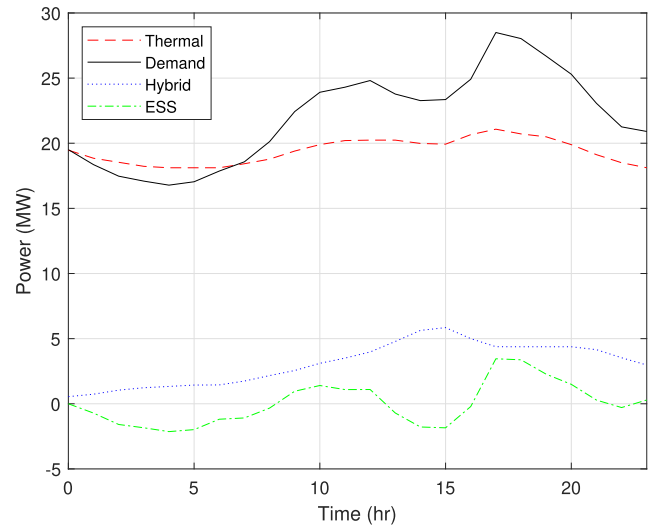

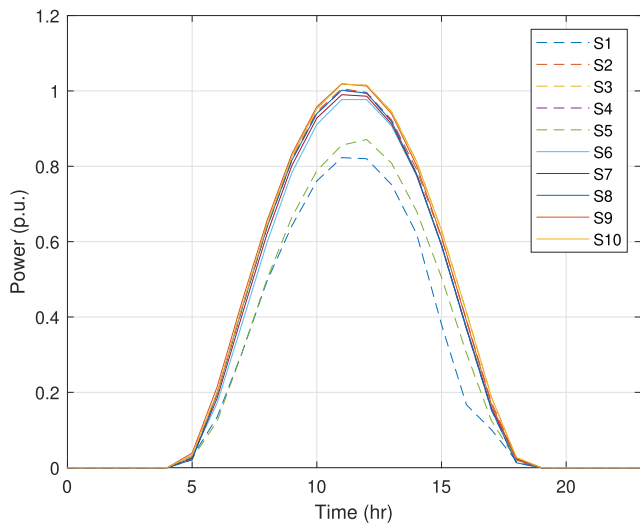**FIGURE 7.** Economic dispatch with ESS during summer case.

FIGURE 6. Hourly solar PV power for ten scenarios considered in summer and winter season.
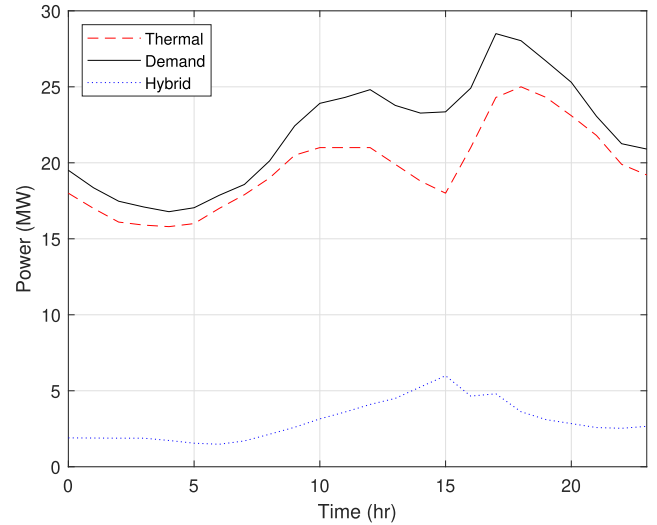

FIGURE 8. Economic dispatch without ESS during summer case.

where, the energy stored in ESS for scenario s at time interval t is denoted by $E_{ESS_{t,s}}$. This represents the state-of-charge (SoC) of the ESS that is calculated hourly for each scenario.

IV. RESULT AND DISCUSSION

Based on the modelling framework formulated in Section III, five scenarios of wind and solar are randomly selected from the historical data [49], for the winter and summer seasons over a horizon of 24 hours. Fig. 5 and Fig. 6 depicts the hourly data sets of the wind speed and solar irradiance scenarios encountered during the winter and summer seasons, respectively. The probabilities (ρ_s) are uniformly distributed between all the scenarios by 0.2, so the total sum of the scenarios is equal to 1. The values of k and c in accordance with the annual numerical values of Riyadh in are taken as 1.95 and 3.70, respectively. The efficiency of the NaS-ESS

is taken at 95% and the power and energy cost is taken as 350 $/kW and 300 $/kWh, respectively [50], [51]. The optimization is performed on GAMS platform [52].

The optimization is achieved based on the two-stage stochastic programming technique. The total cost includes the operation of the thermal generation units, power exchanged from the grid with minimized investment cost of the NaS-ESS. The optimal size and location of the NaS-ESS is calculated at the rated power of 5.61 MW and rated energy of 21.61 MWh. The seasonal based economic dispatch and operation of the HRES system are depicted in Figs. 7–12, with and without the support of the NaS-ESS. From these results, the formulation has been performed for the output power of all the HRES and thermal units for all buses in the network considering an hourly time step. The NaS-ESS acts as an energy buffer to reduce the difference between the varying RES supply, i.e., it servers as a alternative generation
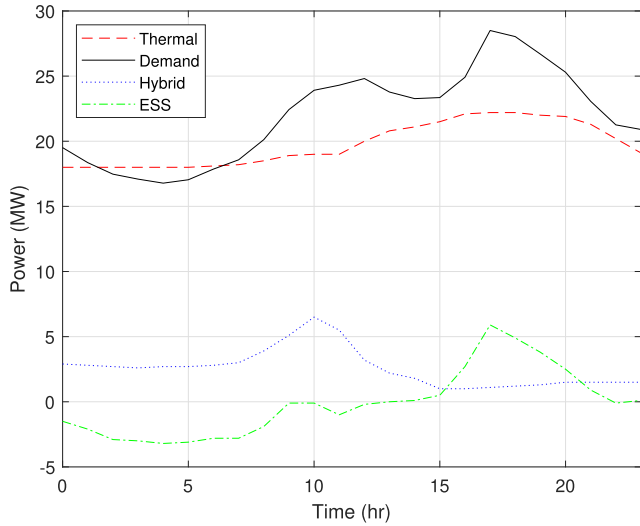
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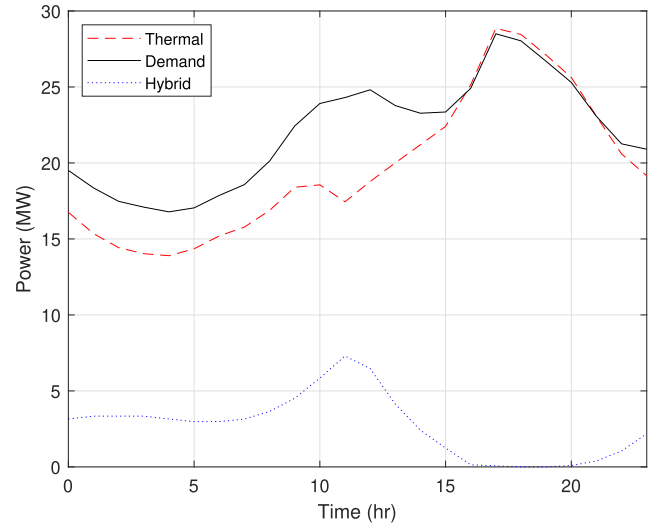**FIGURE 9.** Economic dispatch with ESS during winter case.

FIGURE 11. Economic dispatch and operation without ESS for the SP solution.
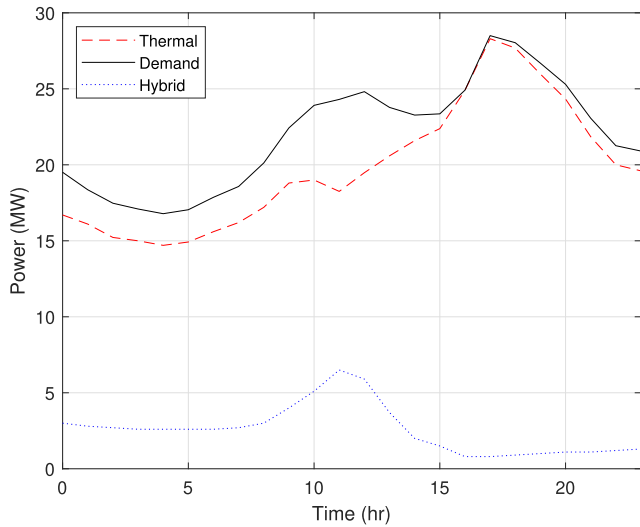

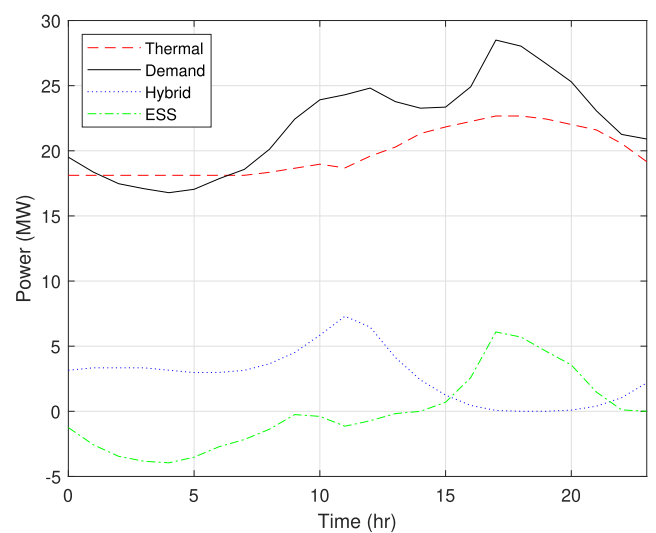**FIGURE 10.** Economic dispatch without ESS during winter case.

FIGURE 12. Economic dispatch and operation with ESS for the SP solution.

source or an additional load which is highlighted by its positive and negative values during its charging and discharging intervals. Accordingly, the SoC is taken as positive during the discharging and negative during the charging hour t. The design and operation of the ESS, depicts an observable difference in the total cost of the energy system.

Furthermore, Table 3 highlights the efficacy of the proposed stochastic methodology over the deterministic method. The results obtained for all the scenarios including the ten cases for the deterministic approach as well as the stochastic method are presented. The advantage of the proposed stochastic optimization technique is the formulation of the second-optimal solution (SP). The results obtained for the deterministic method (S1-S10) facilitates distinctive results and an over-optimistic selection of ESS capacity is required for suitable and economic system operation. This means that the operators will have to dispatch different sets of storage

TABLE 3. Comparative results obtained through deterministic approach (S1-S10) and proposed two-stage stochastic approach (SP).

	Sizing			Allocation	
Scenario	Total cost ($)	P_R^S (MW)	E_R^S (MWh)	Bus No.	NaS Rating (MW)
S1	482995.90	6.08	24.85	3	0.558
S2	477248.95	5.63	22.08	4	0.122
S3	491459.99	5.26	22.38	5	0.605
S4	440403.02	5.43	21.62	6	0.38
S5	470737.52	4.95	17.11	7	1.056
S6	480382.18	5.41	21.08	8	0.46
S7	482691.76	5.38	21.18	9	0.445
S8	473275.98	4.32	15.99	10	0.308
S9	422227.20	5.43	21.62	13	0.219
S10	451735.91	2.54	10.16	14	0.482
SP	432429.00	5.12	21.61	15	0.249
				19	0.232

size in accordance with the variation in the generation which introduces further complexities in optimal ESS dispatch and

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TABLE 4. Reliability comparison between the stochastic and deterministic technique.

Index	Deterministic	Stochastic
Optimized Cost	480382	432429
ASAI	98.4%	99.76%
ASUI	0.0155%	0.0024%
SAIFI (failure/customer)	5.4571	4.8951
SAIDI (hr./customer)	36.4098	28.2045
CAIDI (hr/customer interruption)	6.672	5.761

capacity. On the other hand, the stochastic approach facilitates second optimal solution that reduces over-optimistic selection ensuring optimal energy dispatch considering generation, load, and energy storage. The operational aspect of the power components in the HRES for the SP, without and with the incorporation of NaS in shown in Figures 11 and 12, respectively.

Accordingly, the aim of optimal sizing and allocation of ESS is to improve the reliability of the power network [53]. To demonstrate the reliability enhancement achieved with proposed methodology, a reliability analysis considering the average service availability index (ASAI), average service unavailability index (ASUI), system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), and customer average interruption duration index (CAIDI) is performed with the deterministic case to analyze the equipment availability between the two methodologies.

Table 4 shows that reliability indices of the proposed stochastic technique is more enhanced with higher contribution towards the reliability of the HRES system. Observably, deterministic approach facilitates optimization in accordance with the associated generation and load profiles. However, it proves to be sub-optimal due to the increment in the degree of variation introduced with the incorporation of RES. Therefore, the proposed two-stage stochastic programming technique provides a global optimal solution that is reasonably cost efficient in comparison to the deterministic technique. The stochastic technique is implemented in cases that requires a single optimal solutions for multiple scenarios. This provides an advantage to the stochastic programming technique over the deterministic technique that heavily relies on the accuracy and availability of a bulk historical data of the RES and the system.

V. CONCLUSION

In this paper, a two-stage stochastic optimization methodology is formulated for capacity optimization and optimal allocation of NaS-ESS units to optimize the overall system costs. The optimization framework is tested and validated on a hybrid renewable based 24-bus RTS network. A 24-hour data set of ten scenarios are considered to formulate the planning framework of the test system. Based on the uncertainty probabilistic data and operation an optimal size and placement of the ESS is determined to facilitate a cost-efficient solution. The results obtained illustrated the positive impact of ESS towards the cost reduction by facilitating a

cheaper solution to the uncertainty of the power flow through controllable charging and discharging process. Furthermore, a comparative analysis based on reliability indices of power system was presented to demonstrate the efficacy of the proposed two-stage stochastic programming over the deterministic method. Based on the results obtained, an observable reliability enhancement combined with minimized cost is achieved by the proposed stochastic optimization technique. Besides, the proposed programming technique has a promising applicability towards power system planning wherein the uncertainty variables are very high, especially in large power system networks.

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