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Optimizing a Distributed Wind-Storage System Under Critical Uncertainties Using Benders Decomposition

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ABSTRACT A method for calculating the optimal size of an energy storage system (ESS) under wind uncertainties is presented based on Benders decomposition for stochastic programming in this paper. The ESSs are becoming essential components in microgrids due to significantly higher penetration of renewable energy sources. Integrating renewable energy sources coupled with ESSs in a power system enhances the power system reliability by increasing its availability and reducing its total cost of operation and maintenance. In addition, the ESS connected to a microgrid should be optimally sized to be able to provide the necessary power and minimize the total cost of investment and operation. In order to optimally size a storage system, a constrained optimization problem is solved using a probabilistic optimization method because the forecast of their output power cannot be determined accurately. In this paper, a probabilistic optimization problem is solved using the Benders decomposition for stochastic programming method to optimally size an ESS. This ESS will be integrated and connected to a grid-connected microgrid that has wind power generation. The simulation results prove the effectiveness of the proposed optimal sizing methodology.

INDEX TERMS Energy storage system, wind uncertainty, renewable energy, Benders decomposition, stochastic optimization.

NOMENCLATURE

ρ_s	Probability of scenario s
C_i	Number of interrupted customers for event i
CMG_{ex}	Cost of microgrid related to exchanged power
CMG_{units}	Cost of microgrid related to its units
D_t	Demand at hour t
E_{ESS_t}	Energy stored in ESS at hour t
E_{ESS}^R	Rated energy of ESS
EC_{ESS}	Energy cost of ESS per MWh
F_t	Fixed cost of unit i
I	Set of units
i	Unit index
IC_{ESS}	Investment cost of ESS
MDT_i	Minimum down time of unit i
MUT_i	Minimum up time of unit i
NI	Number of units
NS	Number of scenarios
NT	Number of hours
P_i^{max}	Maximum power of unit i
P_i^{min}	Minimum power of unit i
P_M^{max}	Maximum exchanged power
P_W^{max}	Rated wind power
P_{ESS_t}	Power produced by ESS at hour t
P_{ESS}^R	Rated Power of ESS
$P_{i,t}$	Power generated by unit i at hour t
P_{M_t}	Power exchanged with the main grid
$P_{W_{t,s}}$	Wind power at hour t in scenario s
PC_{ESS}	Power cost of ESS per MW
RD_i	Ramp down rate of unit i
RU_i	Ramp up rate of unit i
S	Set of scenarios

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s	Scenario index
SD_i	Shut down cost of unit i
SU_i	Start up cost of unit i
T	Set of hours
t	Hour index
$T_{i,t}^{OFF}$	OFF time of unit i at hour t
$T_{i,t}^{ON}$	ON time of unit i at hour t
$u_{i,t}$	Commitment state of unit i at hour t
V_i	Variable cost of unit i
v_R	Rated wind speed
v_{CI}	Cut-in wind speed
v_{CO}	Cut-out wind speed
$v_{t,s}$	Wind speed at hour t in scenario s
$y_{i,t}$	Start up indicator of unit i at hour t
$z_{i,t}$	Shut down indicator of unit i at hour t

I. INTRODUCTION

Microgrids are power systems of a small size. Microgrids are designed and built to supply customers connected to them with electrical energy. Microgrids might be islanded or grid-connected [1]. If it is connected to the main grid, the microgrid is able to exchange power through importing and exporting to the main grid. There are several features in microgrids such as distributed generators, renewable energy sources, storage systems, and controllable loads [2]. Those features make microgrids more flexible, reliable, and efficient [3].

The differences between centralized systems and microgrids are shown in Figure 1. There are other reasons to establish microgrids; and they are reducing production, maintenance and operation cost, enhancing reliability, limiting emissions, and improving power quality [5]. Uncentralism means the reliability and availability of a microgrid improved due to distributed generators. Usually, microgrids are integrated and connected to renewable energy sources. Those sources have the ability to make the system more economical than centralized systems which are dependent on conventional generators. When renewable energy sources are integrated with a microgrid, the operation cost reduces extremely. This is because the operation cost of the renewable energy sources is negligible in comparison with conventional generators which their operation cost is dependent on fuel costs. Renewable energy is available freely but sources required to convert the renewable energy to electrical energy need investment cost. The authors in [6] review the techniques and methods of integration of renewable distributed generation units into a distribution system. One of the other important components that could be connected to a microgrid is a storage system. There are many storage technologies that are rapidly improving and there are many applications of them in microgrids [7]. For instance, their contribution to support an emergency load is one of the important applications. Also, an ESS can deliver peaks with electrical energy [8]. The ESSs make power operation more economic and they decrease costs like sources of renewable energy. Moreover, they are able to charge and store electrical energy during low-price periods. In addition, they are able to discharge and supply the stored energy in during high-price periods [1]. Therefore, this process leads to a more economic system that its operation cost is less. Incorporating and integrating renewable energy sources and ESSs improve and increase the performance, reliability and availability [9]. Furthermore, smart Energy Management System (SEMS) is a system used to coordinate different components and devices in a microgrid. Those components include renewable energy sources and ESSs. The SEMS has some objectives and the primary objective of it is to generate and create appropriate set points for different sources and ESSs to minimize costs and optimize power dispatch, or distribution of powers, economically. Figure 4 illustrates a typical SEMS [10].

Smart grids are a smart type of microgrids and they are bi-directional power and communication networks improving the reliability of an electric system. They have all stages found in a power system and those stages are generation, transmission and distribution. In addition, they have ESSs which increase the reliability of a power system significantly. Also, an ESS decreases the total operating cost in a smart grid and saves a large portion in the fuel and maintenance costs (see, e.g., [11] and references therein). Smart grids could be small-scale or large-scale systems. Furthermore, smart grids are green and they produce much fewer emissions than transitional power systems as well as microgrids.

Electric vehicles are considered as ESSs. They charge and discharge as well as other ESSs. ESSs should be optimally sized before integrating them to a microgrid [8]. There are many techniques to find the optimal size of an ESS. The ESS has its optimal size when this size minimizes the total cost of investment and operation. In addition, in grid-connected microgrids, the costs and revenues of exchanged power are included in the total cost [3]. There is a mathematical relationship between the size of an ESS and its investment cost as well as its microgrid operation cost. The investment cost increases linearly as the size increases. However, the operation cost decreases exponentially as the size increases [1]. The sum of those two costs is the total cost. The objective is to calculate the size at the minimum total cost [12]. Figure 5 illustrates this relationship. The ESS should be at its optimal size because an oversized ESS leads to a high investment cost while an undersized ESS might not the ability to provide economic and operational benefits [1]. The authors in [13] propose a methodology to optimally size an ESS for future autonomous systems.

The optimal size of an ESS is calculated using one of the optimization techniques. Some of those techniques are mixed-integer linear programming (MILP) [8], mixed-integer non-linear programming (MINLP) [14], dynamic programming (DP) [15], [16], particle swarm optimization (PSO) [17], two-stage stochastic programming [18], distributionally robust optimization [19], model predictive control (MPC) [20]. The parameters of optimization problems could be either certain or uncertain. Deterministic optimization methods are used to solve optimization problems with certain

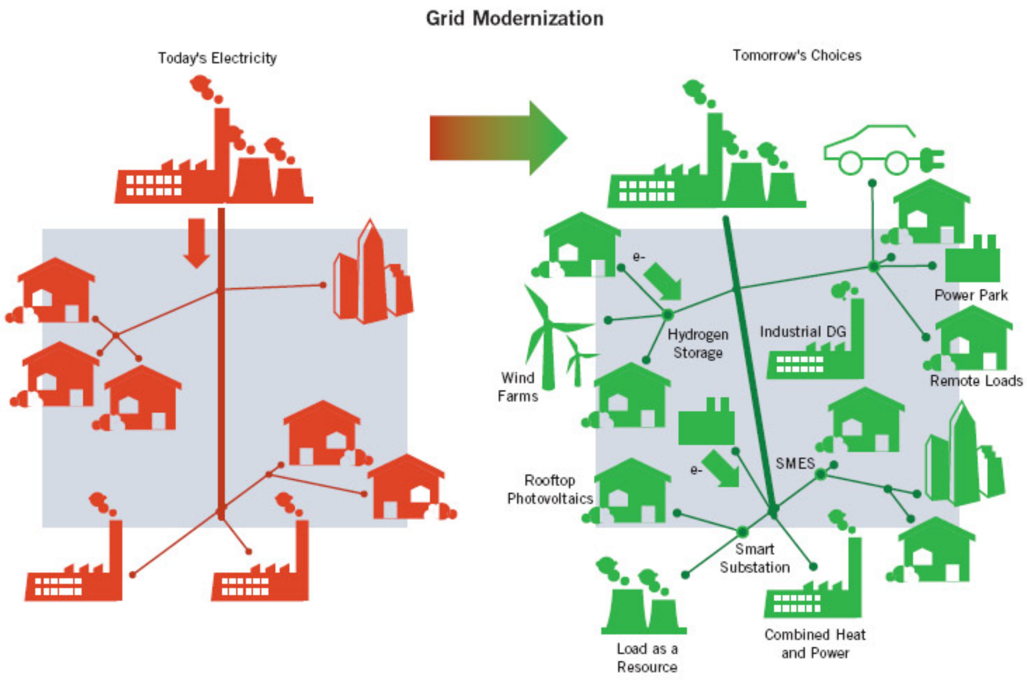

FIGURE 1. Schematic of centralized and distributed systems [4].

parameters whereas probabilistic methods are used to solve problems having uncertain parameters. Moreover, there are several algorithms in addition to optimization techniques to find the optimal size of an ESS. The authors in [21] have proposed a technique to optimally size a hybrid ESS (HESS). This HESS consists of rechargeable batteries and ultracapacitors. Moreover, the authors in [22] have presented a methodology to optimize the joint capacity of renewable energy and a HESS.

Stochastic optimization or robust optimization are used to solve optimization problems that have uncertainty in their parameters [18]. In addition, the heuristic algorithm is used as well to solve probabilistic optimization problems. The authors in [23] explained this algorithm and one of its applications in power system optimization. They used the algorithm to find the optimal operation of distributed generators in a microgrid. Moreover, the authors in [8] proposed an algorithm to optimally size a battery ESS (BESS) in an islanded microgrid. The objective of this algorithm is to find the size of the BESS that minimizes the total cost. This algorithm is explained in details in [8]. Figure 2 shows this technique and algorithm briefly and how they are used to optimally size the BESS.

One of the very attractive options to enhance and improve the flexibility of microgrid planning and operation is the ESS. Also, as discussed, an ESS can absorb energy when prices are low or there is excessive generation. After that, it returns this energy when prices are high or generation is low [24]. ESSs have many technologies. Some of those technologies are superconducting magnetic energy storage system (SMES) [25], compressed air energy storage (CAES) [26],

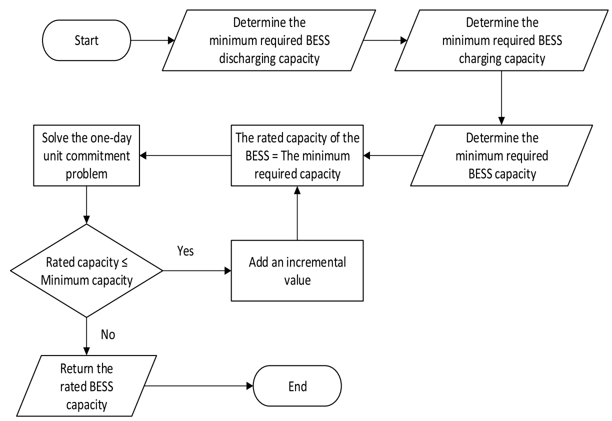

FIGURE 2. The flowchart of the proposed algorithm.

super-capacitor energy storage [27], pumped hydro storage [28], battery energy storage (BESS) [29], flywheel energy storage system [30], and power to gas storage method [31].

In power system optimization, different objective functions related to an ESS are used [24]. Some of them are compensate grid voltage fluctuations [25], overcome the destabilizing effect of instantaneous constant power loads in DC microgrids [27], prevention of transient under-frequency load shedding [32], reliability enhancement [33], wind uncertainty management [34], fault ride through the support of grid-connected VSC HVDC-based offshore wind farms [30], phase balancing [35], wind curtailment reduction and congestion management [36], and active power loss payment minimization [37]. In addition, ESSs could be optimized with other distributed generators in a distribution system [38].

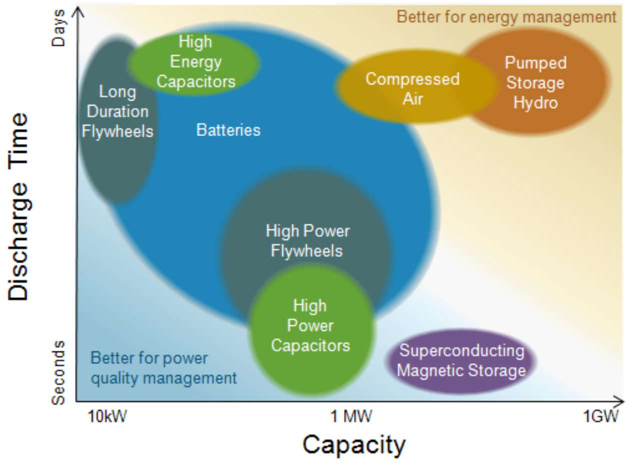

FIGURE 3. Electricity storage technologies [41].

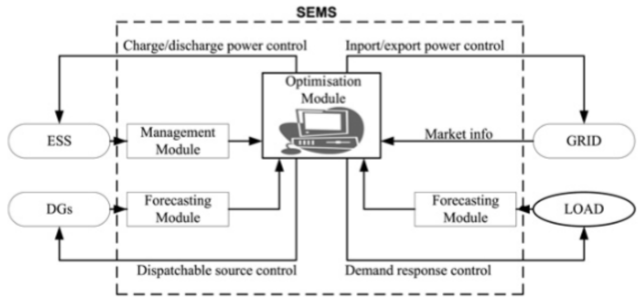

FIGURE 4. Inputs and outputs of SEMS.

Different types of ESSs have been designed and developed. Some of them are already available commercially. The rest of them are still under research to be improved. Different ESS technologies have different charging and discharging characteristics. Also, the charging and discharging rates are different among those different technologies. Figure 3 illustrates the power and discharge rate of different ESS technologies. Several criteria are used to compare the different ESS technologies. The authors in [39] have compared different characteristics as well as advantages and disadvantages of ESS technologies. Reliability is an extremely important factor used to evaluate a certain power system. Reliability assessment of a power system is important for both sides; suppliers and customers. Reliability of a power system means the system should be available to supply electrical energy when it is needed at an economic and reasonable cost. Many technologies and devices have been developed to enhance and increase the reliability of power systems. ESSs enhance the microgrid reliability when they are integrated with it [40] in addition to the other benefits that an ESS provides for a microgrid. ESSs increase the availability in many ways. One of them is that they support in shaving the demand, especially at peak periods. Moreover, when an ESS is established, it does not cost in terms of production or operation. There are other reliability indices and they enhance as well after integrating the ESS [3].

When renewable energy sources are integrated to a power system, the uncertainty matters because the output power from those sources cannot be determined accurately. Also, this depends mainly on forecasting which cannot be absolutely true. In addition, reliability gets more importance nowadays and many technologies are being developed to enhance the reliability. The missing gap in the literature is that there is no method to optimally size an ESS for a microgrid under wind uncertainties. In order to find the optimal size of an ESS for a microgrid connected to renewable energy sources, the uncertainties must be taken into account. The problem in this case is called a probabilistic optimization problem which is different from deterministic optimization problems. Stochastic optimization and robust optimization are two methods used to optimize such problems. Stochastic programs are complicated and more difficult to formulate [42]. There are many solution approaches to solve stochastic optimization problems. Some of those approaches are decomposition, statistically based methods, stochastic decomposition, methods for multi-stage problems and computational illustration [42]. Another method to optimally size an ESS connected to a system having renewable energy sources is generic sizing methodology using pinch analysis and design space [43]. One of the decomposition techniques used to solve very large stochastic optimization problems is Benders decomposition [44]. Benders decomposition is a technique used to solve stochastic programming problems where uncertainties are represented with scenarios.

This paper discusses a technique to optimally size an ESS to be integrated into a microgrid connected to a main grid under wind uncertainties using the Benders decomposition in very large systems. A new model has been proposed for optimal sizing of an ESS considering wind uncertainties in system modeling, which is critically important in power systems containing intermittent renewable energy sources such as wind. Benders decomposition is a great technique when there are many scenarios because it simplifies the problem and its algorithm is easy to follow in coding. So, this technique can be used in sizing an ESS using wind data from many years efficiently.

The remainder of the paper is organized as follows. Section II explains the equations used to calculate the optimal size of and ESS. Section III shows a simple case study used to test the proposed technique of optimal sizing of an ESS. Section IV shows and illustrates the simulation results after solving the optimization problem of the case study. Section V is the conclusion of the paper.

II. PROBLEM FORMULATION

The problem formulation is subdivided into the following subsections.

A. BENDERS DECOMPOSITION

Stochastic optimization problems are solved as explained in this paragraph generally. Wind uncertainty is modeled to be included in the optimization problem. Multiple wind speed scenarios are generated for the optimization problem. Distribution probabilities are assigned to each scenario. Of course, the sum of all probabilities must be 1. Each scenario will be multiplied by its probability and the production will be summed. The total is a new scenario that will be included in a deterministic optimization problem.

The formulation of Benders decomposition is explained in [45]. The two-stage stochastic linear programming problem can be formulated as shown in the following equation.

$$\left.\begin{aligned} \min_x \ c^T x + E_\omega Q(x,\omega) \\ Ax = b \\ x \geq 0 \end{aligned}\right\} \tag{1}$$

specifically

$$\left.\begin{aligned} Q(x,\omega) = \min_y \ d_\omega^T y \\ T_\omega x + W_\omega y = h_\omega \\ y \geq 0 \end{aligned}\right\} \tag{2}$$

where E_ω is the expectation, and ω is the scenario with respect to the probability space (Ω, P). Discrete distributions P only are considered in the following equation.

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

So, the deterministic equivalent can be formulated as:

$$\left.\begin{aligned} \min_x \ c^T x + \sum_\omega p(\omega) d_\omega^T y_\omega \\ Ax = b \\ T_\omega x + W_\omega y_\omega = h_\omega \\ x \geq 0, \ y_\omega \geq 0 \end{aligned}\right\} \tag{4}$$

The structure $T_\omega x + W_\omega y_\omega = h_\omega$ is called L-shaped, and it can be expanded as shown in the following equation.

$$\left.\begin{array}{llll} T_1 x + W_1 y_1 & & & = h_1 \\ T_2 x & + W_2 y_2 & & = h_2 \\ & & & . \\ & & & . \\ & & & . \\ T_k x & & + W_k y_k & = h_k \end{array}\right\} \tag{5}$$

Moreover, the algorithm of Benders decomposition is explained in Algorithm 1.

If the subproblems are infeasible, slightly different formulated cuts are needed to be included. The subproblems here are assumed to be solved to an optimal feasible solution.

B. ESS OPTIMAL SIZING

Stochastic programming based on Benders decomposition is used to optimally size an ESS. In order to calculate the optimal size, the model of one of the famous power system

Algorithm 1 Benders Algorithm

Step 1: Initialization
$v := 1$ ▷ Iteration number
$UB := \infty$ ▷ Upper bound
$LB := -\infty$ ▷ Lower bound
Solve initial master problem:

$$\left.\begin{aligned} \min_x \ c^T x \\ Ax = b \\ x \geq 0 \end{aligned}\right\} \tag{6}$$

$\overline{x}^v := x^*$ ▷ Optimal values
Step 2: Sub problems

for $\omega \in \Omega$ **do**
Solve the sub problem:

$$\left.\begin{aligned} \min_y \ d_\omega^T y_\omega \\ W_\omega y_\omega = h_\omega - T_\omega \overline{x}^v \\ y_\omega \geq 0 \end{aligned}\right\} \tag{7}$$

$\overline{y}_\omega^v := y_\omega^*$ ▷ Optimal values
$\overline{\pi}_\omega^v := \pi_\omega^*$ ▷ Optimal dual values

end for
$UB := \min_x \ UB, c^T \overline{x}^v + \sum_{\omega\in\Omega} p_\omega d_\omega^T \overline{y}_\omega^v$
Step 3: Convergence test
if $(UB - LB)/(1 + LB) \leq TOL$ **then**
Stop: required accuracy achieved
Return $\overline{x}^v$
end if
Step 4: Master problem
Solve the master problem

$$\left.\begin{aligned} \min_x \ c^T x + \theta \\ Ax = b \\ \theta \geq \sum_{\omega\in\Omega} p_\omega(-\overline{\pi}_\omega^l [T_\omega x + W_\omega \overline{y}_\omega^l - h_\omega]), \\ l = 1, \ldots, v-1 \\ x \geq 0 \end{aligned}\right\} \tag{8}$$

$\overline{x}^v := x^*$ ▷ Optimal values
$\overline{\theta}^v := \theta^*$
$LB := c^T \overline{x}^v + \overline{\theta}^v$
Go to Step 2

optimization problems is used. This problem is the unit commitment problem. ESS constraints are added to the unit commitment problem and the solution will include the solution of the unit commitment and optimal size. The unit commitment problem is explained in [46] and [12]. In addition, ESS constraints that should be added to the model of unit commitment are explained in [12]. The proposed optimization problem

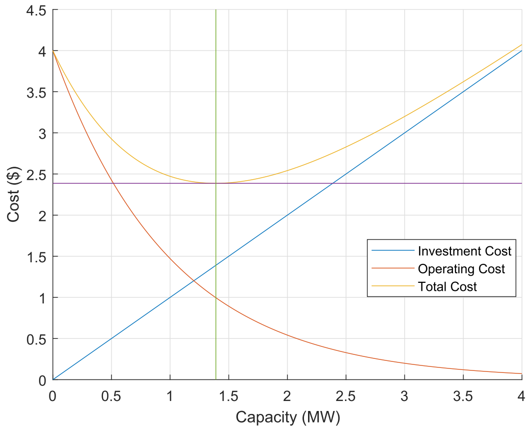

FIGURE 5. Cost vs ESS size.

has been modeled and a GAMS (General Algebraic Modeling System) code has been developed to solve the problem. Developing GAMS codes is explained in [47] and [24].

1) OBJECTIVE FUNCTION

The objective function of the optimization problem is the cost function. The objective is to minimize the total cost. Therefore, the total cost includes the costs os ESS investment, operation and exchanged power. The objective function of the optimal sizing problem for a given horizon is formulated in the following equation.

$$min\ CMG_{units} + CMG_{ex} + IC_{ESS} \tag{9}$$

where CMG_{units} is the operation cost of microgrid distributed generators, CMG_{ex} is the cost or revenue of the exchanged power imported from the main grid or exported to it, and IC_{ESS} is the investment cost needed to establish the ESS.

The operation cost of microgrid distributed generators is calculated using the equation formulated in (10). The decision variables u, y, and z are binary variables. This means that they have only two values which are either 1 or 0. If $u_{i,t}$ is 1, this means that the generator i at hour t is ON, and if it is 0, the generator is OFF. Also, if $y_{i,t}$ is 1, this means the generator i starts up at hour t. In addition, if $z_{i,t}$ is 1, the generator i at hour t shuts down. So, the $y_{i,t}$ and $z_{i,t}$ are 1 during the first hour the generator starts up and shuts down, respectively. The values of $y_{i,t}$ and $z_{i,t}$ are 0 during the rest of the hours. Since the values of $u_{i,t}$, $y_{i,t}$ and $z_{i,t}$ are integers, MILP should be used to solve the optimization problem. The fixed cost of unit i, F, is fixed if the unit i is ON. This cost is calculated during all hours the unit is committed at. The output power of the unit does not matter in calculating the fixed cost. However, the variable cost of unit i, V, is variable and it is dependent on the output power of the unit i.

$$CMG_{units} = \sum_{t=1}^{NT}\sum_{i=1}^{NI}[F_i u_{i,t} + V_i P_{i,t} + SU_i y_{i,t} + SD_i z_{i,t}] \tag{10}$$

where i is the unit index, NI is the number of units, t is the hour index, NT is the number of hours, F_i is the fixed cost or no-load cost of unit i, V_i is the variable cost of unit i and it is related to the output power of unit i, $P_{i,t}$ is the output power of unit i at hour t, SU_i is the start up cost of unit i and SD_i is the shut down cost of unit i. $u_{i,t}$, $y_{i,t}$, and $z_{i,t}$ are binary variables represent the commitment state of unit i at hour t, start up indicator of unit i at hour t and shut down indicator of unit i at hour t, respectively.

The cost function used to calculate the cost of a generator is a nonlinear function. It is quadratic. However, in (10), it has been linearized to make the optimization problem simpler and faster to model and solve. The quadratic function could be used in the objective function for more accurate results.

The following equation shows how to calculate the cost of imported power from the main grid or revenue of exported power to the main grid. This cost is positive when power is imported because the objective function calculated the cost. Thus, when power is exported to the main grid, the cost is negative because of the value of the objective function will be less.

$$CMG_{ex} = \sum_{t=1}^{NT} \gamma P_{M_t} \tag{11}$$

where γ is electricity price per one megawatt of power bought from or sold to the main grid and P_{M_t} is the exchanged power between the microgrid and main grid at hour t. The sign convention in P_{M_t} is that it is positive when the power flows from the main grid to the microgrid and it is negative when the power flows from the microgrid to the main grid.

The ESS investment cost is formulated in the following equation. The parameters in this equation are the unit prices of ESS power and energy. Furthermore, the decision variables are the rated power and energy of the ESS. These two variables represent the required optimal size of the ESS.

$$IC_{ESS} = PC_{ESS}\ P^R_{ESS} + EC_{ESS}\ E^R_{ESS} \tag{12}$$

where PC_{ESS} is the power cost of the ESS per one megawatt, P^R_{ESS} is the rated power of the ESS, EC_{ESS} is the energy cost of the ESS per one megawatt hour and E^R_{ESS} is the rated energy of the ESS.

2) SYSTEM CONSTRAINTS

System constraints include generator constraints and balance equations. The balance equation is an important constraint because the generated power must be equal to the load at the same time. If generated power is greater than the load, the system frequency increases. In addition, if the generated power is less than the load, the system frequency decreases. This variation is system frequency could collapse the system or results in a blackout. This is why the output power from generators, wind power and ESS discharging power must be equal to the load and ESS charging power. [48] proposes a coordinated frequency regulation framework for optimization. Sometimes, reserve is added to the constraint so that the generated power must be equal to the load and reserve. The reserve is added to the balance equation to overcome the

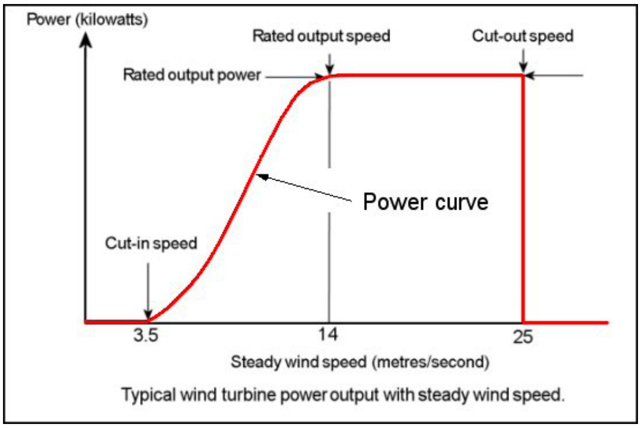

FIGURE 6. Wind power vs Wind speed [50].

continuous load variations, so that the output power must be equal to the summation of demand and reserve at every hour. In addition, the emissions constraint [49] could be added as well in some optimization problems. In multi-objective unit commitment problems, the objectives might be minimizing the cost and emissions at the same time [24]. In this paper, the balance constraint is formulated as:

$$\sum_{i=1}^{NI}[P_{i,t} + P_{ESS_t} + P_{M_t} - \sum_{s=1}^{NS} \rho_s P_{W_{t,s}}] = D_t \quad \forall t \in T,\ \forall s \in S \tag{13}$$

where s is the scenario index, NS is the number of scenarios, ρ_s is the probability of scenario s, S is the set of scenarios, P_{ESS_t} is the power stored to or produced by the ESS at hour t, $P_{W_{t,s}}$ is the wind power at hour t in scenario s, D_t is the demand at hour t and T is the set of hours. The sign convention in P_{ESS_t} is that it is positive when it is produced and negative when it is stored.

Wind power is calculated from wind speed and it is calculated as formulated below [7].

$$P_{W_{t,s}} = \begin{cases} 0 & v_{t,s} < v_{CI} \text{ or } v_{t,s} \geq v_{CO} \\ P_W^{max}\dfrac{v_{t,s} - v_{CI}}{v_R - v_{CI}} & v_{CI} \leq v_{t,s} < v_R \\ P_W^{max} & v_R \leq v_{t,s} < v_{CO} \end{cases} \tag{14}$$

where P_W^{max} is the rated wind power, $v_{t,s}$ is the wind speed at hour t in scenario s, v_{CI} is the cut-in wind speed, v_{CO} is the cut-out wind speed and v_R is the rated wind speed. Figure 6 shows how the output wind power changes with wind speed [50].

The exchanged power between the main grid and microgrid is limited because of the limit of the transmission line connecting the two systems. A constraint is needed to limit this power and it is dependent on the capacity of the transmission line. The exchanged power is negative when power is exported and it is positive when it imported from the main grid. This constraint is formulated as:

$$-P_M^{max} \leq P_{M_t} \leq P_M^{max} \quad \forall t \in T \tag{15}$$

where P_M^{max} is the maximum capacity of the transmission line connecting between the microgrid and main grid.

Different generators have different characteristics. These characteristics have some limits such as maximum power. These limits are formulated as constraints to be included in the optimization problem. Generators have minimum limits so they with stability. Also, each generator cannot infinite power because there is a maximum limit. This constraint is formulated in the following equation. Minimum and maximum limits must be multiplied by $u_{i,t}$, the commitment state of a generator i at hour t. This is because if a generator is OFF, the output must be zero. The output power will have values all the time if the limits are not multiplied by the state because the output power should be between the minimum and maximum limits all the time.

$$P_i^{min} u_{i,t} \leq P_{i,t} \leq P_i^{max} u_{i,t} \quad \forall i \in I,\ \forall t \in T \tag{16}$$

where P_i^{min} is the minimum power that can be produced by unit i, P_i^{max} is the maximum power that can be produced by unit i and I is the set of units.

Ramp up and ramp down limits are two variables limiting the rate of increasing and decreasing the output power of a generator. The output power of a certain generator cannot be increased or decreased freely. A constraint must be formulated to represent these two limits. This constraint is formulated in the following equation.

$$P_{i,t} - P_{i,t-1} \leq RU_i \quad \forall i \in I,\ \forall t \in T \tag{17}$$

where RU_i is the ramp up rate of unit i.

$$P_{i,t-1} - P_{i,t} \leq RD_i \quad \forall i \in I,\ \forall t \in T \tag{18}$$

where RD_i is the ramp down rate of unit i.

When a generation unit starts up, it has to be ON for some time before it shuts down. This time is known as the minimum up time. Also, when a generation unit shuts down, it has to be OFF for some time before it starts up. This time is known as the minimum down time. These two constraints are formulated below.

$$T_{i,t}^{ON} \geq MUT_i[u_{i,t} - u_{i,t-1}] \quad \forall i \in I,\ \forall t \in T \tag{19}$$

where $T_{i,t}^{ON}$ is the ON time of unit i at hour t and MUT_i is the minimum up time of unit i.

$$T_{i,t}^{OFF} \geq MDT_i[u_{i,t-1} - u_{i,t}] \quad \forall i \in I,\ \forall t \in T \tag{20}$$

where $T_{i,t}^{OFF}$ is the OFF time of unit i at hour t and MDT_i is the minimum down time of unit i.

The generation unit cannot start up and shut down at the same time. This is a logic constraint and it is modeled in the following equation.

$$y_{i,t} - z_{i,t} = u_{i,t} - u_{i,t-1} \quad \forall i \in I, \forall t \in T \tag{21}$$

3) ENERGY STORAGE SYSTEM CONSTRAINTS

ESS constraints limit the ESS charging and discharging powers of an ESS. The ESS power is limited by its rated power, which is the optimal size. The ESS cannot charge or discharge more than its rated power. The ESS acts as a load when it charges and acts as a generator when it discharges. Also, the charging power is assumed to be negative whereas the discharging power is assumed to be positive. This constraint is formulated as:

$$-P^{R}_{ESS} \leq P_{ESS_t} \leq P^{R}_{ESS} \quad \forall t \in T \tag{22}$$

The stored energy in the ESS is limited by its rated energy. Of course, the stored energy is always positive. This constraint is formulated as:

$$0 \leq E_{ESS_t} \leq E^{R}_{ESS} \quad \forall t \in T \tag{23}$$

where E_{ESS_t} is the energy stored in the ESS at hour t.

The equation to calculate the stored energy at a specific hour is formulated in (24). The stored energy is called the state of charge and there are methods developed to optimize it [51].

$$E_{ESS_t} = E_{ESS_{t-1}} - P_{ESS_t} \quad \forall t \in T \tag{24}$$

III. A CASE STUDY

A grid-connected microgrid is considered as a case study for sizing of an ESS under wind uncertainties. The case study is presented with data needed to solve the optimization problem. The results are introduced and discussed in Section IV. The system that will be studied consists of three thermal generators which are distributed generators in the microgrid. The unit commitment problem is solved using stochastic programming for a scheduling horizon of two years. The load data has been taken from the IEEE Reliability Test System (RTS-96) for the first year [52]. For the second year, the same load profile has been repeated with an increase of 5%. The reserve and emission constraints are not considered in this case study. Weibull distribution is used to generate wind speed scenarios using Weibull distribution parameters of Dhahran city. Those parameters have been calculated from historical data. Since there is uncertainty and wind speed cannot be forecasted accurately, many scenarios should be considered to handle the uncertainty and randomness. In this paper, instead of taking scenarios from historical data, new scenarios have been generated using the parameters. Considering different scenarios is one of the methods used to handle the randomness in stochastic optimization. Ten scenarios of wind speed have been created randomly using the Weibull distribution parameters for monthly wind distribution calculated in Dhahran for 19 years [53]. Those parameters are shown in Table 1. In this table, K represents the shape parameter and c represents the scale parameter. The probability density function of Weibull distribution used to calculate the wind speed at each hour is illustrated in (25). Those ten scenarios are assumed to be actual data taken from ten different years. The annual numerical values of k and c are 2.35 and 4.98, respectively. Figure 7 shows the Weibull distribution for annual wind speeds and wind frequency histogram for Dhahran [53] and Table 2 illustrates the average annual wind speeds in Dhahran for all scenarios. The probabilities of all scenarios are equal, which means that ρ_s is equal to 0.1 for all scenarios. The ten scenarios have been repeated twice to cover the horizon of two years.

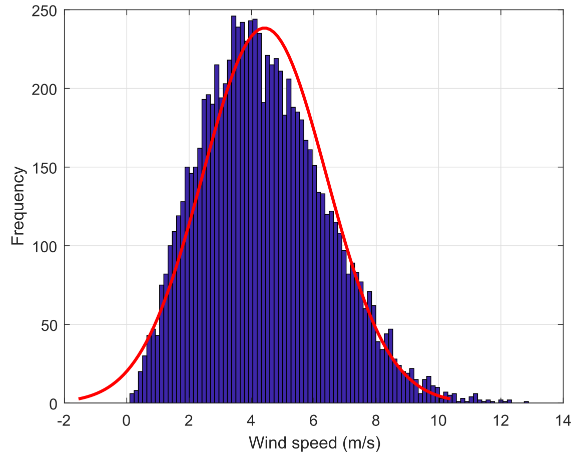

FIGURE 7. Wind frequency histogram and Weibull distribution for all wind speeds in Dhahran.

TABLE 1. Weibull parameters for monthly wind speed distribution in Dhahran.

Month	k	c
JAN	2.40	4.77
FEB	2.45	4.85
MAR	2.55	5.15
APR	2.40	5.06
MAY	2.40	5.52
JUN	2.60	6.51
JUL	2.50	5.54
AUG	2.30	4.91
SEP	2.20	4.18
OCT	2.05	4.09
NOV	2.20	4.38
DEC	2.00	4.68

$$f(t, c, k) = \begin{cases} \frac{k}{c}(\frac{t}{c})^{k-1} e^{-(\frac{t}{c})^k} & t \geq 0 \\ 0 & t < 0 \end{cases} \tag{25}$$

Table 3 illustrates the generator characteristics. The characteristics are from [46], except the minimum up and down times. Table 4 shows the values of the parameters. Figure 8 illustrates the load curve. Also, the load duration curve is shown in this figure. The horizon will be two years. Ten scenarios of wind speeds have been created and they are shown in Figure 9. The scenarios are shown for only one year

TABLE 2. Average annual wind speeds in Dhahran for all scenarios.

Scenario	Wind speed (m/s)
Scenario 1	4.4446376
Scenario 2	4.4169281
Scenario 3	4.4102231
Scenario 4	4.4032716
Scenario 5	4.4007090
Scenario 6	4.4340644
Scenario 7	4.3894760
Scenario 8	4.3762805
Scenario 9	4.4285103
Scenario 10	4.3670960

TABLE 3. Characteristics of generation units.

Unit No.	Fixed Cost ($)	Variable Cost ($/MW)	Start Up Cost ($)	Shut Down Cost ($)	Min. Capacity (MW)
1	9	20	40	20	5
2	7	18	30	20	3
3	5	15	20	20	2
Unit No.	**Max. Capacity (MW)**	**Ramp Down Rate (MW/h)**	**Ramp Up Rate (MW/h)**	**Min. Down Time (h)**	**Min. Up Time (h)**
1	20	15	15	1	1
2	30	15	15	1	1
3	40	20	20	1	1

in this figure. They are represented in average daily speeds. The same scenarios have been repeated for the second year. Figure 10 shows the hourly speed for the ten scenarios during the first twenty-four hours.

The unit commitment problem to find the output power of each generator, imported and exported power, and the ESS discharging and charging powers. A comparison will be made and the unit commitment problem will be solved in two cases. The first case represents the microgrid without an ESS whereas the second case will represent the microgrid after integrating it with an optimally sized ESS. The differences in total costs and reliability will be investigated. The optimization problem of this system has been modeled in GAMS (General Algebraic Modeling System) [54] and has been solved in the NEOS Server [55] which is a free online service for solving numerical optimization problems.

TABLE 4. Values of other model parameters.

Parameter	PC_{ESS}	EC_{ESS}	γ	P_M^{max}
Value	\$1200	\$300	\$20	10 MW
Parameter	P_W^{max}	v_{CI}	v_R	v_{CO}
Value	15 MW	1 m/s	5 m/s	11 m/s

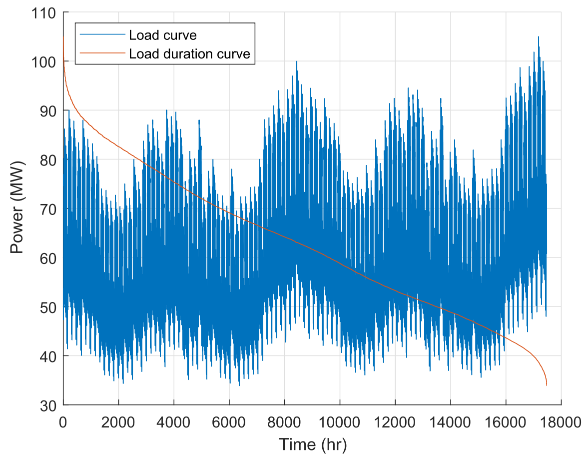

FIGURE 8. Load curve and load duration curve.

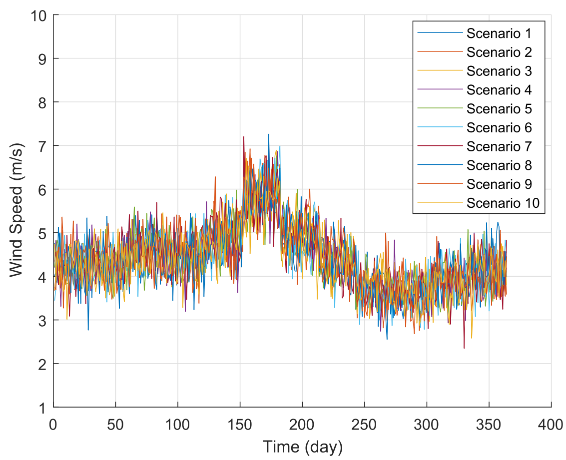

FIGURE 9. Average daily wind speeds of the ten scenarios.

IV. RESULTS AND DISCUSSIONS

The optimization problem has been solved using stochastic programming based on the technique of Benders decomposition. The total cost which includes the operation of generators, exchanging power with the main grid and ESS investment has been minimized. Also, the optimal size of the ESS has been calculated. The rated power is 16.59 MW and the rated energy is 128.84 MWh. The output power of each generator at each hour has been calculated as well as the exchanged power with the main grid at each hour. This is the solution to the unit commitment problem. Figures 11 and 12 illustrate the distribution of powers before integrating the ESS and after integrating it, respectively. As shown in those two figures, the ESS works instead of the most expensive unit, Unit 1, and decreases costs. In those two figures, the positive

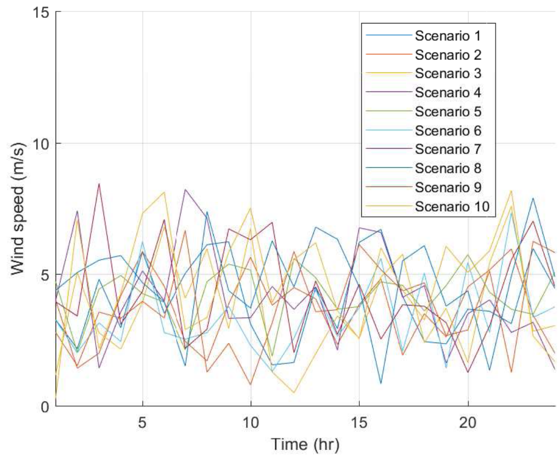

FIGURE 10. Hourly wind speeds during the first twenty-four hours of the ten scenarios.

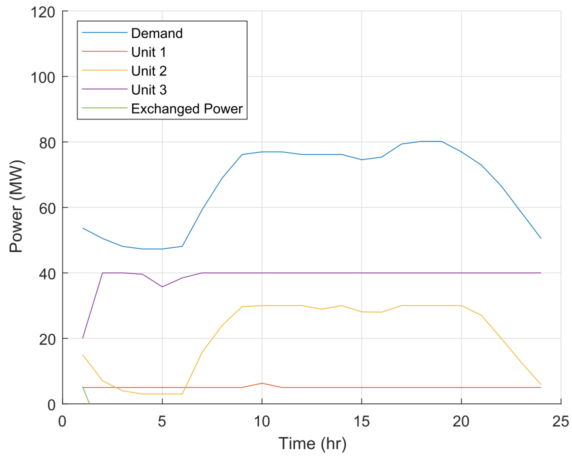

FIGURE 11. Economic dispatch without ESS.

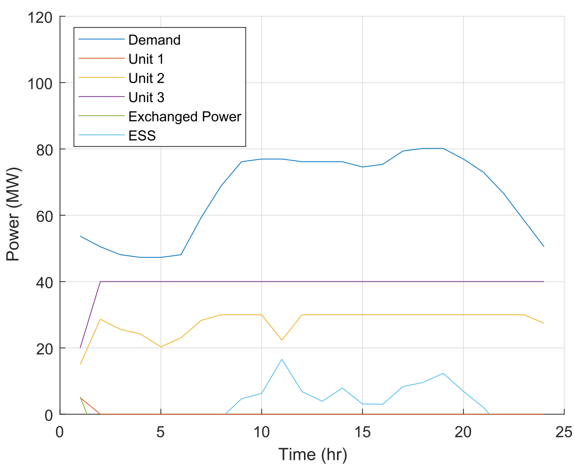

FIGURE 12. Economic dispatch with ESS.

values of powers are only shown. This means that they show the ESS power in the discharging case and the exchanged power in the importing case. The negative values of power, which are the ESS charging power and the exported power to the main grid, are shown in Figure 13. The ESS acts as a

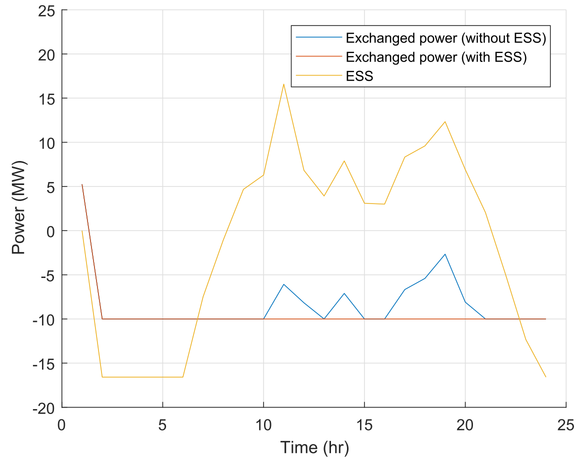

FIGURE 13. ESS power and exchanged power with negative values.

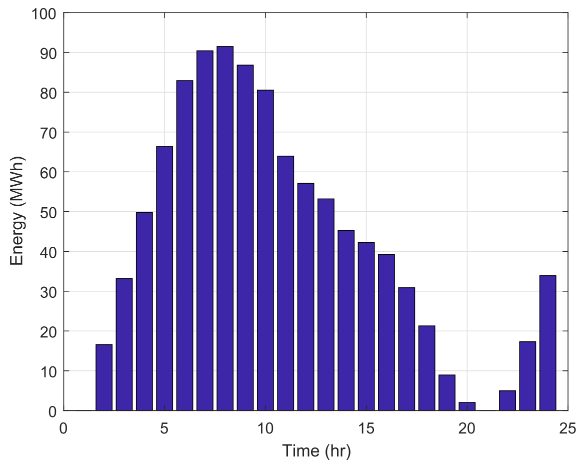

FIGURE 14. Stored energy in ESS.

generator in the discharging case and it acts as load in the charging case. This is like the exchanged power when the main grid is considered as a generator when the power is imported from it and it is considered as a load when the power is exported to it. When the ESS power is positive, this means the stored energy decreases because the discharging power is greater than the charging power. This leads to reducing the stored energy in the ESS. In addition, when the ESS power is negative, this means the charging power is greater than the discharging power, and this leads to increasing the stored energy. The stored energy in the ESS is known as the state of charge. Figure 14 illustrates the state of charge during the first twenty-four hours.

To prove that the solution of stochastic programming method is reasonably optimal, the ten scenarios, which are assumed previously as actual data for ten different years, have been solved separately using the mixed-integer linear programming method. The results are shown in Table 5 and they are compared to the solution of the stochastic programming method in Table 6. The solution of the probabilistic optimization method is the second optimal solution after the solution of Scenario 6. So, this shows that the probabilistic technique

TABLE 5. Results of all scenarios solved separately.

Scenario	Total cost ($)	P_S^R (MW)	E_S^R (MWh)
S1	14,634,417.23	11.79	86.23
S2	14,652,256.34	11.59	83.76
S3	14,648,323.41	11.84	85.50
S4	14,399,562.33	19.97	129.43
S5	14,393,281.42	19.96	136.42
S6	14,380,884.59	19.75	138.91
S7	14,414,730.03	19.81	135.50
S8	14,691,929.52	11.58	85.34
S9	14,645,579.66	11.69	84.33
S10	14,429,380.07	20.71	146.98
SP	14,392,584.15	16.59	128.84

TABLE 6. Comparison of results of all scenarios with SP solution.

Scenario	% Total cost	$\%P_S^R$	$\%E_S^R$
S1	-1.6803%	28.9064%	33.0716%
S2	-1.8042%	30.1084%	34.9909%
S3	-1.7769%	28.5996%	33.6401%
S4	-0.0485%	-20.4079%	-0.4634%
S5	-0.0048%	-20.3461%	-5.8826%
S6	0.0813%	-19.0800%	-7.8221%
S7	-0.1539%	-19.4598%	-5.1736%
S8	-2.0799%	30.1612%	33.7609%
S9	-1.7578%	29.5432%	34.5429%
S10	-0.2557%	-24.8912%	-14.0825%

gives a reasonable solution compared to the deterministic technique of the ten scenarios. The stochastic programming technique is used when there is more than one scenario and it gives better results as shown in Tables 5 and 6. Although the investment cost of the storage system in the stochastic programming solution is higher compared to other scenarios, the total cost is still lower. The objective is to minimize the total cost, not the investment cost. The solution of Scenario 6 is lower than the stochastic programming solution but it reflects only one scenario instead of all scenarios. The results of deterministic and probabilistic optimization problems are illustrated also in Figures 15, 16 and 17 to be read and compared easily.

Benders decomposition is a method that allows the solution of very large optimization problems that have special block structure. In this paper, the block structure occurs in representing the uncertainty with different scenarios. This method is used to solve large problems more efficiently in less time.

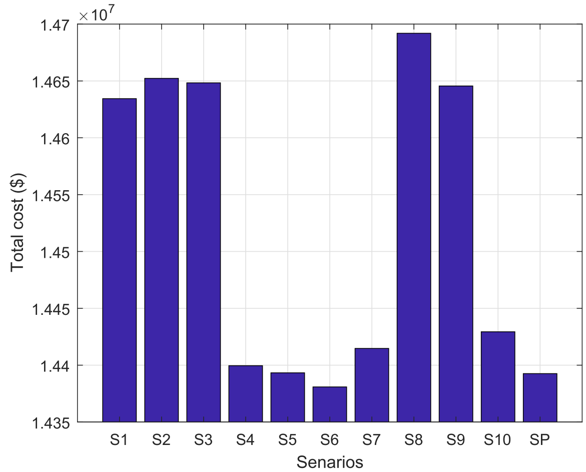

FIGURE 15. Total cost of all scenarios.

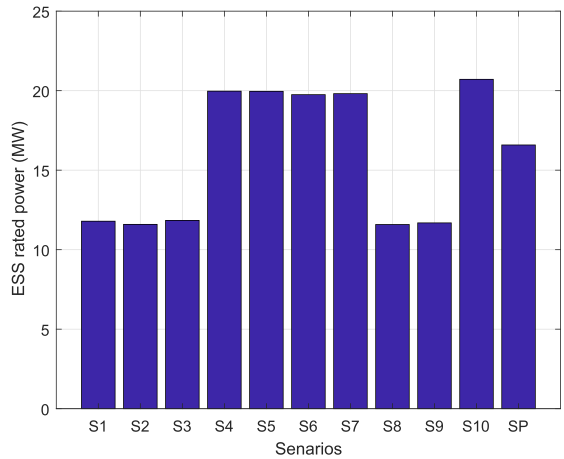

FIGURE 16. ESS rated power of all scenarios.

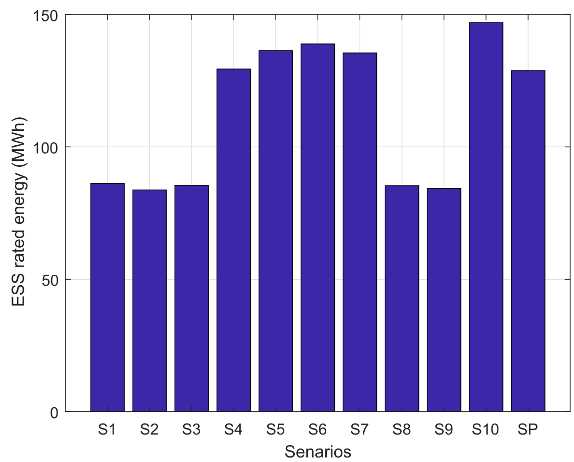

FIGURE 17. ESS rated energy of all scenarios.

The difference will be more noticeable and valuable in optimizing very large power systems. To evaluate the efficiency of this method, the case study has been solved using the well-known two-stage stochastic programming method [18] for comparison. Benders decomposition is faster in solving this optimization problem by 77.83%. The time difference is not significant in this problem because the power system

TABLE 7. Comparison between the two cases.

Term	Case-1	Case-2	%Change
Net Cost ($)	7.108261E+6	7.096726E+6	-0.1625%
ASAI	9.9995E-01	10.0000E-01	0.0047%
ASUI	5.2200E-05	4.7454E-06	-90.9091%

is small. The time difference will become more important in optimizing very large power systems and many hours could be saved when the optimization problem is solved using Benders decomposition.

Table 7 shows the net cost in Cases 1 and 2. The net cost in Case 1 includes only the operation cost of distributed generators while the net cost in Case 2 includes the operation cost in addition to the ESS investment cost. Furthermore, it is shown in the table that the reliability indices enhance after integrating the ESS in Case 2. Average System Availability Index (ASAI) and Average System Unavailability Index (ASUI) have been calculated with other reliability indices to investigate the enhancement of microgrid reliability.

Benders decomposition has been used to optimally size an ESS to be integrated with a microgrid. This technique is very useful in large power systems where the number of decision variables and constraints is extremely huge. This technique simplifies the way of solving the optimization problem as shown in this simple case study.

V. CONCLUSION

This paper has presented a methodology to calculate the optimal size of an ESS for a grid-connected microgrid under wind uncertainties using stochastic programming based on Benders decomposition. Benders decomposition is a mathematical technique used to solve very large optimization problems. Benders decomposition has been proved to be used for optimal sizing of an ESS. Benders decomposition is very beneficial in large power systems that their optimization problems have lots of constraints and variables. It simplifies the way to solve large optimization problems and saves effort and time. The needed data to use Benders decomposition is several scenarios associated with their probabilities. In this paper, the algorithm of Benders decomposition has been explained with all equations used in this technique. There are many purposes of integrating an ESS with a certain microgrid. One of them is to improve and increase its reliability. It is proved with numbers that connecting an ESS to a microgrid has reduced the total cost. The cost has decreased after integrating the ESS although it includes the ESS investment cost. This shows the economic feasibility of the power system.

REFERENCES

[1] D. W. Gao, *Energy Storage for Sustainable Microgrid*. New York, NY, USA: Academic, 2015.
[2] M. A. Abdulgalil, A. M. Amin, M. Khalid, and M. AlMuhaini, "Optimal sizing, allocation, dispatch and power flow of energy storage systems integrated with distributed generation units and a wind farm," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Oct. 2018, pp. 680–684.
[3] M. A. Abdulgalil and M. Khalid, "Enhancing the reliability of a microgrid through optimal size of battery ESS," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 9, pp. 1499–1508, 2019.
[4] F. Kienle and C. de Schryver, "100% green computing at the wrong location?" IEC-IEEE Challenge, Cham, Switzerland, Tech. Rep. 2012-03-1128, 2012.
[5] S. Bahramirad and E. Camm, "Practical modeling of smart grid SMS storage management system in a microgrid," in *Proc. Transmiss. Distrib. Conf. Exposit. PES (T D)*, May 2012, pp. 1–7.
[6] T. Adefarati and R. C. Bansal, "Integration of renewable distributed generators into the distribution system: A review," *IET Renew. Power Gener.*, vol. 10, no. 7, pp. 873–884, 2016.
[7] S. Bahramirad, W. Reder, and A. Khodaei, "Reliability-constrained optimal sizing of energy storage system in a microgrid," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2056–2062, Dec. 2012.
[8] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of energy storage for microgrids," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 142–151, Mar. 2012.
[9] S. Shakti, S. Mukesh, and K. S. Chandra, "Optimal power scheduling of renewable energy systems in microgrids using distributed energy storage system," *IET Trans. Renew. Power Gener.*, vol. 10, no. 9, pp. 1328–1339, Oct. 2016.
[10] C. Chen, S. Duan, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *IET Renew. Power Generat.*, vol. 5, no. 3, pp. 258–267, 2011.
[11] L. Zhou, Y. Zhang, X. Lin, C. Li, Z. Cai, and P. Yang, "Optimal sizing of PV and BESS for a smart household considering different price mechanisms," *IEEE Access*, vol. 6, pp. 41050–41059, 2018.
[12] S. Bahramirad and H. Daneshi, "Optimal sizing of smart grid storage management system in a microgrid," in *Proc. IEEE PES Innov. Smart Grid Technol. (ISGT)*, Jan. 2012, pp. 1–7.
[13] U. Akram, M. Khalid, and S. Shafiq, "An improved optimal sizing methodology for future autonomous residential smart power systems," *IEEE Access*, vol. 6, pp. 5986–6000, 2018.
[14] P. P. Gupta, P. Jain, S. Sharma, and R. Bhakar, "Reliability-security constrained unit commitment based on benders decomposition and mixed integer non-linear programming," in *Proc. Int. Conf. Comput., Commun. Electron. (Comptelix)*, Jul. 2017, pp. 328–333.
[15] T. A. Nguyen, M. L. Crow, and A. C. Elmore, "Optimal sizing of a vanadium redox battery system for microgrid systems," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 729–737, Jul. 2015.
[16] M. A. Abdulgalil, M. N. Khater, M. Khalid, and F. Alisamail, "Sizing of energy storage systems to enhance microgrid reliability," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Feb. 2018, pp. 1302–1307.
[17] T. Kerdphol, Y. Qudaih, and Y. Mitani, "Battery energy storage system size optimization in microgrid using particle swarm optimization," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur. (ISGT-Eur.)*, Oct. 2014, pp. 1–6.
[18] Y. Huang, P. M. Pardalos, and Q. P. Zheng, *Electrical Power Unit Commitment: Deterministic and Two-Stage Stochastic Programming Models and Algorithms*. New York, NY, USA: Springer, 2017.
[19] P. Xiong, P. Jirutitijaroen, and C. Singh, "A distributionally robust optimization model for unit commitment considering uncertain wind power generation," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 39–49, Jan. 2017.
[20] N. T. Mbungu, R. Naidoo, R. C. Bansal, and M. Bipath, "Optimisation of grid connected hybrid photovoltaic–wind–battery system using model predictive control design," *IET Renew. Power Gener.*, vol. 11, no. 14, pp. 1760–1768, 2017.
[21] L. Zhang, X. Hu, Z. Wang, F. Sun, J. Deng, and D. G. Dorrell, "Multiobjective optimal sizing of hybrid energy storage system for electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 1027–1035, Feb. 2018.
[22] U. Akram, M. Khalid, and S. Shafiq, "An innovative hybrid wind-solar and battery-supercapacitor microgrid system—Development and optimization," *IEEE Access*, vol. 5, pp. 25897–25912, 2017.
[23] N. Nikmehr and S. Najafi-Ravadanegh, "Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm," *IET Renew. Power Gener.*, vol. 9, no. 8, pp. 982–990, 2015.
[24] A. Soroudi, *Power System Optimization Modeling in GAMS*. Cham, Switzerland: Springer, 2017.
[25] A. M. Gee, F. Robinson, and W. Yuan, "A superconducting magnetic energy storage-emulator/battery supported dynamic voltage restorer," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 55–64, Mar. 2017.

[26] C. Krupke, J. Wang, J. Clarke, and X. Luo, "Modeling and experimental study of a wind turbine system in hybrid connection with compressed air energy storage," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 137–145, Mar. 2017.
[27] X. Chang, Y. Li, X. Li, and X. Chen, "An active damping method based on a supercapacitor energy storage system to overcome the destabilizing effect of instantaneous constant power loads in DC microgrids," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 36–47, Mar. 2017.
[28] B. Steffen, "Prospects for pumped-hydro storage in Germany," *Energy Policy*, vol. 45, pp. 420–429, Jun. 2012.
[29] J. M. Lujano-Rojas, R. Dufo-López, J. L. Bernal-Agustín, and J. P. Catalão, "Optimizing daily operation of battery energy storage systems under real-time pricing schemes," *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 316–330, Jan. 2017.
[30] M. I. Daoud, A. M. Massoud, A. S. Abdel-Khalik, A. Elserougi, and A. Ahmed, "A flywheel energy storage system for fault ride through support of grid-connected VSC HVDC-based offshore wind farms," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 1671–1680, May 2016.
[31] C. Park, R. Sedundo, V. Knazkins, and P. Korbakorba, "Feasibility analysis of the power-to-gas concept in the future Swiss power system," in *Proc. CIRED Workshop*, Helsinki, Finland, Jun. 2016, pp. 1–5.
[32] S. Pulendran and J. E. Tate, "Energy storage system control for prevention of transient under-frequency load shedding," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 927–936, Mar. 2017.
[33] C. L. Borges and D. M. Falcao, "Optimal distributed generation allocation for reliability, losses, and voltage improvement," *Int. J. Elect. Power Energy Syst.*, vol. 28, no. 6, pp. 413–420, Jul. 2006.
[34] P. Maghouli, A. Soroudi, and A. Keane, "Robust computational framework for mid-term techno-economical assessment of energy storage," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 3, pp. 822–831, 2016.
[35] S. Sun, B. Liang, M. Dong, and J. A. Taylor, "Phase balancing using energy storage in power grids under uncertainty," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3891–3903, Sep. 2016.
[36] L. S. Vargas, G. Bustos-Turu, and F. Larraín, "Wind power curtailment and energy storage in transmission congestion management considering power plants ramp rates," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2498–2506, Sep. 2015.
[37] A. Soroudi, P. Siano, and A. Keane, "Optimal DR and ESS scheduling for distribution losses payments minimization under electricity price uncertainty," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 261–272, Jan. 2016.
[38] M. Khalid, U. Akram, and S. Shafiq, "Optimal planning of multiple distributed generating units and storage in active distribution networks," *IEEE Access*, vol. 6, pp. 55234–55244, 2018.
[39] A. A. Akhil, G. Huff, A. B. Currier, B. C. Kaun, D. M. Rastler, S. B. Chen, A. L. Cotter, D. T. Bradshaw, and W. D. Gauntlett, *DOE/EPRI Electricity Storage Handbook in Collaboration with NRECA*. Albuquerque, NM, USA: Sandia Nat. Laboratories, 2013.
[40] Y. Chen, Y. Zheng, F. Luo, J. Wen, and Z. Xu, "Reliability evaluation of distribution systems with mobile energy storage systems," *IET Renew. Power Gener.*, vol. 10, no. 10, pp. 1562–1569, 2016.
[41] (Dec. 2011). *Electricity Storage Technologies Can be Used for Energy Management and Power Quality*. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=4310
[42] J. L. Higle, "Stochastic programming: Optimization when uncertainty matters," *Tuts. Oper. Res.*, pp. 30–53, Oct. 2005.
[43] A. S. Jacob, R. Banerjee, and P. C. Ghosh, "Sizing of hybrid energy storage system for a PV based microgrid through design space approach," *Appl. Energy*, vol. 212, pp. 640–653, Feb. 2018.
[44] E. Kalvelagen, "Benders decomposition with GAMS," in *Amsterdam Optimization Modeling Group*, 2002.
[45] E. Kalvelagen, *Benders Decomposition for Stochastic Programming with GAMS*, 2003.
[46] E. Castillo, A. J. Conejo, P. Pedregal, R. Garcia, and N. Alguacil, *Building and Solving Mathematical Programming Models in Engineering and Science*, vol. 62. Hoboken, NJ, USA: Wiley, 2011.
[47] D. Chattopadhyay, "Application of general algebraic modeling system to power system optimization," *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 15–22, Feb. 1999.
[48] U. Akram and M. Khalid, "A coordinated frequency regulation framework based on hybrid battery-ultracapacitor energy storage technologies," *IEEE Access*, vol. 6, pp. 7310–7320, 2018.
[49] D. N. Simopoulos, Y. S. Giannakopoulos, S. D. Kavatza, and C. D. Vournas, "Effect of emission constraints on short-term unit commitment," in *Proc. MELECON IEEE Medit. Electrotech. Conf.*, May 2006, pp. 973–977.
[50] Accessed: Jan. 15, 2019. [Online]. Available: http://www.wind-power-program.com/popups/powercurve.htm
[51] J. Zou, C. Peng, J. Shi, X. Xin, and Z. Zhang, "State-of-charge optimising control approach of battery energy storage system for wind farm," *IET Renew. Power Gener.*, vol. 9, no. 6, pp. 647–652, 2015.
[52] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, W. Li, R. Mukerji, D. Patton, N. Rau, D. Reppen, A. Schneider, M. Shahidehpour, and C. Singh, "The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee," *IEEE Trans. Power Syst*, vol. 14, no. 3, pp. 1010–1020, Aug. 1999.
[53] S. Rehman, T. O. Halawani, and T. Husain, "Weibull parameters for wind speed distribution in Saudi Arabia," *Sol. Energy*, vol. 53, no. 6, pp. 473–479, Dec. 1994.
[54] Accessed: Jan. 15, 2019. [Online]. Available: https://www.gams.com/
[55] Accessed: Jan. 15, 2019. [Online]. Available: https://neos-server.org/neos/

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