

Generation Scheduling of Active Distribution Network with Renewable Energy Resources Considering Demand Response Management

A. Afraz¹, B. Rezaeealam^{1,*}, S.J. SeyedShenava², M. Doostizadeh¹

¹Department of Electrical Engineering, Lorestan University, Khorramabad, Iran

²Department of Electrical Engineering, University of Mohaghegh Ardabili, Ardabil, Iran

Abstract- The scheduling of electricity distribution networks has changed dramatically by integrating renewable energy sources (RES) as well as energy storage systems (ESS). The sizing and placement of these resources have significant technical and economic impacts on the network. Whereas the utilization of these resources in the active distribution network (ADN) has several advantages, accordingly, the undesirable effects of these resources on ADN need to be analyzed and recovered. In this paper, a hybrid ADN, including wind, PV, and ESS, is investigated in 33 buses IEEE standard system. First of all, optimal energy management and sizing of the RES and ESS are the purposes. Secondly, as demand response (DR) is another substantial option in ADNs for regulating production and demand, an incentive-based DR program is applied for peak shaving. Forasmuch as this method has uncertainty, due to its dependence on customer consumption patterns, the use of inappropriate incentives will not be able to stimulate customers to reduce their consumption at peak times. Accordingly, the climatic condition uncertainty, which is another factor of variability on the production side, is minimized in this paper by relying on the Monte Carlo estimation method. Besides, the optimization problem, which is formulated as optimal programming, is solved to calculate the optimal size and place of each RESs and ESS conditions regarding power loss, voltage profile, and cost optimization. Furthermore, a geometric, energy source and network capacity, and cost constraints, are considered. The results confirm the effectiveness of proposed energy management and cost reduction in the studied test system.

Keyword: Active distribution network, Demand response, Energy storage system, Renewable energy resource, Demand management

1. INTRODUCTION

All life on earth depends upon some way energy. The demand for electric power is rapidly increasing across the world. In general, today, energy is supplied through renewable resources and non-renewable resources. Electricity, though rather high-priced, is the cleanest and, one may say, the most crucial one among all kinds of energy resources. Looking at it the other way, fossil fuels, as a part of non-renewable resources, have a detrimental impact on the environment, as perceived by climatologists all over the world. Besides, it's costly to extract, process, and transport them to the consumer. Also, the deficiency of these resources has raised their prices. For the reason that higher energy

consumption means more high-priced energy generation, there is a crucial need for some dominant energy consumption modifications [1,2]. Whereas more renewable energy sources are required in future energy systems, by immediately increasing the penetration of renewable energy in the power network, electricity networks tend to a significant transition from stable passive distribution networks with unidirectional electricity transmission to active distribution networks with bidirectional electricity transmission.

Reference [3] provides a complete overview of the issues related to energy storage resources in active networks. In this paper, location, measurement, economic and social effects, energy security, planning, and implementation of energy storage resources in the network, are investigated. In Ref. [4], the sizing and placement of battery in power systems and wind turbines are evaluated to reduce the cost and system losses. Different strategies for loss reduction and cost optimization are investigated, although other essential objective

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*Corresponding author:

E-mail: rezaee.bh@lu.ac.ir (B. Rezaeealam)

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functions and restrictions are not considered yet. The results indicate that the participation of the cost function in the objective function significantly alters the results of the placement and sizing of wind turbines and energy storage resources.

In Ref. [5], the optimal location of energy storage systems in active distribution networks is accomplished using the bee colony algorithm. The simulation is performed using the DIGSILENT, which the results of the honey colony optimization compared with the PSO algorithm. The results indicate improved voltage profiles, reduced power losses, and enhanced performance of the active distribution network. In References [6-8], the control of the loads and resources of the DER energy distributor have investigated the interaction of an active distribution network and the electricity market. Due to the flexibility of Active distribution networks, they are introduced into three types of integrated load, energy generator, and also as an additional service to the electricity market. The connection between grids is carried out by the MC grid controller or the EMS Energy Management System. Proper design of the system is essential for ensuring the stability, reliability, and economical operation of the grid. In Ref. [9], an overview of advanced methods for modeling the uncertainty in the distribution network design is applied. The advantages and disadvantages of each method, are also stated. Investigations indicate that the proper choice of the procedure is proportional to the type of input variables of the uncertainties and the planning problem. The proper installation of a rooftop photovoltaic system in active distribution networks can improve the voltage profile, decrease energy losses, and improve reliability. In reference [10], the location, measurement, and charge/discharge of the daily energy storage system in active distribution networks are investigated by integrating the photovoltaic system. Simulations are done in MATLAB and DIGSILENT software. The results express that the over-voltage and energy losses are reduced by using the stated method, environmental pollution is diminished, and economic profitability is increased.

Using partitioning strategy to solve the voltage fluctuation problem, decentralized modeling for controlling the voltage of renewable resources, and applying the sensitivity matrices of some of the topics discussed in Ref. [11]. The results of

simulations in 34 and 69 distribution test systems show the convincing performance of the proposed method. In Ref. [12], two centralized and decentralized control methods are provided for controlling active networks connected to the principal network in the electricity market. In the first method, the local DER controller receives commands from the MC, and in the decentralized model, the local DER controller is used to maximize the decision function's target. The purpose of this paper is to maximize the profit of the grid by participating in the electricity market that is not studied other objectives and network operation limits. Additionally, a more flexible and compatible demand response program is required. A new voltage control method for radial active distribution networks is proposed to the effective voltage regulation with high penetration of distributed generation in Ref. [13]. This method has a low computational load and reduces active power losses. Ref. [14] proposed an economic strategy to reduce costs based on a 24-hour forecast that the EMS predicts using the neural network to generate output and load. Besides, optimal load distribution is calculated based on economic analysis using the meta-optimization method.

The higher penetration of renewable energy sources results in reverse power flows, voltage, and critical issues in distribution networks. In Ref. [15], the problem of planning a medium voltage network with the influence of renewable resources is investigated. In this paper, the optimal location of the energy storage resources and the sub-loader tap changers are implemented, simultaneously. The use of a second-order programming model and a nonlinear model of a sub-chip loader transformer yield significant results. In Ref. [16], a review of optimal locating strategies and energy storage systems sizing in active distribution networks is carried out. Technologies and benefits of using energy storage systems, new methods for optimal allocation, and control strategies are investigated. In Ref. [17], long-term planning is done to optimize the design of distributed generations and installed batteries. Furthermore, short-term planning optimizes the performance of the generation units of production and batteries. The reactive power for DGs and batteries is considered, and the battery charge depth is optimized as a design variable for batteries. A probabilistic planning model with

uncertainty and the development of a multi-objective optimization method for the proposed model in active distribution networks are given in Ref. [18]. In Ref. [19], the integration of the ESS, based on ADN management methods, is prepared to improve the network performance. In this paper, the size of ESS and its placement to reduce constraints and ameliorate the utilization of active distribution networks are investigated. On account of the advantages of using energy storage systems in distribution networks, a statistical programming method for voltage regulation with a high penetration level of renewable resources is studied in Ref. [20].

Based on what is mentioned above, there is a crucial need for optimal allocation and operation scheduling of renewable energy resources, as well as energy storage systems in active distribution networks. Besides, by rapidly increasing sustainable energy resources penetration into the grid, the definition of new constraints and objective functions seems necessary that is not considered yet. Furthermore, as the demand response program includes uncertainty, and by developing active networks, utilizing a flexible and appropriate demand response program is imperative to investigate its impact on ADNs. Furthermore, a practical and potent strategy is obliged to assess the optimal allocation of resources, besides energy scheduling and manageable demand response with strict and existent restrictions at the same time.

The purpose of this paper is the placement and sizing of the wind and solar resources with battery energy storage in the 33-IEEE standard to reduce the investment and operational costs of the energy storage system. A novel stochastic method is utilized to predict the wind power output applying Monte Carlo scenarios. The output results of the voltage profile and overall cost of the system are indicated the proper performance of the proposed strategy despite all strict constraints such as geometric constraints, voltage stability index, voltage deviation, and capacity constraints of RES along with demand response management constraints..

2. LOAD AND ENERGY RESOURCES MODELING

Wind and solar energy are being extensively used in distribution networks among various sources of distributed generation. Accurate modeling and

predicting the wind speed and solar radiation are very complicated. In this paper, firstly, the wind speed is predicted based on the Weibull method, and then its output power is calculated. For these calculations, the hourly values of wind speed and radiation are considered. The meteorological statistical data is utilized to model wind and solar power systems in which is explained in the results and discussion section. Also, to address the existent uncertainties in the system's loads the probability density function (PDF) method is employed. Furthermore, to amend PDF for the related period of one year, 4 days have been opted as representatives of each season of that year. Each particular day, which is the representative of a season, is divided into 24-hour segments, each of which has a PDF for the corresponding load at that hour. Additionally, the electrical pricing is based on the Queensland, Australia electric price in 2015. The average electrical prices for a day from every season are anticipated in a way that every 24-hour price represents a relevant season (4×24).

2.1. Statistical method for wind speed estimation

Wind energy is an intermittent resource which its output varies directly depending on the wind speed. Even though wind energy output can be predicted with a high degree of accuracy through the use of wind energy forecasting, there is always some uncertainty about future wind output simply because weather systems are not utterly predictable. Uncertainty of wind speed can be modelled from the probability distribution function of wind power. Prior research [21, 22] has revealed that the wind speed at a given location most nearly follows a Weibull distribution over time. This function is given as Eq. (1).

$$f_v(v) = \left(\frac{k}{c}\right) \left(\frac{v}{c}\right)^{(k-1)} (e)^{-(v/c)^k}, 0 < v < \infty \quad (1)$$

The Weibull PDF is given by Eq. (2) for later use in conjunction with the wind power probability function.

$$F_v(v) = \int_0^v f_v(\tau) d\tau = 1 - e^{-(v/c)^k} \quad (2)$$

Where V is wind speed random variable, v is wind speed, c is a scale factor at a related location, and k is shape factor at a related location.

It should be noted that the statistical properties of

wind speed must be considered to achieve an accurate model for wind speed. Wind speed varies from year to year and changes seasonally. For example, the mean wind speed is high in winter and low in summer. Therefore, using statistical methods to simulate the wind speed should be more effective than Weibull simulation. By considering that in Weibull simulation, each simulated value is independent of all other simulations, Monte Carlo [23, 24] approach and statistical properties of wind speed like autocorrelation are considered to achieve an accurate model for wind speed. The advantages of this method are using historical wind data speed of Queensland-Australia for 20 years, not using predefined distribution for the wind speed.

2.2. Wind turbine (WT) modeling

A wind turbine extracts the energy from moving air masses to convert it into electric energy. Wind power acts on the rotor blades into torque, and subsequently, the rotational energy is used within a generator for electricity production. The power generated from the wind turbine can be expressed by Eq. (3) [25, 26].

$$P_{wind}(t) = \begin{cases} 0 & ; V < V_{Cut-in} \text{ or } V > V_{Cut-out} \\ P_r & ; V_r \leq V \leq V_{Cut-out} \\ P_r \left(\frac{V^k(t) - V_{Cut-in}^k}{V_{Cut-in}^k - V_r^k} \right) & ; V_{Cut-in} \leq V \leq V_r \end{cases} \quad (3)$$

where P_r is the rated power of the WT, V_{Cut-in} is the cut-in wind speed, V_r is the rated wind speed, $V_{Cut-out}$ is the cut-out wind speed, and k is the Weibull shape parameter. If the number of wind turbines is N_{wind} , the overall produced power is $P_{wind}(t) = N_{wind} \times p_{wind}(t)$.

2.3. PV system modeling

The output power of the photovoltaic system is a function of solar radiation, panel area, temperature, and solar absorption capacity of the solar panel, which is expressed by Eq. (4) [27].

$$P_{pv-out} = P_{N-pv} \times \frac{G}{G_{ref}} \times [1 + K_t ((T_{amb} + (0.0256 \times G)) - T_{ref})] \quad (4)$$

The sun radiation amount and ambient temperature in the standard conditions are considered as $G_{ref} = 1000 \text{ W/m}^2$, and $T_{ref} = 25^\circ \text{C}$, respectively. Also, G , T_{amb} and K_t , denote the sun radiation rays amount, temperature around the cell,

and temperature coefficient for the maximum power, respectively.

2.4. Non-dominated sorting genetic algorithm II (NSGA-II)

The planning problem of energy systems is a nonlinear and complex problem with many constraints. The high penetration level of renewable energy systems influences this problem and increases its computational burden. Solving this enormous problem without the use of optimization algorithms remains complicated and time-consuming. Moreover, there is no doubt that a satisfactory answer doesn't reach the exact optimal solution. In this work, NSGA-II proposed to solve the planning problem to find a fast and reliable solution. This algorithm, to reduce the computational complexity of GA and other similar multi-objective evolutionary algorithms, is proposed by Deb in references [28, 29].

3. PROBLEM FORMULATIONS

Right now, the power system is undergoing significant transformations. The continuous replacement of conventional energy sources by large scale renewables as well as increased deployment of different loads such as electric transportation systems are the major agents of these transformations. Therefore, General restructured grids face major technical and economic challenges that must be solved flexibly. Considering the direct link of distribution networks with the consumers and high-level penetration of renewables sources in this system, the challenges such as power losses, voltage profile, and stability along with demand-side management are critical for ADN.

In this paper, the existing wind and solar potentials of the region are first extracted using forecasts made by Monte-Carlo statistical strategy. According to the problem constraint, 25 percentage of the load demand has to be supplied by renewable energy sources. But given the periodic nature of wind power and the time limitation of solar power generation, integrating these resources with energy storage systems is essential.

After determining the power capacity of these resources, the flexible demand response strategy is applied to peak-load shaving and cost reduction of the system. Determining the proper placement of RES and BESS plays a key role in loss reduction and improving the voltage profile of the grid. Hence, the optimal placement of sources is the next step of this

paper. Various technical, economic, and geometric constraints have been applied to scheduling the contribution of solar and wind resources. Also, power losses, voltage profile and voltage stability constraints in the optimal placement step by NSGA-II algorithm are added. The theoretical issues are discussed and finally, the results of simulations are extracted and investigated as follows.

3.1. Objective functions

The classic problem of electric networks is the economic load dispatch of generating resources to achieve the least operating costs. Besides, there is a need to expand the limited economic optimization problem to include constraints on system operation to guarantee the security of the network, through preventing the collapse of the system due to unanticipated conditions. Due to the rapidly increasing integration of RES, the problem of load dispatch has changed, and the objective function and constraints of the problem modification are required.

1) Power Loss Reduction

In this paper, active network power loss reduction is considered as an objective function, which is expressed mathematically as (5).

$$f_1 = \min \left(\sum_{se=1}^{N_{se}} \sum_{t=1}^{N_t} \sum_{i=1}^{N_b-1} P_{i,loss}^t \right) \quad (5)$$

$P_{i,loss}^t$ is power loss at line i and time t . Also, N_b is the number of buses. N_{se} is the number of seasons of each year (1 to 4).

2) Voltage Stability Index (VSI)

VSI is an index that demonstrates the stability of the active distribution system [30]. By rapidly increasing the penetration of renewable energy resources, VSI has become a crucial index to evaluate network loading and avoid voltage collapse. Hence, in the presence of a tremendous amount of energy resources, it is imperative to consider this index as an objective function. Eq. (6) represents the mathematical formulation for the voltage stability index as a second objective function. To support the security and stability of the distribution system, the VSI rate should be greater than zero. Otherwise, the distribution system is under critical instability situations.

$$VSI_{m_2} = |V_{m_1}|^4 - 4(P_{m_2} \times X_i - Q_{m_2} \times R_i)^2 - 4(P_{m_2} \times R_i + Q_{m_2} \times X_i) |V_{m_1}|^2 \quad (6)$$

$$f_2 = \max \left(\sum_{m=1}^{N_b} \sum_{i=1}^{N_b} \sum_{m=2}^{N_b} VSI_{mi}^t \right), f_2 = \frac{1}{f_2}$$

Where P_i , Q_i , R_i , and X_i are the real power, reactive power, resistance, and reactance of the branch i that connect bus m_1 to m_2 , respectively. Also, P_{m_2} and Q_{m_2} are real and reactive loads at bus m_2 ; V_{m_1} and V_{m_2} are sequentially the voltage quantities of the buses m_1 and m_2 . Besides, VSI_{m_2} and VSI_{mi} are the VSI for bus m_2 and the whole system, respectively ($mi = 2, 3, 4 \dots N_b$). f_2' is the total value of the Voltage Stability Index during the planning horizon that desired to be maximized. Consequently, f_2 is utilized to minimize the objective function.

3) Planning Total Cost

The economic objective function in this section includes the installation and maintenance cost of the renewable distributed generation and energy storage units. Also, energy purchasing costs are considered. Total cost is formulated as Eq. (7).

$$f_3 = \min \left(\sum_{i=1}^{n_{ESS}} (C_{invESS} + C_{MESS}) + \sum_{i=1}^{n_{DG}} (C_{invDG} + C_{MDG}) \right. \quad (7)$$

$$\left. + \sum_{n=1}^{N_{yr}} \sum_{se=1}^4 \sum_{h=1}^{24} DR_{Cost\ n,se,h} + \sum_{n=1}^{N_{yr}} \sum_{se=1}^4 \sum_{h=1}^{24} C_{Purchase\ n,se,h} \right)$$

Here, N_{yr} is the year of the planning horizon, n_{ESS} is the number of energy storage, and n_{DG} is the number of distributed generation. C_{invESS} and C_{invDG} are the energy storage system and DG investment cost. Also, C_{MDG} and C_{MESS} are the cost of distributed generation and energy storage system maintenance, respectively. Besides, $DR_{Cost\ n,se,h}$ and $C_{Purchase\ n,se,h}$ are the demand response and the purchased energy costs in the n th year, season se , and hour h .

3.2. Network Constraints and Demand Response Management

In addition to the proposed ADN planning framework and objective functions, we should consider a set of limitations in operating the distribution network. These indispensable constraints in the ADN planning process are as follows:

3.2.1. Position of RES

Bus 1 is the substation or slack bus, so the position

of the RES should not be used at bus 1.

$$2 \leq RES_{position} \leq n_{buses} \quad (8)$$

3.2.2. Voltage Magnitudes

The voltage magnitude of every bus at every hour of the planning horizon must be in an acceptable range.

$$V_{min}^t \leq V_i \leq V_{max}^t \quad (9)$$

3.3. Constraints of RES

To solve the optimization problem, the following constraints must be considered for RES.

3.3.1. Kirchhoff law or system power balance

According to Kirchhoff law or system power balance, the generated power and consumption power should be equal in order that the power system be stable.

$$\begin{aligned} N_{WT} \times P_{WT}(t) + N_{PV} \times P_{PV}(t) + P_d(t) \\ = P_{load}(t) + P_c(t) \end{aligned} \quad (10)$$

Where $N_{WT}(t)$, $N_{PV}(t)$ are the number of WTs, and the number of PVs, respectively. $P_{WT}(t)$, $P_{PV}(t)$ are the rated power of WT, and PVs. $P_c(t)$ and $P_d(t)$ are the charge and discharge power and $P_{load}(t)$ is the load power.

Energy storage is used for balancing generation and consumption power. The new state of charge for the battery bank is given as Eq. (11).

$$SOC(t) = SOC(t-1) + P_c(t)\eta_c - P_d(t)/\eta_d \quad (11)$$

In the above relations, $SOC(t)$ and $SOC(t-1)$ are the battery bank state of charge at the times t and $t-1$, respectively, η_c is the efficiency of the charging batteries, and η_d is the efficiency of the discharging batteries.

The initial state of charge at the beginning of the simulation is considered as Eq. (12).

$$SOC(0) = SOC_b \times E_{bmax} \quad (12)$$

SOC_b is 0.2, and E_{bmax} is the maximum capacity of the batteries, $SOC(0)$ is the initial state of charge.

3.3.2. Energy storage constrains

The constraint in the following equations is imposed for charge and discharge to prevent a reduction in the lifetime of each battery.

$$SOC_{max}(t) = SOC_b \times E_{bmax} \quad (13)$$

$$SOC_{min}(t) = SOC_b \times E_{bmin} \quad (14)$$

Where SOC_b is considered 0.2, E_{bmax} , and E_{bmin} are the maximum and minimum capacity of the ESS.

To prevent simultaneous charge and discharge of the ESS, these constraints considered, which M is the large positive number that must be greater than the capacity of the batteries.

$$P_c(t) \leq M \times ieec(t) \quad (15)$$

$$P_d(t) \leq M \times ieed(t) \quad (16)$$

$$ieec(t) + ieed(t) \leq 1 \quad (17)$$

$$ieec \text{ and } ieed \in \{0,1\}$$

Where, $ieec$ and $ieed$ are the charge and discharge status of the battery bank at the time t , respectively.

3.3.3. Economic constraints

Cost limitation of PV panels, wind turbines, and energy storage are considered, which the installation cost of components should not exceed assuming maximum available budget.

$$\begin{aligned} C_{int_pv} \times N_{pv} + C_{int_wind} \times N_{wind} \\ + C_{int_bat} \times N_{bat} \leq C_{bg} \end{aligned} \quad (18)$$

C_{int_pv} , C_{int_wind} and C_{int_bat} are the unit installation cost of a PV panel, WT, and ESS. C_{bg} is the maximum available budget.

3.3.4. Geometric constraints

The limited available ground area for the installation of the wind turbines and PV panels is considered a concern for wind and PV energy production. A_b and S_b are the primary ground area occupied by a wind turbine and PV, respectively. A_{max} and S_{max} are the available area for wind turbine and PV, respectively:

$$N_{wind} \times A_b \leq A_{max} \quad (19)$$

$$N_{PV} \times S_b \leq S_{max} \quad (20)$$

3.3.5. Capacity constraints of ADNs

Due to the simultaneous exploitation of existing PV and Wind power, consistently, the minimum number of these energy resources must be considered. Also, because of geometric and cost restrictions, the maximum number of renewable resources must be indicated.

$$N_{PV}^{min} \leq N_{PV}^k \leq N_{PV}^{max} \quad (21)$$

$$N_{WT}^{min} \leq N_{WT}^k \leq N_{WT}^{max} \quad (22)$$

N_{PV}^{min} , N_{PV}^{max} , N_{WT}^{min} and N_{WT}^{max} are the minimum and the maximum number of the WTs and PVs, which calculated by the Eqs. (23-26).

$$N_{PV}^{min} = \frac{\alpha \sum_{t=1}^{24} P_L(t)}{\sum_{t=1}^{24} P_{PV}(t)} \quad (23)$$

$$N_{PV}^{\max} = \frac{\beta \sum_{t=1}^{24} P_L(t)}{\sum_{t=1}^{24} P_{PV}(t)} \quad (24)$$

$$N_{WT}^{\min} = \frac{\gamma \sum_{t=1}^{24} P_L(t)}{\sum_{t=1}^{24} P_{WT}(t)} \quad (25)$$

$$N_{WT}^{\max} = \frac{\lambda \sum_{t=1}^{24} P_L(t)}{\sum_{t=1}^{24} P_{WT}(t)} \quad (26)$$

Where α , β , γ , and λ are the scaling factors. $P_L(t)$, $P_{PV}(t)$ and $P_{WT}(t)$ are load, PV, and wind turbine output powers at time t , respectively.

3.4. Demand Response Management

The electric power system today requires the right balance of demand and supply. Also, smooth and stable delivery, as well as environmentally friendly produced electricity, is essential to avoid climate change. Furthermore, electricity consumption should be reduced or shifted to eliminate environmental emissions, decrease costs, ensure safe electricity supply, and enable more integration of renewable intermittencies. Security of supply and rising demand are two factors impelling demand-side management and demand response is the method for reducing or shifting electricity consumption at the demand side, and there are many varieties within the concept. According to IEEE expression, demand-side management is a profile of measures to improve the energy system at the side of consumption. It ranges from improving energy efficiency by using better materials, over smart energy tariffs with incentives for specific consumption patterns, up to sophisticated real-time control of distributed energy resources [15]. There are different models for demand response programs, direct load control, and price response control are two defined options. Load control enables customers to sign a contract about the reduction that could be controlled automatically without any further action from them. Price response control requires a higher degree of customer participation, but that degree depends on the model. This demand elasticity (E) of electricity price (EP) [3] is described by (27).

$$E = \left(\frac{EP_0}{P_{L0}} \right) \left(\frac{\partial P_L}{\partial EP} \right) \quad (27)$$

Where EP_0 and P_{L0} are initial electricity price and load demand, respectively. ∂EP and ∂P_L illustrate the variation in electricity price and load demand from their initial values, respectively. The

price-responsive load's response is characterized based on the load pattern with the electricity price fluctuation. Inflexible loads cannot shift from one time to another with the price change and they are also sensitive to a single period only and are denominated as self-elasticity. Moreover, some flexible loads, that can shift from peak hours to off-peak periods have a sensibility to a multi-period, can be described as cross elasticity. Accordingly, the price-responsive loads' operation for 24 hours can be epitomized by the price elasticity matrix (PEM), which is a 24×24 matrix with self-elasticity coefficients as diagonal elements and cross elasticity coefficients as off-diagonal elements [16]. In DRP, the price-responsive customers change their electricity demand according to (28).

$$P_L = P_{L0(h)} \exp \left(E_{(h)} \frac{EP_{(h)} - EP_{0(h)} + A_{(h)}}{EP_{0(h)}} \right) \quad (28)$$

Where A is the incentive value and $EP_{(h)}$ is the price of electricity at the h th hour.

4. SIMULATION RESULTS AND DISCUSSION

The simulations are performed in two stages. In the first step, considering the region's solar and wind power potential, location and cost constraints, the number and capacity needed to supply roughly 25% of demand load power by renewable sources and BESS are determined. The optimal number of renewables is also obtained for four seasons. In the second step, the optimal placement of renewable sources and BESS is assigned according to the voltage profile index, voltage stability index, and system power losses.

Step 1: In this study, weather and geographical information of Queensland-Australia are utilized to investigate the scheduling of a hybrid system. This area is desirable to extend the WT system because it receives the highest amount of wind power throughout the year. Also, the solar irradiation potential of there is suitable for active distribution networks. The profile of a typical daily load is shown in Figure 1. Also, techno-economical parameters of microgrid components and the PEM are tabulated in Table 1 and Table 2, respectively.

Figure 2 displays the wind speed in Queensland-Australia for a year. The results and comparison of the Monte Carlo and Weibull simulation versus measured data at Queensland-Australia are evaluated

in Figures 3 and 4. As depicted in Figure 3, the probability density of the Monte Carlo simulation results gives a competent fit to measured data. By comparing Figures 3 and 4, the validity of the Monte Carlo simulation is proven. A slight deviation is at the top of the Weibull simulation curve, which is more than the Monte Carlo simulation.

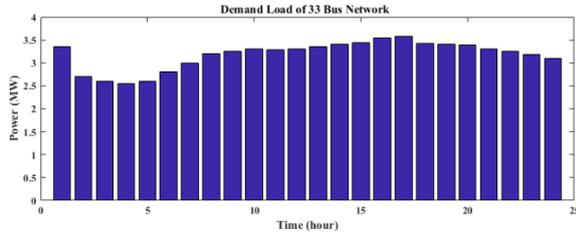


Fig. 1. Daily load profile

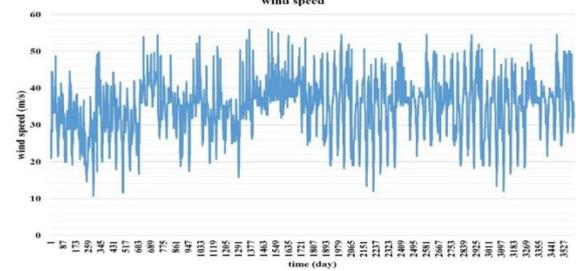


Fig. 2. Mean wind speed for one year

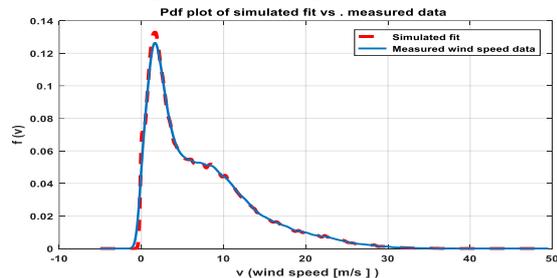


Fig.3. Monte Carlo simulation result

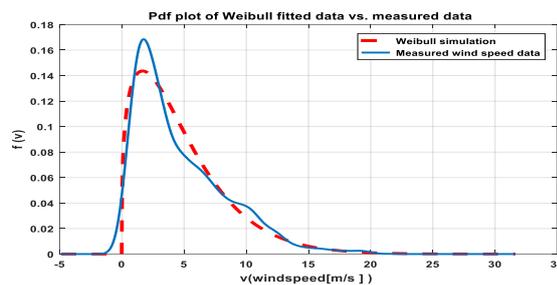


Fig. 4. Weibull simulation results

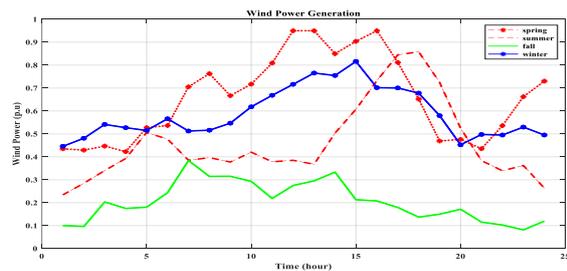


Fig. 5. Mean wind power generation in each season

As wind speed is dependent on weather conditions, the wind power generation of 4 days in each season is considered and shown in Figure 5. This variability stems from the fact of wind patterns variation not only by region but also by the time of the year.

Table 1. The grid data

wind		Battery	
P_r	15 kw	$E_{b \max}$	700 kwh
$C_{Invwind}$	28000 \$/unit	$E_{b \min}$	13/2 kwh
Available area for wind	80 m ²	C_{Invbat}	580 \$/unit
PV		η_{batt}	85%
C_{Invpv}	3600 \$/unit	η_c	90%
P_N^{PV}	2 kw	η_d	85%
Available area for PV	1.7 m ²		
Budget available	5000000\$		

Table 2. Price elasticity matrix

	Low	Off-peak	peak	Off-peak	peak
Low	-0.08	0.03	0.034	0.03	0.034
Off-peak	0.03	-0.11	0.04	0.03	0.04
peak	0.034	0.04	-0.19	0.04	0.01
Off-peak	0.03	0.03	0.04	-0.11	0.04
peak	0.034	0.04	0.01	0.04	-0.19

In turn, the amount of power generated by wind farms can change considerably from season to season. This issue is also right for the solar system. Therefore, similar diagrams for the solar system are presented in Figure 6. Moreover, Figure 7 illustrates the seasonal mean hourly electricity prices for Queensland-Australia in 2015, which were rendered by the Australian Energy Market Operator (AEMO) [31].

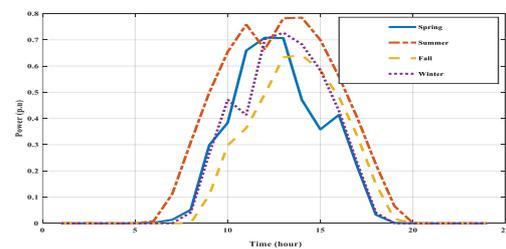


Fig. 6. Mean PV power generation in each season

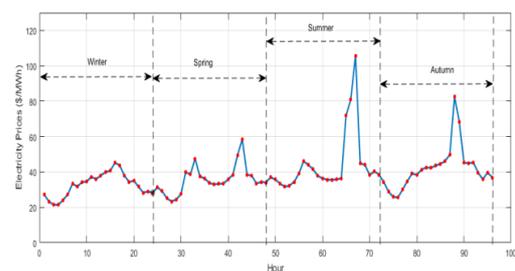


Fig. 7. Seasonal mean hourly electricity price

For the application of the methodology, MATLAB codes are employed. The simulation consists of two sections, planning and operation parts. At first, distributed generations and energy storage systems are allocated based on their restrictions, and then the EDPR program is applied to every particle, simultaneously. Finally, objective functions are calculated, and the Pareto front is extracted based on the NSGA program. The power management strategy for a hybrid ADN system is performed to maintain power supplying to the load demand. NSGA-II algorithm is applied to obtain the best configuration of the system and for sizing the components. The objective function is the minimization of the total cost. The solution deals with the optimum component size of the grid. By considering the results of simulations, the minimum number of WT and PV are considered 10 and 50, and the maximum number is 329 and 1617, respectively. The impact of budget and geometric constraints into a microgrid size optimization is analyzed in two scenarios.

Scenario 1: cost minimization with considering the budget and geometric constraints.

Scenario 2: cost minimization by considering all constraints and EDRP.

The optimization is performed separately for one sample day each in the season of the year, for considering both the load and seasonality variability of wind speed and solar radiation. In this scheduling problem, because of choosing four days, which represent four seasons in a year, there is no continuity between days. So, energy interchange between ESS and the load-generation system must be settled in each day.

The results determine that the NSGA-II algorithm provides optimum wind, PV, and ESS ratings. The best-founded solution and associated costs for the planning horizon of the ADN are presented in Tables 3 and 4. Hence, by extending the number of renewable sources, investment, maintenance, and energy purchasing from DGs' operators' costs have risen. On the contrary, the power loss cost has diminished, and the VSI has amended. The optimization results for the sample days are reported in Figure 8 and Figure 9 for scenario one and scenario 2, respectively. Figure 8 presents the generation scheduling for sample day (fall season of last year in the planning horizon) without a demand response program, and figure 9 shows the generation scheduling on the same day with the EDPR program. Figure 10 exposes the flexibility of loads in

the demand response program that has shifted from peak hours to off-peak times.

Comparison the results of Table 3, illustrates the energy profiles during the spring season, which the use of 104 wind turbines, 1870 solar panels, and two ESSs are proposed. During this season, the wind speed is very high, which is also present during the night when the PV system is not generating electricity. The PV power plant produced energy in the most hour of the day (6-19 0'clock) because spring days are long. The PV generation provides up to 42% of the total energy requested by the loads. The use of only wind turbines and solar panels provides the total energy of the load, and ESS provides 3% of total energy. ESS charges in the day that PV produces. It discharges in the night that in these hours' wind speed is the lower. It means in spring, ESS charging and discharging are lower, and it increases its life duration. The results for the summer season are approximately similar to those obtained for spring. The wind speed conditions in this season are not favorable, so, the number of wind turbines is increased to 147. Nevertheless, the summer radiation is the most favorable weather conditions. Thereby, 4 ESS units are used to store energy during the day and discharge during the night. During the fall season, the optimization solution recommends using 338 wind turbines, 2408 panels, and 4 ESS units. Because of the low energy production of the solar panels during cloudy days in fall, the number of recommended wind turbines is the highest for this season. Wind power produces 53% of the total generation. Besides, in fall, days start getting smaller, and PV produces 40% of generation. So, two ESS units are used. Moreover, 7% of total energy is consumed by charging ESS during the day that PV and wind generate power. Also, discharging happens in the night when PV does not provide power. During the winter, 113 wind turbines are sufficient for satisfying load consumption. Also, 1870 PV panels and 4 ESS units must be installed. Accordingly, ESS units counterbalance low PV production similar to the fall, but wind generation is more than the fall generation.

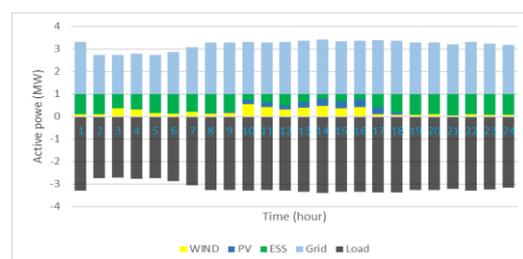


Fig. 8. Production and consumption in the desired ADN

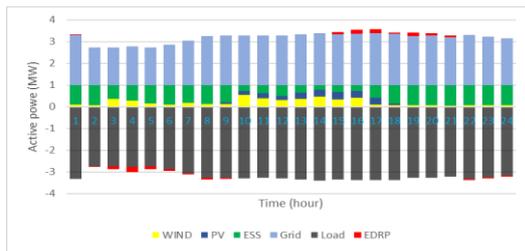


Fig. 9. Production and consumption in the desired ADN with DRP

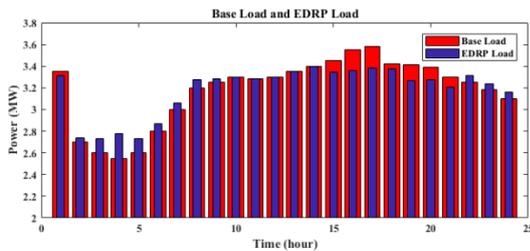


Fig. 10. Load demand for 10% value of PEM

Table 3. Optimal component size and total cost for the first scenario

	Scenario 1			
	Spring	Summer	Fall	Winter
Number of WT	104	147	338	113
Number of PV	1870	1870	2408	1870
BESS	2	4	4	4
Cost ($\times 10^3$ \$)	24080999	27145231	29741531	26415467

Table 4. Optimal component size and total cost for second scenario

	Scenario 2			
	Spring	Summer	Fall	Winter
Number of WT	104	147	329	111
Number of PV	1617	1617	1617	1617
BESS	2	2	4	4
Cost ($\times 10^3$ \$)	21889736	24863739	24658187	23838120

Since, due to the lack of adequate sun radiation, the most unfavorable condition occurs in fall, we opted this season to evaluate in the subsequent step.

Step 2: In the second step of the simulation, based on the NSGA II multiple solutions, the optimal locating of the sources is determined according to the system power loss, cost, and voltage stability. In this step, five combination cases of PV, WT, and batteries are selected from the NSGA II optimal placement programs' outputs.

The results of the simulations are presented in Table 5. Additionally, the optimal number and location of PV, WT, and BESS with power losses and total cost, are demonstrated in this table. By increasing the number of DGs, and their optimal allocation, the power losses and demand

management costs are reduced. Figure 11 illustrates the power loss diagram of each bus by changing the position of the sources. Moreover, Figure 12 displays the voltage deviations that points, Case 5 has the lowest, and Case 1 has the highest VSI amount. Similarly, voltage profiles for 5 case studies are shown in Figure 13.

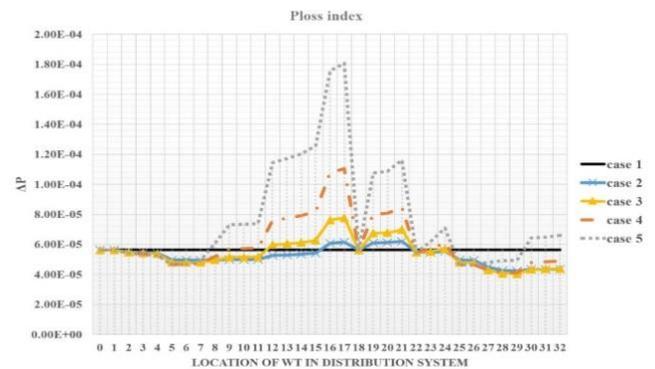


Fig. 11. Power loss index in 5 case studies



Fig. 12. Voltage stability index in 5 case studies

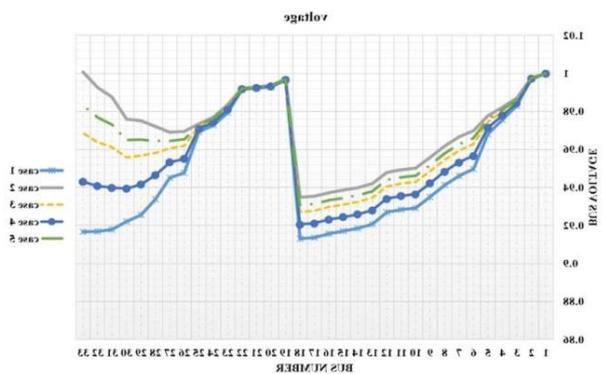


Fig. 13. Voltage profiles for 5 case studies

Furthermore, Figure 14 represents the NSGA II algorithms Pareto front for objective functions. A detailed look at the Figure reveals the variation between objective functions that gives an overview to the planners to determine an effective solution among feasible response.

Table 5. Placement, power losses, and DM cost of 5 case studies

Case Studies	Wind Energy		PV Energy		Battery Energy Storage		Power Losses (MWh)	Demand Management Cost (\$)
	No. of WT	Locations	No. of PV	Locations	No. of BESS	Locations		
Case 1	0	---	0	---	0	---	20/31	56106
Case 2	2	18, 29	2	7, 27	2	24, 30	19/81	55622
Case 3	3	18, 29, 30	2	10, 27	2	24, 30	19/51	54196
Case 4	3	18, 29, 30	3	13, 27, 30	2	28, 30	18/43	53974
Case 5	3	18, 29, 30	3	13, 24, 30	3	27, 28, 30	18/15	51807

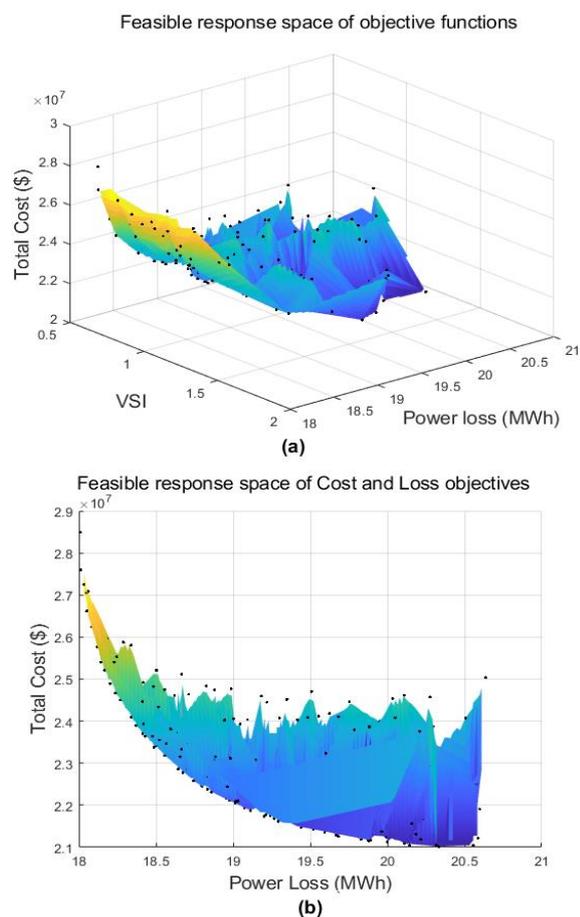


Fig. 14. NSGA II feasible response space of objective functions. (a) For all three objective functions, and (b) For total cost and loss

5. CONCLUSION

The penetration of renewable energy sources in ADN with its advantages in the field of environmental pollution and reduction of dependence on fossil fuel sources offers significant challenges for energy networks. These issues need to

be addressed by appropriately locating and sizing of RES along with ESS due to their alternate nature of solar and wind energy resources. Meanwhile, with the development of information technology infrastructures and their applications in power grids, the issue of load management also plays an essential role in the generation schedule. In this paper, the problem of optimal placement and sizing of the wind and solar resources with battery energy storage in the 33-IEEE standard bus is implemented based on a flexible demand response program with the NSGA-II Algorithm. A novel stochastic method to the prediction of wind power using Monte Carlo scenarios is presented. The outputs of the voltage profile and overall cost of the system indicated the proper performance of the proposed strategy despite all strict constraints such as geometric constraints, voltage stability index, voltage deviation, capacity constraints of RES, and demand response management constraints.

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