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Application of Machine Learning for Optimal Wind Farm Location

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***Abstract*–Presence of renewable sources of energy in power systems is vital to cope the negative impacts of environmental climate change. The drift in autonomous power network situations offers a strong possibility of wind generation to become one of the key contributors in sustainable energy. This paper presents a methodology for determining the optimal location of a wind farm in a power transmission network based on security assessment. The optimization problem is devised with an objective of minimizing mean system operating cost, considering both *(N-1)* line and *(N-1)* bus outages. Moreover, machine learning algorithm is applied to predict the optimal wind farm location in a computationally efficient manner. The IEEE 39-bus test system is used to test and validate the effectiveness of the proposed approach. DIgSILENT PowerFactory and MATLAB were utilized for optimal power flow simulations and machine learning prediction algorithm, respectively. The results give a unique solution for optimal location of wind generation, along with a priority order list, which is useful when integrating multiple wind farms in the power transmission system.**

Keywords-Climate change; machine learning; optimal power flow; power system security; wind generation

I. INTRODUCTION

Due to the rising demand for energy and the need for sustainable energy, the use of renewable energy, particularly wind power, is increasing [1-3]. To decrease harmful carbon dioxide emissions, and to expand the generation range for attaining the goal of power supply security, numerous nations have lately vowed to attain concise future aims, associated with the electric power consumption, using renewable sources of energy [4-5]. Thus, it is important to replace the conventional thermal generators in the system with wind generators. For this purpose, the optimal network location for wind generation needs to be determined. To attain the goals of renewable energy in an economical way, it is essential to optimally utilize the current transmission capacity, even if this necessitates the production of wind power in areas with relatively less attractive wind resources. Many techniques have been suggested to simplify the process of determining optimal wind farm locations [6]. Most of the associated research is based on the objective of maximization of the profit of investors [7]. However, the main drawback is that this research neglects the wind farm integration effects. Consequently, some studies suggest approaches for wind power integration, based on the requirements of the power grid, such as loss reduction, and voltage regulation [8-9]. However, those theoretical integration strategies may not be established, as the anticipated wind farm locations do not certainly entice investors. In [10], the optimal placement is made using reducing short-term variability in power output, while capitalizing power output. In [11], transmission security constraints and unit commitment are incorporated in the problem preparation that fulfils an anticipated wind energy infiltration level while minimizing capital cost.

Diverse optimization algorithms are discussed in the literature to attain optimal size and location of renewable energy sources, such as PV (photovoltaic) generators and wind farms. A combination of Chu-Beasly Genetic Algorithm (CBGA) and particle swarm optimization (PSO) algorithm is applied to optimally locate wind, PV, and small-scale hydro generation [12]. The PSO algorithm has relatively lower performance for finding the global optimum. In case of CBGA, designing an objective function and getting the representation and operators right can be difficult. Moreover, it is computationally expensive i.e., time-consuming. A constrained discrete PSO technique is suggested in [13] to determine optimal sites and sizes of PV, wind turbines, and capacitor banks. References [12-13] considered a constant output of the renewable energy system (RES). In [14], optimal location of PV is determined by using PSO for loss reduction. Reference [15] proposed a planning process to classify the optimal locations and parameters of distributed units of storage with wind farms to decrease network bottlenecks.

Reference [16] suggested an analytical method for determining the size of solar PV and battery. The analytical method, in general, lacks robustness, can only consider single objective and single solar farm at a time. Reference [17] proposed the optimization of the substation location of a wind farm using metaheuristic algorithms. In [18], the PSO algorithm was used to optimize the location and size of wind farm. Reference [19] presented a linear programming-based optimization procedure to find the optimal positions to connect wind farms to attain anticipated renewable energy. It is not simple to determine the objective function mathematically in a linear programming problem. Also, it is difficult to specify the constraints even after the determination of the objective function.

Reference [20] applied the gradient-based optimization and numerical smoothing to discover optimal wind farm location and size. The reader can refer to [21-22] for a detailed description of various optimization methods applied in power systems. Although, these classical conventional approaches are simple to comprehend, and easy to implement, however, these algorithms can prove to be very complex when applied to large-scale systems and can be very time-consuming (this is the challenging issue which needs to be addressed). Also, they have very poor convergence and cannot be applied to optimization of more than one objective. Therefore, soft computing methods are required to overcome these shortcomings. These approaches offer various advantages over the conventional classical approaches. For instance, they need much fewer iterations to compute the global minima (or maxima), and can easily handle complex objective function, incorporating multiple generation sources of a large-sized practical power system. Although, machine learning has been applied for solving optimal power flow (OPF) problem in [23-26]; but to the best of author's knowledge, it has not been used to determine the optimal location of a wind farm in a transmission system. Thus, in this paper, firstly, the nonlinear optimization is performed using an iterative interior-point algorithm, and consequently, supervised machine learning is applied to reduce the computation efforts of the nonlinear OPF problem.

Power system security is the ability of the network to survive unexpected disturbances, such as short-circuit faults or unforeseen loss of network components. Security also considers system operating conditions and probability of disturbances [27-29]. Security assessment is further separated into two types: static (steady state) and dynamic (transient) security assessment [29]. The goal of the former is to determine whether, following the occurrence of a disturbance, there is a new steady-state operating point. On the other hand, dynamic security assessment deals with the ability of the power system to reach a stable point, when a severe transient disturbance, such as a three-phase fault on a transmission line, sudden loss of generators, or loss of a large load, occurs.

Normally, *(N-1)* deterministic security criterion is used for power system transmission planning. This criterion has two key flaws. Firstly, the impacts of single component failure events are analyzed, but their probabilities of occurrence are usually overlooked. Secondly, multiple component failures are excluded from consideration. Moreover, it is hard to consider with all the uncertainty factors using deterministic methods, including uncertainties in load forecast and the location of future generation [30]. Generally, *(N-1)* security criterion considers line outages. However, in this paper, in addition to conventional security assessment, considering *(N-1)* line outages, *(N-1)* bus outages, will be utilized in identifying the optimal location of wind farm in a transmission network. Based on the literature review, it is concluded that most works on determining optimal location of wind farms deals with distribution networks. Moreover, incorporating *(N-1)* bus outages for this determination is not considered in any work. The chief contributions of this paper are: (1) formulation of a cost-optimal wind farm location that identifies locations to set up wind farms, based on security analysis, incorporating both *(N-1)* line and *(N-1)* bus outages, and consequently, (2) applying machine learning to reduce the computation efforts of a nonlinear OPF problem.

The remainder of the paper is organized as follows. Section II discusses the mathematical formulation for OPF problem. Section III describes the interior-point algorithm for conducting OPF. Section IV discusses computation procedure. Section V describes a brief overview of machine learning approach for determining optimal wind farm location. Section VI describes the case study and simulations. Section VII discusses the results obtained, and finally, Section VIII concludes the paper along with suggested future research directions.

II. Mathematical Formulation

The mathematical formulation of OPF, incorporating conventional thermal and wind generation, is described below. Refer to Table I for description of various variables used.

TABLE I. Description of Variables Used

Variable	Description
C_{si}	system operating cost (thermal and wind) in ($/hr)
C_s	mean system operating cost ($/hr)
N_s	number of Monte-Carlo (MC) samples
C_i	mean operating cost ($/hr) of thermal generator *i*
C_w	mean operating costs ($/hr) of wind generator *W*
P_{Gi}	mean electrical power output (MW) of thermal generator *i*
P_w	mean electrical power output (MW) of wind generator *W*
C_{LINE}	mean optimal operating cost of the system, considering all individual *(N-1)* line outages.
C_{BUS}	mean optimal operating cost of the system, considering all *(N-1)* bus outages
C_T	objective function of the optimization problem
P_D	mean system load demand
P_L	mean system transmission losses
a, b, c	cost coefficients of thermal generator *i*
d, e, f	cost coefficients of wind generator *W*

Let C_{si} denote the system operating cost, incorporating cost of conventional thermal generators and wind generator, for i^{th} MC sample. Let C_s denote the mean system operating cost. The total MC simulations, N_s, are limited to 1000, as they are sufficient to achieve suitable convergence. Mathematically,

$$C_s = \frac{\sum_{i=1}^{N_s} C_{si}}{N_s} \tag{1}$$

$$C_s = \sum_{i=1}^{9} C_i(P_{Gi}) + C_w(P_w) \tag{2}$$

$$C_i(P_{Gi}) = a + bP_{Gi} + cP_{Gi}^2 \tag{3}$$

$$C_w(P_w) = d + eP_w + fP_w^2 \tag{4}$$

where C_i and C_w are the mean operating costs ($/hr) of thermal generator *i* and wind generator *W*, respectively; P_{Gi} and P_w are the mean electrical power outputs (MWs) of thermal generator *i* and wind generator *W*, respectively; *a*, *b*, and *c* are cost coefficients of thermal generator *i*, and *d*, *e*, and *f* are cost coefficients of wind generator *W*.

Let C_{LINE} be the mean optimal operating cost of the system, considering all individual *(N-1)* line outages. The total lines in the considered test system (IEEE 39-bus) are 34. Mathematically,

$$C_{LINE} = C_{L1} + C_{L2} + ...C_{L34} \tag{5}$$

where C_{L1} denotes the mean optimal system operating cost when Line 1 is out of service, C_{L2} denotes the mean optimal system operating cost when Line 2 is out of service, and similarly for other notations.

Let C_{BUS} be the mean optimal operating cost of the system, considering all *(N-1)* bus outages. The total buses in the considered test system are 39. Mathematically,

$$C_{BUS} = C_{B1} + C_{B2} + ...C_{B39} \tag{6}$$

where C_{B1} denotes the mean optimal system operating cost when Bus 1 is out of service, C_{B2} denotes the mean optimal system operating cost when Bus 2 is out of service, and similarly for other notations.

Let C_T be the objective function of the optimization problem. Mathematically,

$$\text{Minimize } C_T = C_{Line} + C_{Bus} \tag{7}$$

Subject to

$$\sum_{i=1}^{9} P_{Gi} + P_w = P_D + P_L \tag{8}$$

$$P_{Gi}(\min) \le P_{Gi} \le P_{Gi}(\max) \tag{9}$$

$$P_w(\min) \le P_w \le P_w(\max) \tag{10}$$

$$Q_{Gi}(\min) \le Q_{Gi} \le Q_{Gi}(\max) \tag{11}$$

$$Q_w(\min) \le Q_w \le Q_w(\max) \tag{12}$$

$$S_k(\min) \le S_k \le S_k(\max) \tag{13}$$

$$V_k(\min) \le V_k \le V_k(\max) \tag{14}$$

$$Tk(min) \le Tk \le Tk(max) \tag{15}$$

where P_D and P_L denote mean system load demand and mean system transmission losses, respectively. Equations (9)-(12) represents active and reactive power limits of thermal and wind generators; (13) represents branch flow limits, i.e., maximum loading of transmission lines/transformers (100%), and (14) represents the voltage limits of busbars (0.95-1.05 per unit). Equation (15) represents transformer tap constraint, where Tk is the transformer tap *k*; $Tk(min)$ is the minimum of transformer tap *k* and $Tk(max)$ is the maximum of transformer tap *k*.

Security constrained optimal power flow (SCOPF) deals with OPF in the presence of *(N-1)* power system elements outage. Normally, the element is transmission line or a generator. The secure operation of a power system requires that there are no uncontrollable contingency violations. Therefore, in this case, the minimization of the objective function is done considering contingencies. The SCOPF regulates the controls to the base case (pre-contingency condition) to avert violations in the post-contingency states. If there are sufficient controls available in the network, the solution minimizes the objective function, and the network imposes contingency violations [31].

III. Interior Point Algorithm

In this paper, the OPF performs a non-linear optimization based on an iterative interior-point algorithm, which is the AC optimization function in DIgSILENT PowerFactory software [32]. This algorithm is preferred due to its various benefits. This algorithm has a polynomial time asymptotic complexity $O(n^{3.5}L^2 \log L \log\log L)$, where L is the number of bits of input to the algorithm. Also, this algorithm is better for large, sparse problems because the linear algebra required for the algorithm is faster. This algorithm can solve problems for which no strictly feasible points exist. It can be used to detect the infeasibility of certain linear programming problems. Interior-point iterations can be parallelized to an extent (depending on problem structure). The opportunities for parallelism in the simplex method are more limited. In short, this algorithm provides a simple and fast approach for solving constrained optimization problems. The aim of the optimization is to minimize an objective function $f(x)$, subject to the equality and inequality constraints, which are forced by the load flow equations and various power system elements, respectively. This is summarized mathematically as follows:

$$Min\ f(x) \tag{16}$$

Subject to

$$g(x) = 0 \tag{17}$$

$$h(x) \le 0 \tag{18}$$

where $g(x)$ represent the load flow equations and $h(x)$ is the set of inequality constraints. Introducing a slack variable for each inequality constraint,

$$g(x) = 0 \tag{19}$$

$$h(x) + s = 0 \tag{20}$$

$$s \ge 0 \tag{21}$$

Incorporating logarithmic penalties and minimizing the function,

$$\text{Min}[\, f(x) - u.\sum_i \log(s_i)] \tag{22}$$

where u is the penalty-weighting factor. To alter the contribution of penalty function, we define,

$$f_{pen} = \sum_i \log(s_i) \tag{23}$$

To the overall minimization, the penalty weighting factor u will be decreased from an initial value to a target value (both values being defined by the user). The lesser the minimum penalty-weighting factor, the lower the applied penalty for a solution. The flowchart to solve the OPF based on an interior-point method is shown in Fig. 1. The five main steps are: (1) Initialize primal and dual variables of the problem, considering the non-negativity conditions, as they must be satisfied. Select safety value, centering and barrier parameters, (2) compute Newton direction by solving the system of equations, (3) determine the step size length and accordingly, update the variables, (4) compute the barrier parameter, and (5) if convergence criteria are fulfilled, then optimal solution is found; otherwise return to Step 2.

IV. Computation Procedure

As mentioned before, the major task of this paper is to determine the optimal location of a wind farm in a power transmission network, based on security assessment, for a study period of 5 years. The IEEE 39-bus test system is chosen to validate the proposed approach. The computation procedure is outlined in Fig. 2. In the first step, normal (Gaussian) distribution is used to characterize the randomness of wind active power as suggested by [33-34]. The mean μ is chosen to be the original value of thermal generation, which is replaced, and standard deviation σ is chosen to be 5% of the mean value. Similarly, a normal distribution is used to define the uncertainty in system loads. The active power of each load is assigned a mean μ equal to the original load value, as given in test system data in [35], and a standard deviation σ equal to 5% of the mean value. After defining the Normal PDF for loads, steady state OPF is conducted to determine the mean system optimal operating cost, under base case (no line/bus outage). The test system (IEEE 39-bus) consists of ten synchronous generators. Each one is replaced individually (one at a time) by a wind generator having the same MW (and MVA) rating as of the synchronous generator. Then, SCOPF is conducted incorporating all individual *(N-1)* line outages. Similarly, SCOPF is conducted incorporating all individual *(N-1)* bus outages. Consequently, value of C_T is obtained for each synchronous generation replacement. In the end, based on C_T values, optimal location of wind farm is determined, and consequently, a priority order list of wind generators is established.

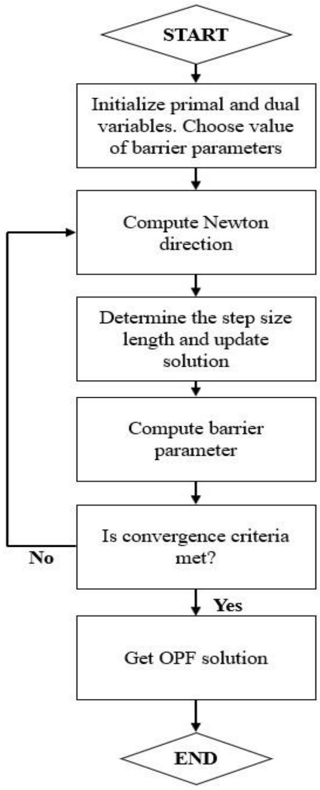

Fig. 1. Interior-point algorithm-based OPF

V. Machine Learning for Optimal Wind Farm Location

Machine learning is the study of computer algorithms that improve automatically through experience. It is basically a subset of artificial intelligence (the ability of the system to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation) [36]. Machine learning algorithms build a mathematical model based on sample data, known as “training data”, to make predictions without being explicitly programmed to do so [36]. There are three major kinds of machine learning as shown in Fig. 3 [37].

Supervised learning is a type of machine learning algorithm or approach which builds a mathematical model of a set of data that contains both the inputs and the desired outputs. This can be used for (1) output prediction (regression) and (2) classification [38]. Unsupervised learning is used to identify the hidden patterns in datasets, and reinforcement learning algorithm learns from the environments and acts accordingly. This paper focuses on supervised learning.

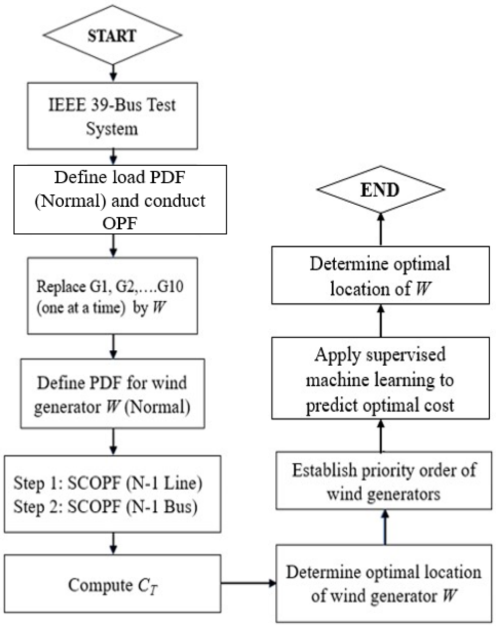

Fig. 2. Computation procedure for optimal location of wind farm *W*

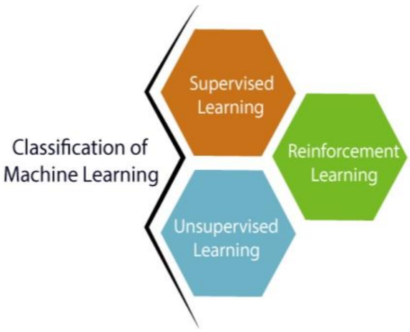

Fig. 3. Machine learning classification

Supervised learning is preferred due to various reasons. It allows to collect data or produce a data output using the previous experiences. It helps to optimize performance criteria using experience. Most importantly, it is very useful in solving various types of real-world computation problems. Various algorithms can be used for supervised learning such as artificial neural networks (ANNs), decision trees (DTs), support vector machines (SVMs), random forests, etc. [39] as outlined in Fig. 4; however, this paper uses ANNs to accomplish the task of training for supervised machine learning. This is because ANNs offer various advantages. For instance, they can be trained with any number of inputs and layers. They have numerical strength that can perform multiple tasks simultaneously. The learning methods of ANN are quite robust to noise in the training data. The training examples may contain errors, which do not affect the final output.

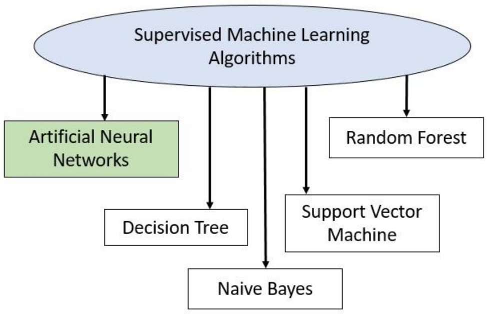

Fig. 4. Supervised machine learning major types

An ANN normally consists of a set of connected nodes (known as artificial neurons), which replicate the features of the biological neurons [40]. Each neuron can communicate a signal to other neurons, which, in return, processes it. A simple diagram of feedforward neural network is shown in Fig. 5.

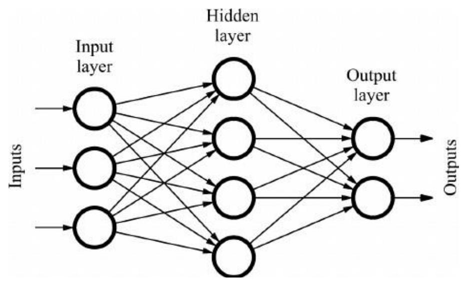

Fig. 5. Feedforward ANN

ANN is usually used to predict the values for a set of new inputs, when the network is trained for existing data. To quantify the performance of the prediction, mean squared error (*MSE*) is usually used. Mathematically, it is given by

$$MSE = \frac{\sum_{i=1}^{N} (f_i - y_i)^2}{N} \tag{24}$$

where N denotes total number of data points; f_i and y_i denote the predicted and actual value of output, respectively.

Backpropagation algorithm is normally used to adjust weights and biases of neural network. This algorithm is perhaps the most central building block in a neural network. It was first introduced in 1960s, and almost 30 years later, it was disseminated by Rumelhart, Hinton and Williams. The algorithm is essentially used train a neural network through a technique called chain rule. In simple words, after each forward pass through a network, backpropagation performs a backward pass while adjusting the weights and biases of the model. The detailed discussion of the algorithm is beyond the scope of this paper.

The activation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}):

$$Aj(\overline{x},\overline{w}) = \sum_{i=0}^{n} xiwji \tag{25}$$

As evident, the activation depends only on the inputs and the weights. If the output function would be the identity (i.e., output equals activation), the neuron would be called linear. The most common output function is the sigmoidal function:

$$Oj(\overline{x},\overline{w}) = \frac{1}{1+e^{Aj(\overline{x},\overline{w})}} \qquad (26)$$

The goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and there is a need to adjust the weights to minimize the error. The error function for the output of each neuron can be defined as:

$$Ej(\overline{x},\overline{w},\overline{d}) = (Oj(\overline{x},\overline{w}) - dj)^2 \qquad (27)$$

In the next step, the backpropagation algorithm computes how the error depends on the output, inputs, and weights. After determining this, the weights can be adjusted using the method of gradient descent:

$$\Delta wji = -\eta \frac{\partial E}{\partial wji} \qquad (28)$$

VI. Case Study and Simulations

The well-known IEEE 39-bus test transmission system, also known as the New England system, operating at 345 kV, was used to conduct the required simulations. The numerical data and parameters were taken from [41]. It consists of 10 thermal generators, 34 transmission lines and 12 transformers. The one-line diagram is shown in Fig. 6. The coefficients of generator cost curves for thermal generators are taken from [42]. For representing wind cost, a linear cost function, based on parameters from [43], is used. This practice is in coherence with the research conducted in [44]. As a single wind generator is considered in this work, it is assumed its cost parameters remain the same, wherever it is connected in the network. It is assumed that the independent system operator (ISO) is buying wind energy from an Independent Power Producer (IPP) [45], according to cost parameters based on [43]. Therefore, the wind cost is incorporated as operating cost in the system. N_S MC simulations are used to sample load and wind probability density functions (PDFs), while conducting optimal power flow. DIgSILENT PowerFactory software was used to conduct the required simulations. DIgSILENT Programming Language (DPL) and optimal power flow toolbox was used to write scripts and run simulations, for OPF and SCOPF, respectively.

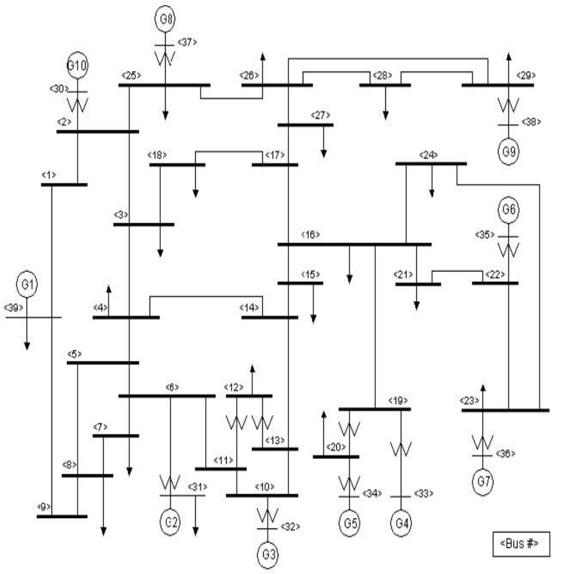

Fig. 6. IEEE 39-bus test system

VII. Results and Discussion

The value of C_{LINE} and C_{BUS} for each synchronous generation replacement is shown in Fig. 7 and Fig. 8, respectively. Consequently, the value of C_T for each synchronous generation replacement is shown in Fig. 9. Referring to Fig. 7 and Fig. 8, W1 indicates that synchronous generator G1 is replaced by wind farm *W*. Similarly, W2 indicates that synchronous generator *G2* is replaced by wind farm *W*, and similarly for other notations. Moreover, it is assumed that all considered locations for wind farms are rich in wind resources, and there is no social or political hindrance involved for placing wind farm, anywhere in the network.

As evident from Fig. 9, W10 gives the highest cost. Thus, this location is least optimal. W1 gives lowest cost, thus optimal location for wind farm is Bus 39 (*G1* is located at Bus 39).

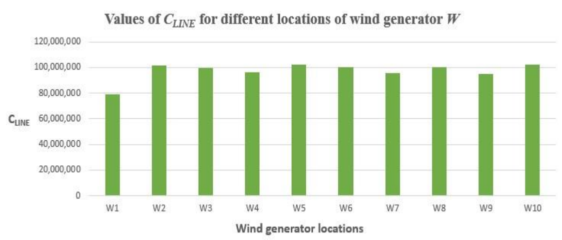

Fig. 7. Values of C_{LINE} for different locations of *W*

Therefore, based on C_T values, a priority list of wind locations can be constructed, as shown in Table II. In this table, "1" indicates the highest priority and "10" the lowest. If wind generations are to be added in the network, the synchronous generation should be replaced based on this priority list.

In the second part, supervised machine learning was applied to a neural network, based on a feedforward architecture. MATLAB's neural network toolbox was used to accomplish this task. The flowchart for the process is shown in Fig. 10.

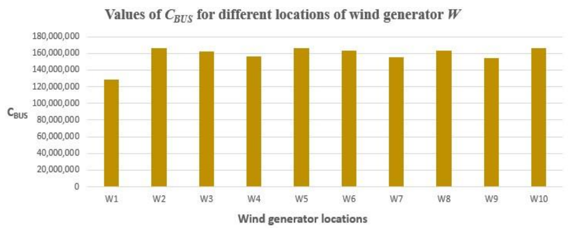

Fig. 8. Values of C_{BUS} for different locations of *W*

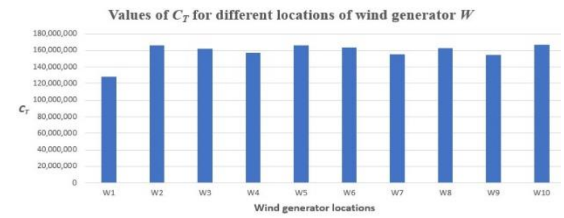

Fig. 9. Values of C_T for different locations of *W*

TABLE II. PRIORITY ORDER LIST FOR W BASED ON C_T VALUES

Priority order	Wind generation location
1	W1 (Bus 39)
2	W9 (Bus 38)
3	W7 (Bus 23)
4	W4 (Bus 19)
5	W3 (Bus 10)
6	W8 (Bus 37)
7	W6 (Bus 35)
8	W2 (Bus 31)
9	W5 (Bus 20)
10	W10 (Bus 30)

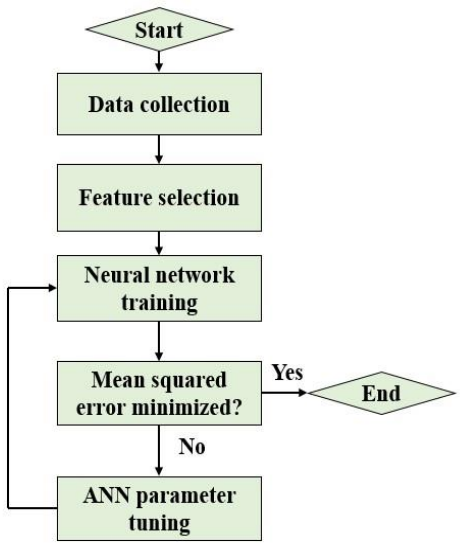

Fig. 10. Feature selection and ANN training process

Line/bus number was used as input data and optimal cost was used as output data. 100 lines/50 buses (one at a time) were randomly taken out, and consequently, corresponding optimal cost was determined using nonlinear OPF. The cost values were normalized such that they lie between 0 and 1 (with 1 being the highest cost for a single line/bus outage). This data was used as the training data for the neural network model. Levenberg-Marquardt algorithm, also known as damped least squares, was used to train the neural network. This algorithm is popular among the researchers, as it gives a fast convergence and enhanced training performance [46-47]. The number of neurons used in the hidden layer were set to 50. The sigmoid function was used as the activation function (this function is used to determine the output of a neuron in an ANN). Other activation function, such as hyperbolic tangent, rectified linear unit, swish and softmax may be used; however, the use of activation function does not drastically impact the results presented in this paper. Their detailed discussion is beyond the scope of the presented paper; however, an avid reader may refer to [48] for a detailed description of numerous neural network activation functions.

The output results are shown in Figs. 11-14. As evident from Fig. 11, the value of correlation coefficient, *R*, is quite close to 1 (in all cases: training, validation and testing), thus, the prediction accuracy is about 99%, which is quite high. Referring to Fig. 12, it shows the best validation performance for the training model. This means the *MSE* is reduced as much as possible, which is 1.24×10^{-7} in this case. Similarly, for bus data, the prediction accuracy is about 98%, as evident from Fig. 13. The corresponding learning curve (based on *MSE*) is shown in Fig. 14, demonstrating the optimum validation performance (0.0594) at epoch 720. It must be noted that an epoch is essentially a measure of the number of times all the training vectors are used once to update the weights. For complete and accurate training, all the training samples pass through the learning algorithm simultaneously in one epoch, before weights and biases are updated [49].

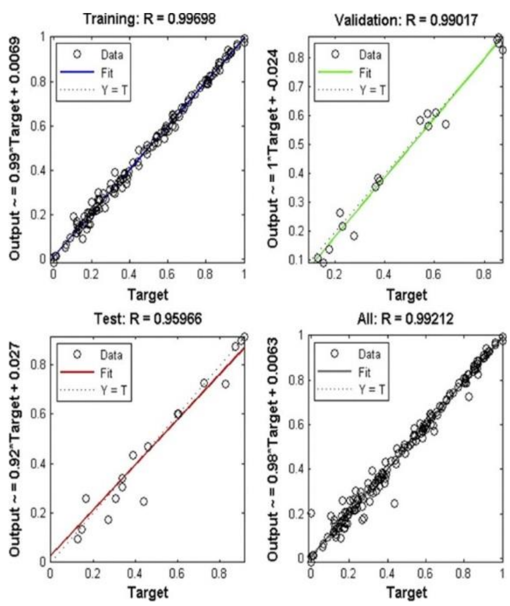

Fig. 11. Predicted vs. actual values (single line outage)

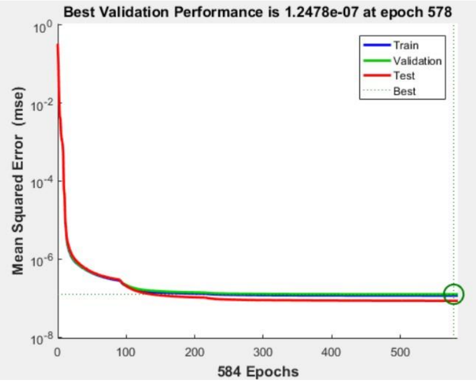

Fig. 12. Best validation performance (at epoch 578) for optimal cost (learning curve for neural network)

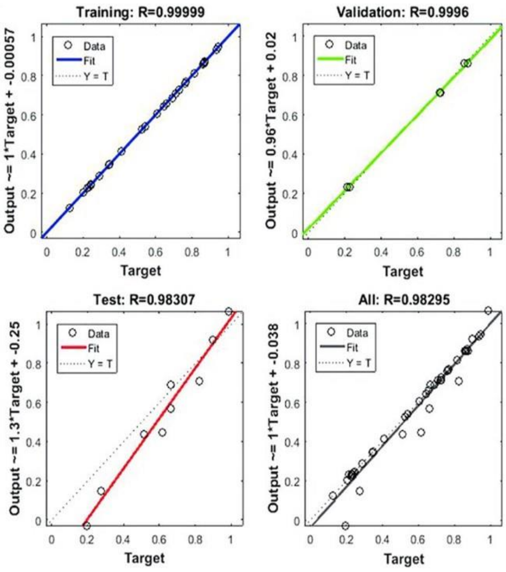

Fig. 13. Predicted vs. actual values (single bus outage)

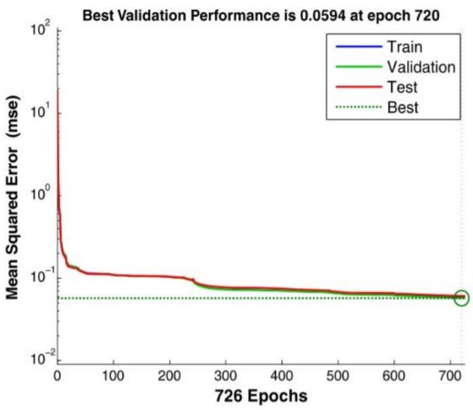

Fig. 14. Best validation performance (at epoch 720) for optimal cost (learning curve for neural network)

By using machine learning algorithms, the total cost C_T can be predicted for any wind farm location, without solving the cumbersome nonlinear OPF problem. Thus, to conclude the discussion, optimal wind farm location was found, for a power transmission system, based on power system security assessment. For IEEE 39-bus test system, it was found that Bus 39 is the optimal wind farm location. For integrating multiple wind farms, a priority order list was also established. This is very helpful for power system planners, as it gives a quick idea for locating wind farm for gaining maximum economic benefits, considering both the line and bus outages.

Various other research [26, 50-53] have been performed to evaluate optimal operating cost using machine learning approaches. Table III displays the comparison of performance metric (correlation coefficient, R), for the proposed approach with similar research. As evident, the result obtained by the proposed approach is comparable to similar research, and hence this validates its effectiveness for the desired application of optimal cost prediction, in the presence of uncertainties.

As mentioned before, various research papers [18, 54-62] have applied conventional approaches for optimal wind farm location; however, the proposed approach is computationally efficient than these approaches as it uses machine learning to reduce the computation burden of a nonlinear OPF/SCOPF problem. Table IV provides a summary of advantages and disadvantages of some main approaches used for renewable generation (including wind farm) placement [63].

Recent research [64-65] indicate that machine learning has various applications in power systems, considering the increasing uncertainties and the popularity of deregulated electricity market [66-76]. Moreover, recent research literature [77-82] has indicated the significance of using artificial intelligence and machine learning in various wind power applications. Also, numerous research papers [25, 83-85] have strongly suggested the application of machine learning data-driven approaches for OPF/SCOPF.

TABLE III. COMPARISON OF PROPOSED APPROACH WITH SIMILAR RESEARCH

Approach type	Value of R
Proposed in this paper	0.992
[26]	0.990
[50]	0.978
[51]	0.951
[52]	0.876
[53]	0.975

VIII. CONCLUSION AND FUTURE WORK

In this paper, a methodology based on security assessment was applied to determine the optimal wind farm location in a transmission system. IEEE 39-bus test system was used to test the effectiveness of the desired approach. The results show that synchronous generation G1 (at Bus 39) should be replaced by the wind farm, considering the minimization of C_T as the objective function. Thus, Bus 39 is the optimal wind farm location. Moreover, if G10 (at Bus 30) is replaced by the wind farm, C_T has the highest value, thus, it is the least desirable wind farm location. In addition to that, a priority order list was formulated which can help in integrating multiple wind farms in the power transmission system. Therefore, the proposed method is significant to power system planners to determine the optimal location of wind farms under reorganized situation of power systems. To counter the issue of computation time, a machine learning approach was proposed to predict the optimal cost of the system based on a single line/bus outage. This can predict the value of C_T for any wind farm location, without solving the cumbersome nonlinear OPF. This is specifically helpful for large-scale power systems. The main technical benefit of the proposed approach is that it gives faster prediction of OPF computation when compared to conventional methods. Moreover, the economic benefit of the proposed approach is that it allows power system planners to make rapid critical decisions (based on the neural network-based model of OPF/SCOPF predictor). This, in turn, prevents the possibility of equipment damage and cascading outages due to prolonged decision-making, thereby providing a huge economic advantage.

As a future work, the proposed approach can be applied for determining optimal location of solar farms, considering correlation among solar generation and system load. Other soft computing techniques such as fuzzy computing and Chaos theory can be applied, and their performance can be compared with that of neural networks. Moreover, other kinds of neural networks based on convolution and radial basis activation functions, can be applied. Reinforcement learning for OPF/SCOPF can also be explored.

TABLE IV. ADVANTAGES AND DISADVANTAGES OF WIND FARM PLACEMENT APPROACHES

Approach	Advantages	Disadvantages
Analytical Method	Easy to implement, high precision factor, computational time efficiency	Fewer literature examples, lacks robustness, only can consider single objective and single renewable generator at a time
Mixed Integer Nonlinear Programming	High precision factor, computational time efficiency	Hard to implement and understand
Evolutionary Algorithm	Efficient performance for finding the global optimum, easy to find literature examples	Relatively harder to code, premature convergence, possibility of trapping into local optima, lower precision factor
Simulated Annealing	Ease of implementation, ability to provide reasonably good solutions for many combinatorial problems, robustness	Relatively lower performance for finding the global optimum, large computational time
Differential Evolution	Fewer parameters setting, capable of handling complex optimization problems	Unstable convergence, possibility of trapping into local optima
Particle Swarm Optimization	Easy to code with few equations, easy to find literature examples	Relatively lower performance for finding the global optimum, fewer literature examples
Tabu Search	Efficient performance for achieve an optimal or sub optimal solution, capable to escape from local minimum	Relatively harder to code due to many parameters to be tuned, lower precision factor
Firefly Algorithm	Easy to understand and code	Slow convergence, fewer literature examples
Imperialist Competition Algorithm	Capable of handling complex optimization problems	Relatively harder to code due to many parameters to be tuned, fewer literature examples
Artificial Intelligence Approaches	Efficient performance, fewer iterations, easy to find literature examples	May trap in local minima, various setting parameters, difficult to code

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