International Journal of Power and Energy Systems, Vol. 44, No. 10, 2024
An Open Access Paper

REMEDIAL ACTION SCHEME FOR WIND POWER INJECTION WITH MINIMUM TRANSMISSION LINE LOSS

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Abstract

The rise in power demands and concern over climate change is leading to increased penetration of wind energy into the grid. However, the transmission network infrastructure is not equipped for such a transition. Transmission lines are responsible for the transfer of electric power from generating stations to load centres and consumers. In this process, the lines incur losses which affect the quality of power. Also, it has an economic impact on the utilities. Therefore, such losses must be minimised so that the power quality can be improved and economic losses are less. With the increase in the percentage of wind energy integration in the grid, the transmission line losses are increasing. To address this problem, a remedial action scheme (RAS) has been proposed for increasing wind energy penetration in the grid with minimum transmission line losses. To achieve this, the proposed method uses a multi-objective optimisation problem which is solved using the genetic algorithm. For varying transmission line losses, the multi-objective optimisation problem determines the optimal generation from each wind generator. The proposed RAS is tested for the New England 39-bus network and the results highlight the performance of the method to maximise the wind power injection.

Key Words

Genetic algorithm, multi-objective optimisation, remedial action scheme (RAS), transmission line loss, wind energy

1. Introduction

Wind farms are located far away from the load centres and consumers. The power generated from the wind farms has to be carried through transmission lines to the consumers. The power network is divided into three sectors: (i) generation, (ii) transmission, and (iii) distribution.

1.1 Aim and Motivation

In recent years, the amount of global renewable energy, especially wind energy penetration in the grid has rapidly increased. The increment is due to environmental concerns about global warming and climate change [1], [2]. However, the randomness, intermittence, and uncertainty of wind energy seriously affect the reliability of the power system [3], [4]. Improving the penetration rate of wind power generation in the electric grid has become a major problem [5], [6].

Line losses are an essential aspect to consider when evaluating high-power transmission systems [7]. Losses in the transmission network can be classified as technical losses and non-technical losses. Technical losses refer to the electricity used to compensate for power line and transformer losses. Electricity theft, faulty data processing, and measurement errors are examples of non-technical losses. Non-technical losses are more prevalent in the distribution network as compared to the transmission network [8]. Technical losses in the transmission network can be divided into two categories: losses on transmission lines and losses on transformers, with losses on transmission lines taking precedence [9], [10].

1.2 Literature Survey

In [11], the transmission line loss reduction is done based on flexible AC transmission systems (FACTS) and bacteria foraging algorithm (BFA). Optimising the values of on load tap changer (OLTC) transformer taps present in a multi-machine power network, the real power loss of the system is minimised. By fixing the tap positions at the optimised values, a unified power flow controller (UPFC) is introduced in the system. Interline power flow controllers (IPFCs) are used for the reduction of the transmission line loss in [12]. The IPFC is a novel FACTS device that can control power flow in power systems. The IPFC consists of multi-series converters. The power flow through the line can be regulated by controlling both magnitudes and angles of the series voltages injected by an IPFC. However, all of these solutions require capital investment and installation of new equipment in the network.

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(DOI: 10.2316/J.2024.203-0486)

In [13], an approach for optimisation of surveillance test interval of standby equipment with highly uncertain aging parameters, based on genetic algorithm technique and probabilistic safety assessment, is presented. Reduction in transmission line losses and improvement in reliability with the transient and permanent outage of lines in the transmission system is described in [14]. In [15], a multi-objective optimisation technique to estimate the optimal size of wind power plants required to fulfill the varying load demand of different districts in the state of Madhya Pradesh, India, is proposed. The multi-objective problem reduces the monthly difference between energy demand and production in every area, the cost of each unit generated is minimised, and the power supply from one district to the other is reduced. The cumulative analysis of system observability and reliability during an anomaly situation that occurs with a phasor measurement unit (PMU) device due to a cyber-attack is discussed in [16].

In [17], a method to evaluate the effect of optimal transmission switching in reliability improvement due to load curtailments at the load buses is described. Further, reliability indices, such as loss of load probability (LOLP), expected demand not supplied (EDNS), and expected energy not supplied (EENS), are also calculated. Modelling of renewable energy sources and energy storage devices using multistate modeling methods is discussed in [18]. In [19], the cumulative effect of observability and reliability for synchrophasor smart grid networks with the inclusion and exclusion of zero injection bus (ZIB) in the system is presented. In [20], the capacity expansion of generating units to serve the annual incremental peak load demand is discussed and the system sensitivity analysis, risk level, and reliability analysis are analysed with units expansion and probable transmission line switching.

Gurney *et al.* [21] described the loss reduction methods using alterations in the hardware installations as well as software-based constrained optimisation. Modified particle swarm technique [22], hybrid particle swarm optimisation [23], adaptive particle swarm optimisation-differentially perturbed velocity [24], fully informed particle swarm optimisation [25], transmission switching [26], *etc.* are some of the techniques implemented for power loss reduction.

1.3 Contribution of the Present Work

All the above methods are focussed only on the reduction of transmission line loss in the network without taking into consideration the maximisation of wind power injection. The methods have a single objective of reduction of transmission line loss. The proposed work deals with the reduction of transmission line loss as well as the maximisation of wind power injection in the network.

Modern smart power grids make extensive use of real-time data to optimise power system operations. Several approaches are used in the grid to improve grid operations by utilising information gained from real-time data. Remedial action schemes (RASs) are defined by the North American Electric Reliability Cooperation (NERC) Standard [27] as schemes that are designed to detect predetermined system conditions and automatically take corrective actions, such as adjusting or tripping generation, tripping load, or reconfiguring a system. Based on their principle of operation, RAS are broadly classified into three types [28]: (*i*) event-based RAS [29]–[31], (ii) parameter-based RAS [32]–[34], and (iii) response-based RAS [35], [36]. A parameter-based RAS method can be implemented to maximise the wind power injection into the network considering minimum transmission line loss. It can offer an easy and economical solution to increase renewable energy utilisation without the requirement of new transmission facilities [37]. The proposed RAS constitutes of a multi-objective function which maximises the wind power injection into the network considering minimum transmission line loss. Two objective functions are combined to make the multi-objective function. The first function maximises the wind power injection into the network through each wind generator and the second minimises the transmission line loss.

The maximisation of wind power injection into the grid with minimum transmission line loss can be done by installing new transmission lines in parallel to the existing ones. This installation includes a lot of capital investment and time. Hence, it is not a feasible solution to the problem. The proposed RAS operates on the existing system and requires no capital investment. It provides a significant increment in the wind power injection at the same transmission line loss. The proposed RAS is adaptable to any type of wind generator and the output is independent of the type of wind generator considered.

The paper is organised as follows. Section 2 briefly discusses the data acquisition with the help of PMU. The proposed RAS for the maximisation of wind power injection considering minimum transmission line loss is described in Section 3. Results obtained for the different sets of wind generators with varying transmission line loss are presented in Section 4. Discussions are carried out in Section 5 and Section 6 followed by the concluding remarks.

2. Data Acquisition

Real-time data required to optimise power system operations are taken from the PMU installed in the network. It provides synchronised analog and digital data for a wide area network [38]. Analog data comprise of positive-sequence voltage and current phasors. Digital data contain the status of a circuit breaker, relay, and other equipment. The synchronism among the data measured from different buses is achieved with the help of voltage and current waveform using timing signals obtained from the global positioning system (GPS) [39].

The installation cost of PMU makes it difficult to have PMU installed on every bus of the network. So the optimal placement of PMU in the network becomes an important issue. To utilise the PMU's capacity to monitor both the node voltage and the currents of the lines incident to that node, positioning of the PMUs at the most appropriate locations in the system is required to achieve full system observability with the minimum number of PMUs. The optimal placement of PMU for the New England 39-bus network is shown in Fig. 1. For full observability of the

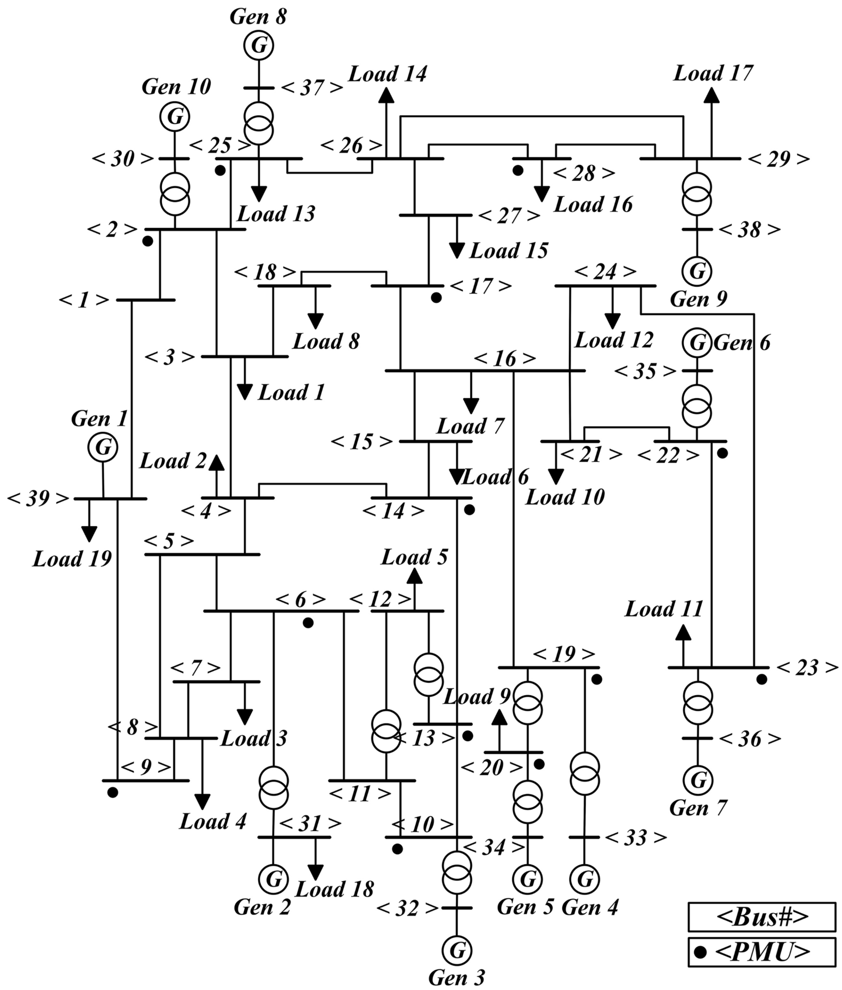

Figure 1. The New England 39-bus network.

network at normal operating conditions, 13 PMUs are required at the given buses: 2, 6, 9, 10, 13, 14, 17, 19, 20, 22, 23, 25, and 28/29 [40]–[42]. If the voltage phasors of all network buses are known, the current phasors of all network branches are also known, and the system is considered fully observed [43]. The PMU installed at Bus 6 as shown in Fig. 1 provides the bus voltage magnitude, angle, and the current through the branches connected with Bus 6. Using these known data sets, the bus voltage magnitude, angle, and the current through the branches connected with Bus 5, Bus 7, Bus 11, and Bus 31 can be calculated.

3. Proposed Method

A multi-objective optimisation problem is used for maximising wind energy penetration and minimising line losses. The optimal values of generation from each wind generator for a specific amount of transmission line loss is also obtained.

3.1 Problem Formulation

The proposed multi-objective optimisation problem has two objectives (a) maximising wind power injection into the network, and (b) minimum transmission line loss.

$$\max_{P_w, P, B, B_0, B_{00}} [f_1(P_w), -f_2(P, B, B_0, B_{00})] \tag{1}$$

Subject to

$$\sum_j P_{\mathrm{ij}} = P_i^g - P_i^d, \quad \forall i, j \in N \tag{2}$$

$$P_{i_{\min}}^g \le P_i^g \le P_{i_{\max}}^g, \quad \forall i \in N \tag{3}$$

$$\delta_{i_{\min}} \le \delta_i \le \delta_{i_{\max}}, \quad \forall i \in N \tag{4}$$

where,

P_w: Column vector of order $W \times 1$ containing entries as the active power generation of the respective wind generators at a particular instant of time.

P: Column vector of order $G \times 1$ containing entries as the active power generation of the respective generators at a particular instant of time.

B: A square matrix of order $G \times G$.

B_0: Column vector of order $G \times 1$.

B_{00}: A constant.

The $B-$terms are called Loss-coefficients or $B-$coefficients, and the $G \times G$ symmetrical matrix B is simply known as the $B-$matrix.

P_{ij}: Active power flow through line connecting buses i and j.

P_i^g: Bus i active power generation.
P_i^d: Bus i active power demand.
δ_i: Bus i voltage angle.
N: Number of buses.
W: Number of wind generators.
G: Number of generators.
P_w is a subset of P.

The first objective function $f_1(\cdot)$ is defined as the summation of active power generation by wind generators, which is expressed as follows:

$$f_1(\cdot) = \sum_{i=1}^{W} P_{w_i} \tag{5}$$

The second objective function $f_2(\cdot)$ is defined as the transmission line loss equation or Kron's loss formula [44], which is expressed as follows:

$$f_2(\cdot) : P_{\text{Loss}} = P^T BP + B_0^T P + B_{00} \tag{6}$$

The total transmission line loss in the network is calculated using Kron's loss formula. The formula takes into account each generator's active power generation and the network's $B-$coefficients. The transmission line parameters (resistance and reactance) are used to determine the network's $B-$coefficients or loss-coefficients.

The active power balance equation for the network is given by (2). The generators must operate between their minimum and maximum active power generation limits represented by (3). Equation (4) bounds the bus voltage angle within its minimum and maximum limits.

3.2 Data Requirement

The data input for the proposed method is divided into three categories.

- **Online:** Online data consists of the bus voltage angle obtained from the PMUs installed in the network. The initial conditions are evaluated using the data obtained from PMUs.
- **Offline:** Network, load, and generation data are obtained from the load dispatch centers. It is used to calculate the total transmission line loss (P_{Loss}) and $B-$coefficients.
- **Forecast:** The weather forecast available from the meteorological department is used to select the sets of wind generators to replace the conventional generators in the network. The output of these sets of wind generators is to be maximized using the proposed RAS.

3.3 Methodology

A flowchart of the proposed RAS is shown in Fig. 2. Initially, the total transmission line loss (P_{Loss}) in the network and $B-$coefficients for the network are calculated. The offline input data required for performing the calculation are (i) bus data, (ii) line data, and (iii) generator and load data. The calculation is performed using Matpower [45] which is a set of power system analysis functions run from within MATLAB [46]. Following this,

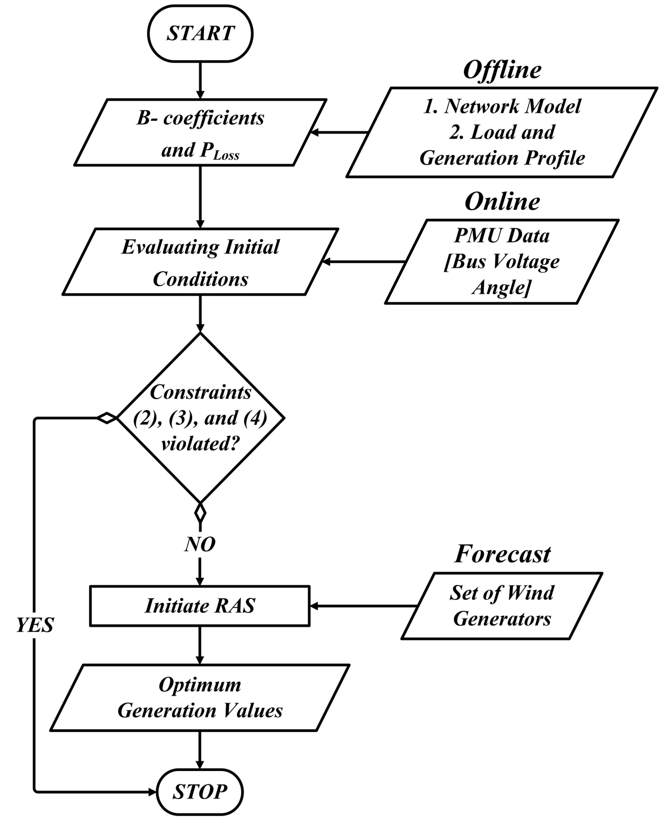

Figure 2. Flowchart of RAS.

the initial conditions are evaluated with the help of online bus voltage angle data obtained from the PMU. Further, the constraints in (2)–(4) are verified to be within their limits before proceeding to initiate the RAS. The $B-$coefficients along with the set of wind generators available in the network are used in the multi-objective optimisation problem which provides the optimum generation from each wind generator for varying transmission line loss. The multi-objective optimisation problem is solved using the MATLAB optimisation toolbox [47] with the help of the genetic algorithm [48], [49]. Genetic algorithms search parallel from a population of points and have the ability to avoid being trapped in a locally optimal solution. It searches globally with a good convergence rate and uses probabilistic selection rules.

4. Results

The proposed RAS is tested on the New England 39-bus network as shown in Fig. 1. The voltage level considered for the New England 39-bus network is 345 kV.

The system specifications are as follows:

- **Generators:** Ten conventional synchronous generators *i.e.*, Gen 1, Gen 2, Gen 3, Gen 4, Gen 5, Gen 6, Gen 7, Gen 8, Gen 9, and Gen 10 are connected at Bus 39, Bus 31, Bus 32, Bus 33, Bus 34, Bus 35, Bus 36, Bus 37, Bus 38, and Bus 30, respectively, with maximum generator power output of 1100 MW each. Gen 2 is connected at the slack bus of the network *i.e.*, Bus 31.

- Twelve transformers, 19 loads, and 34 transmission lines are also present. The baseload demand of the system is 6097.1 MW and 1409.1 MVAR.

Initially, the network is operated with the baseload demand [6097.1 MW] and the base values of generator operating conditions [Gen 1 (250 MW), Gen 2 (Slack Bus), Gen 3 (650 MW), Gen 4 (630 MW), Gen 5 (500 MW), Gen 6 (650 MW), Gen 7 (560 MW), Gen 8 (540 MW), Gen 9 (830 MW), and Gen 10 (1000 MW)]. The total transmission line loss is obtained to be 43.411 MW. Subsequently, the proposed RAS is tested for different cases considering the replacement of a set of conventional generators with wind generators.

Wind generators are introduced at different locations in the network by replacing existing conventional generators that are geographically closer to each other. The wind speed considered in the proposed work is 13 m/s. However, the proposed method is adaptive to every set of wind generators irrespective of the wind speed and geographical location. The results highlight the efficacy of the method in calculating the maximum output of the wind generators. The output of each wind generator for varying losses in the network is also calculated.

4.1 Operation With Three Wind Generators

A set of three conventional generators (Gen 1, Gen 8, and Gen 10) in the network are replaced by wind generators each having a maximum output of 1100 MW.

Considering the baseload condition where the transmission line loss is 43.411 MW, the proposed method attempts to maximise the wind power injection. The output of the proposed method provides the power injection values as follows:

- Gen 1: 664.35 MW
- Gen 8: 649.46 MW
- Gen 10: 1099.94 MW

Under this condition, the transmission line loss is 42.747 MW and the total wind power injection is 2414 MW. It can be observed that there is an increase of 624 MW (34.86%) of power injection from the wind generators without an increase in transmission line loss.

The optimum values of power injection from the selected wind generators for varying transmission line loss are shown in Fig. 3. It can be observed that for a total injection of 2258 MW from the wind generators (Gen 1, 8, and 10), the transmission line loss is 32.902 MW. The output of conventional generators at the same location in baseload condition (no wind generators) is 1790 MW. Therefore, the wind generator injection to the system can be increased by 26.15% with a 24.21% reduction in transmission line loss under the current operating condition. This is due to the fact that the loads are closer to the wind generators for this operating condition. Therefore, more injection from wind generators decreases the overall losses in the lines. Depending on the variation of the loading condition, the proposed method can optimise the generator injections to the network to give maximum wind energy penetration with minimum losses.

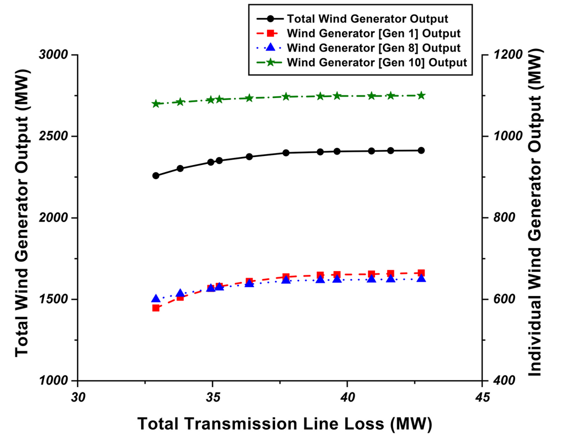

Figure 3. Optimal values of wind power generation with Gen 1, Gen 8, and Gen 10 as wind generators for varying transmission line loss.

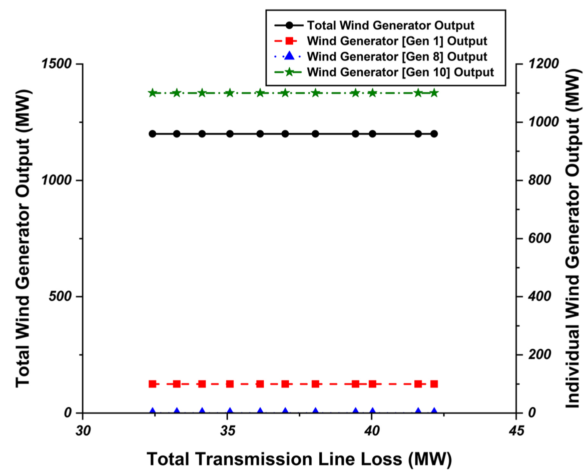

Figure 4. Optimal values of wind power generation with Gen 1, Gen 8, and Gen 10 as wind generators considering Gen 8 is not operational for varying transmission line loss.

The optimal values of wind power generation with Gen 1, Gen 8, and Gen 10 as wind generators considering Gen 8 is not operational for varying transmission line loss are shown in Fig 4. The proposed method tries to minimise the transmission line loss when one of the wind generators is not operational. However, during such failure the maximum amount of wind power injection into the network reduces.

4.2 Operation with Four Wind Generators

In this case, four conventional generators (Gen 3, Gen 4, Gen 5, and Gen 7) in the network are replaced by wind generators. The maximum output of each wind generator is 1100 MW.

For a transmission line loss of 43.608 MW, the optimum power injections from the wind generators are:

- Gen 3: 677.44 MW
- Gen 4: 752.32 MW
- Gen 5: 719.46 MW
- Gen 7: 572.13 MW

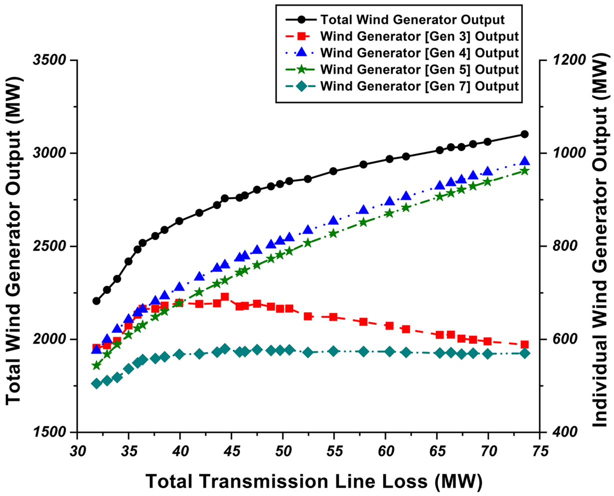

Figure 5. Optimal values of wind power generation with Gen 3, Gen 4, Gen 5, and Gen 7 as wind generators for varying transmission line loss.

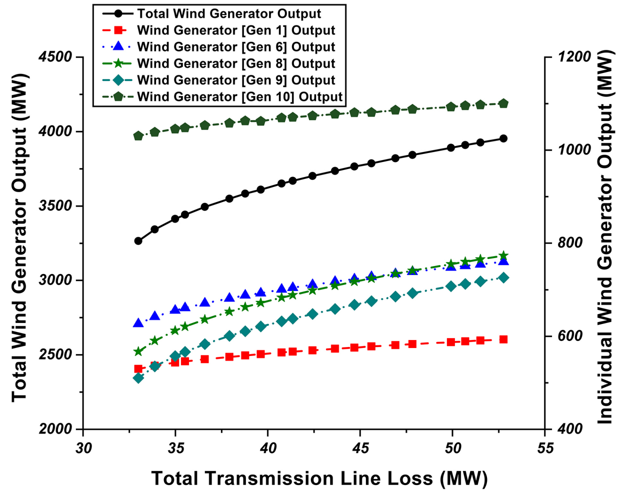

Figure 6. Optimal values of wind power generation with Gen 1, Gen 6, Gen 8, Gen 9, and Gen 10 as wind generators for varying transmission line loss.

An increase of wind power by 381 MW (16.28%) from the baseload condition is achieved.

The maximum injection from selected four wind generators for varying transmission line losses is shown in Fig. 5. It is observed that for a loss of 35.88 MW which is 7.531 MW (17.35%) less than the baseload condition, the total injection of the wind generators can be increased by 143 MW (6.11%). Therefore, the proposed method is reducing the use of conventional generators and increasing the share of renewable sources.

4.3 Operation with Five Wind Generators

Wind generators with a maximum capacity of 1100 MW are used to replace five conventional generators (Gen 1, Gen 6, Gen 8, Gen 9, and Gen 10) in the network.

The optimum wind power injection from Gen 1, 6, 8, 9, and 10 for baseload transmission line loss and minimum transmission line loss is listed in Table 1.

For transmission line loss equal to the baseload condition, an increase of 467 MW (14.28%) of wind power injection is achieved.

For a reduction of transmission loss by 4.629 MW (10.66%) from the baseload condition, the total wind power injection is increased by 314 MW (9.6%). The wind power injection values from the selected five wind generators for varying transmission line losses are shown in Fig. 6.

5. Discussion

The application of the proposed method is independent of the locations of the wind generators in the network. Based on the real-time data of wind power availability and loading condition in the network, the proposed method optimises the wind energy penetration. The output power of the different sets of wind generators is listed in Table 2. The optimum values of wind generator injection are calculated for baseload transmission line loss and minimum transmission line loss. The relevant change (in %) of wind power injection compared to the baseload condition is also highlighted. The increment in power injection is as large as 22.9% (387 MW).

The minimum transmission line loss in the network changes for different sets of wind generators are listed in Table 2. For cases where the load is electrically near to the wind generators, the losses decrease with an increase in wind generator output. However, in some cases, if the loads are electrically far from the generators, the wind generator penetration should be reduced to achieve minimum transmission line loss. This has been highlighted in result 3 of Table 2. In this case, to achieve the minimum transmission line loss of 30.764 MW, a decrement of total wind power by 5% is required. However, for a loss equal to the baseload condition, the injection increases by 11.03%. It has been observed that, for baseload transmission line

Table 1
Optimum Wind Generators Output

Transmission Line Loss (in MW)	Optimum Wind Generators Output (in MW)					
	Gen 1	Gen 6	Gen 8	Gen 9	Gen 10	Total
43.64	573	718	709	659	1078	3737
38.782	559	688	663	611	1063	3584

Table 2
Power Injections for Different Wind Generator Sets

			Baseload Transmission Line Loss (43.411 MW)		Minimum Transmission Line Loss		
			Optimum Wind Generator Output (in MW)	Total Output (in MW) [Change (in %)]	Line Loss (in MW) [Reduction (in %)]	Optimum Wind Generator Output (in MW)	Total Output (in MW) [Change (in %)]
Sets of Wind Generators	1	Gen 4	721.78	2077 [+22.9]	33.599 [22.6]	603.68	1707 [+1.01]
		Gen 5	544.61			477.34	
		Gen 7	810.2			626.06	
	2	Gen 8	553.05	2502 [+5.57]	38.912 [10.36]	515.37	2402 [+1.35]
		Gen 9	900.36			840.95	
		Gen 10	1048.49			1045.6	
	3	Gen 6	656.52	2265 [+11.03]	30.764 [29.13]	648.62	1938 [−5.0]
		Gen 7	939.39			633.03	
		Gen 9	668.93			656	
	4	Gen 6	535.23	3070 [+1.66]	41.731 [3.87]	603.68	3026 [+0.2]
		Gen 8	527.39			477.34	
		Gen 9	931			626.06	
		Gen 10	1076.3			626.06	
	5	Gen 4	828.35	2831 [+6.03]	40.236 [7.31]	776.5	2720 [+1.87]
		Gen 6	832.89			783.58	
		Gen 7	551.91			553.18	
		Gen 9	618.26			606.25	
	6	Gen 1	934.17	3635 [+19.97]	33.256 [23.39]	568.96	3214 [+6.07]
		Gen 3	616.52			624.76	
		Gen 4	561.53			489.28	
		Gen 5	549.71			503.38	
		Gen 10	972.89			1027.3	
	7	Gen 3	588.87	3226 [+7.89]	39.241 [9.61]	577.45	3100 [+3.68]
		Gen 4	582.45			569.67	
		Gen 5	653.06			636.85	
		Gen 6	608			595.52	
		Gen 7	793.15			720.43	

loss, there is an increment in the total power injection, irrespective of the set of chosen generators.

In another scenario, three conventional generators (Gen 3, Gen 4, and Gen 5) in the network are replaced with wind generators having a maximum capacity of 1100 MW. The comparison between optimal values of wind power generation with Gen 3, Gen 4, and Gen 5 as wind generators for varying transmission line loss considering Bus 31 and Bus 38 as slack bus is shown in Fig. 7.

6. Data Error Analysis

The output of the proposed RAS is heavily dependent on the input data quality. The effect of error in input data to the performance of the RAS has been evaluated in this section. Three conventional generators *i.e.*, Gen 1, Gen 8, and Gen 10 in the network are replaced by wind generators with the same maximum generating power output of 1100 MW. For a transmission line loss of 42.747 MW, the total

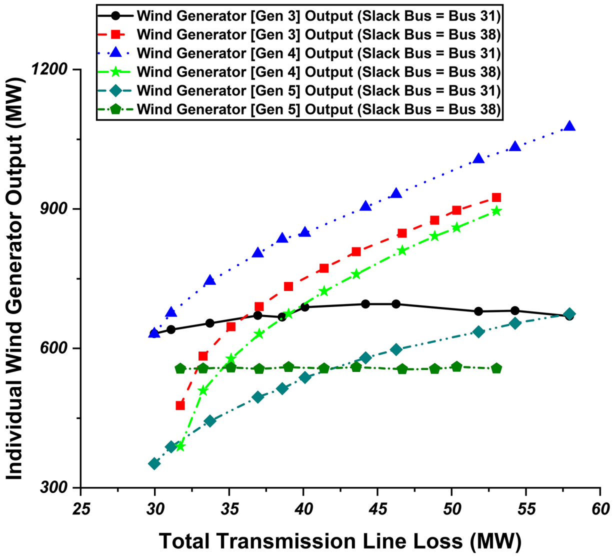

Figure 7. Optimal values of wind power generation with Gen 3, Gen 4, and Gen 5 as wind generators for varying transmission line loss considering Bus 31 and Bus 38 as slack bus.

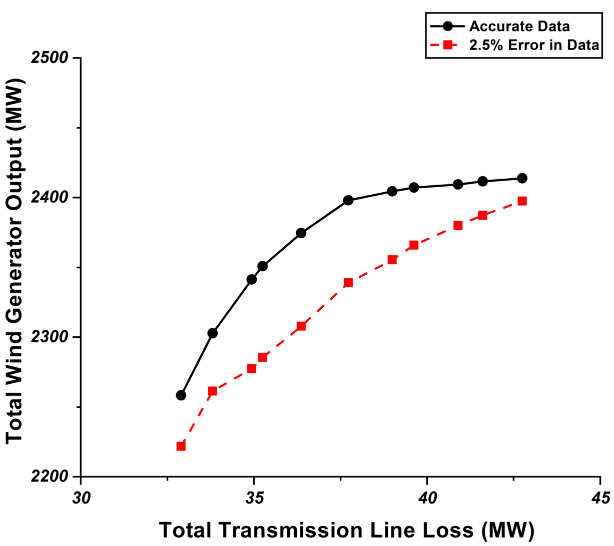

Figure 8. Effect of error in data on total wind power generation for varying transmission line loss.

wind power generation with the accurate network, load, and generation data is 2414 MW. Considering an error of 2.5% in the network, load, and generation data obtained, the total wind power generation reduces to 2397 MW for the same amount of transmission line loss. The error in the network, load, and generation data is considered at each bus of the network. The actual data of active power generation at Bus 36 is 560 MW and active power demand at Bus 20 is 628 MW. With the considered error in the measured data, the active power generation at Bus 36 is 546 MW, and active power demand at Bus 20 is 612.3 MW.

For an error of 2.5% in the data at each bus of the network, the output of the RAS provides an error of 0.7% in the total wind power generation. This shows that the proposed RAS is robust to such a significant amount of erroneous data. The total wind power generation with the accurate and erroneous network, load, and generation data is 2351 MW and 2285 MW, respectively, for a transmission line loss of 35.255 MW. Further, the total wind power generation from these three wind generators with accurate and erroneous data for varying transmission line loss can be observed in Fig. 8.

The proposed algorithm can be implemented in utilities for increased penetration of wind energy in the network. With the improvement in communication technologies, the utilities can obtain real-time data which can be used for the proposed method implementation. The proposed method is robust in nature to deal with potential errors in network, load, and generation data with focus on maximising wind energy penetration and minimising line losses.

7. Conclusions

An increase in penetration of renewable energy in the network can reduce the share of conventional generators in the network, thus reducing carbon emissions. In this paper, a method to optimise the amount of wind power injection into the network considering minimum transmission line loss has been developed. The proposed multi-objective optimisation problem framed is solved using the genetic algorithm. The results are simulated on the New England 39-bus network for different sets of wind generators. It is observed that with the application of the method, an increment in wind energy penetration by 34.86% into the network can be implemented without increasing the losses. Further, the values of maximum wind energy penetrations considering different values of transmission line losses can also be obtained. Thus, the proposed RAS offers a viable and economical solution for maximum utilisation of available wind energy resources without incurring further losses. The robustness of the proposed RAS is also tested with an error of 2.5% in the network, load, and generation data. The resiliency of the proposed method can be further enhanced by considering external disturbances such as faults, natural disasters, and cyber security. These aspects will be considered as a future scope of work.

Acknowledgement

The authors express their gratitude to the Science and Engineering Research Board (SERB), Department of Science and Technology, India, for providing financial support for this research by sponsoring the project “Wide area backup protection using unsupervised machine learning”- SRG/2021/001004.

References

[1] W. Wang, L. Liu, J. Liu, and Z. Chen, Energy management and optimization of vehicle-to-grid systems for wind power integration, *CSEE Journal of Power and Energy Systems, 7*(1), 2021, 172–180.

[2] P. Pinson, L. Mitridati, C. Ordoudis, and J. Østergaard, Towards fully renewable energy systems: Experience and trends in Denmark, *CSEE Journal of Power and Energy Systems, 3*(1), 2017, 26–35.

[3] Y. Chen, Z. Zhang, Z. Liu, P. Zhang, Q. Ding, X. Liu, and W. Wang, Robust N–k CCUC model considering the fault outage probability of units and transmission lines, *IET Generation, Transmission & Distribution, 13*(17), 2019, 3782–3791.

[4] Y. Chen, Z. Zhang, H. Chen, and H. Zheng, Robust UC model based on multi-band uncertainty set considering the temporal correlation of wind/load prediction errors, *IET Generation, Transmission & Distribution, 14*(2), 2020, 180–190.

[5] Y. Shu and Y. Tang, Analysis and recommendations for the adaptability of China's power system security and stability relevant standards, *CSEE Journal of Power and Energy Systems, 3*(4), 2017, 334–339.

[6] S.D. Ahmed, F.S.M. Al-Ismail, M. Shafiullah, and F.A. Al-Sulaima, Grid integration challenges of wind energy: A review, *IEEE Access, 8*, 2017, 10857–10878.

[7] A. Habiburrahman and L. Arya, Comparison of transmission losses and voltage regulation of overhead and gas insulated transmission line, *Proc. IEEE International Conference on Advances and Developments in Electrical and Electronics Engineering* , Coimbatore, 2020, 1–3.

[8] I. Pavičić, I. Ivanković, A. Župan, R. Rubeša, and M. Rekić, Advanced prediction of technical losses on transmission lines in real time, *Proc. 2nd International Colloquium on Smart Grid Metrology* , Split, 2019, 1–7.

[9] L. Rudolf, Software solution of technical losses of the transmission network system line, *Transactions on Electrical Engineering, 2*(4), 2013, 97–101.

[10] A. Ombua and H.A. Labane, High voltage lines: Energy losses in insulators, *The International Journal of Engineering and Science, 6*, 2017, 58–62.

[11] M. Tripathy, S. Mishra, L. L. Lai, and Q. P. Zhang, Transmission loss reduction based on FACTS and bacteria foraging algorithm, *Proc. 9th International Conference on Parallel Problem Solving from* NatureHeidelberg, 2006, 222–231.

[12] S. Jangjit, P. Kumkratug, and P. Laohachai, Reduction of transmission line loss by using interline power flow controllers, *Proc. International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, Chiang Mai, 2010, 450–453.

[13] D. Kančev, B. Gjorgiev, and M.Čepin, Optimization of test interval for ageing equipment: A multi-objective genetic algorithm approach, *Journal of Loss Prevention in the Process Industries, 24*(4), 2011, 397–404. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S09504230 1100026X

[14] A.K. Yadav and V. Mahajan, Transmission line switching for loss reduction and reliability improvement, *Proc. International Conference on Information and Communications Technology*, Yogyakarta, 2019, 794–799.

[15] M.Verma, H. K. Ghritlahre, P. K. Chaurasiya, S. Ahmed, and S. Bajpai, Optimization of wind power plant sizing and placement by the application of multi-objective genetic algorithm (GA) in Madhya Pradesh, India, *Sustainable Computing: Informatics and Systems, 32*, 2021, 100606. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S22105379 21000949

[16] A. K. Yadav and V. Mahajan, Tie-line modelling in interconnected synchrophasor network for monitoring grid observability, cyber intrusion and reliability, *Engineering Review, 42*(2), 2022, 114–132.

[17] A. K. Yadav and V. Mahajan, Reliability improvement of power system network with optimal transmission switching, *Proc. IEEE 1st International Conference on Energy, Systems and Information Processing*, Chennai, 2019, 1–6.

[18] V. Mahajan, S. Mudgal, A.K. Yadav, and V. Prajapati, Chapter 16 - Reliability modeling of renewable energy sources with energy storage devices, *Energy Storage in Energy Markets.* Cambridge, MA, USA: Academic Press, 2021, 317–368.

[19] A. Yadav, Cyber-attack and reliability monitoring of the synchrophasor smart grid network, *Jurnal Kejuruteraan, 34*, 2022, 1149–1168.

[20] A.K. Yadav, S. Mudgal, and V. Mahajan, Reliability test of restructured power system with capacity expansion and transmission switching, *Proc. 8th International Conference on Power Systems*, Jaipur, 2019, 1–6.

[21] J. H. Gurney, R. J. Koessler, J. S. Mumick, F. S. Prabhakara, and G. Shen,, Loss reduction opportunities in EHV transmission systems,*Proc. IEEE Power Energy Society General Meeting*, Calgary, AB, 2009, 1–7.

[22] A. Y. Abdelaziz, S. F. Mekhamer, M. A. L. Badr, F. M. Mohamed, and E. F. El-Saadany, A modified particle swarm algorithm for distribution systems reconfiguration, *Proc. IEEE Power Energy Society General Meeting*, Calgary, AB, 2009, 1–8.

[23] A. Esmin, G. Lambert-Torres, and A. Zambroni de Souza, A hybrid particle swarm optimization applied to loss power minimization, *IEEE Transactions on Power Systems, 20*(2), 2005, 859–866.

[24] K. Vaisakh, M. Sridhar, and K. L. Murthy, Adaptive PSO-DV algorithm for minimization of power loss and voltage instability, *Proc. International Conference on Advances in Computing, Control, and Telecommunication Technologies*, Bengaluru, 2009, 140–144.

[25] T.U. Hassan, R. Zafar, S. Ali Mohsin, and O. Lateef, Reduction in power transmission loss reduction using fully informed particle swarm optimization, *International Journal of Electrical Power & Energy Systems*, *43*(1) 2012, 364–368.

[26] R. Bacher and H. Glavitsch, Loss reduction by network switching, *IEEE Transactions on Power Systems, 3*(2), 1988, 447–454.

[27] North American Electric Reliability Cooperation (NERC), "PRC-012-2 – Remedial Action Schemes (Final Draft), *North American Electric Reliability Cooperation (NERC) PRC-012-2, Tech. Rep.*, Apr. 2016.

[28] R. Liu, A. K. Srivastava, D. E. Bakken, A. Askerman, and P. Panciatici, Decentralized state estimation and remedial control action for minimum wind curtailment using distributed computing platform, *IEEE Transactions on Industry Applications, 53*(6), 2017, 5915–5926.

[29] P. Kundu and A. K. Pradhan, Enhanced Protection Security Using the System Integrity Protection Scheme (SIPS), *IEEE Transactions on Power Delivery, 31*(1), 2016, 228–235.

[30] T. Weckesser, H. Jóhannsson, and J. Østergaard, Real-time remedial action against aperiodic small signal rotor angle instability, *IEEE Transactions on Power Systems, 31*(1), 2016, 387–396.

[31] M. Derafshian Maram and N. Amjady, Event-based remedial action scheme against supercomponent contingencies to avert frequency and voltage instabilities, *IET Generation, Transmission & Distribution, 8*(9), 2014, 1591–1603. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2013.0780

[32] U. Rudez and R. Mihalic, WAMS-based underfrequency load shedding with short-term frequency prediction, *IEEE Transactions on Power Delivery, 31*(4), 2016, 1912–1920.

[33] T. Shekari, A. Gholami, F. Aminifar, and M. Sanaye-Pasand, An adaptive wide-area load shedding scheme incorporating power system real-time limitations, *IEEE Systems Journal, 12*(1), 2018, 759–767.

[34] Y. Zhou, H. Huang, Z. Xu, W. Hua, F. Yang, and S. Liu, Wide-area measurement system-based transient excitation boosting control to improve power system transient stability, *IET Generation, Transmission & Distribution, 9*, 2015, 845–854.

[35] J. Gou, Y. Liu, J. Liu, G.A. Taylor, and M.M. Alamuti, Novel pair-wise relative energy function for transient stability analysis and real-time emergency control, *IET Generation, Transmission & Distribution, 11*(18), 2017, 4565–4575. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2016.1671

[36] Z. Liu, Z. Chen, H. Sun, and Y. Hu, Multiagent system-based wide-area protection and control scheme against cascading events, *IEEE Transactions on Power Delivery, 30*(4), 2015, 1651–1662.

[37] N. Liu and P. Crossley, Assessing the risk of implementing system integrity protection schemes in a power system with significant wind integration, *IEEE Transactions on Power Delivery, 33*(2), 2018, 810–820.

[38] A.G. Phadke, Synchronized phasor measurements in power systems, *IEEE Computer Applications in Power, 6*(2), 1993, 10–15.
[39] S. Kumar, B. Tyagi, V. Kumar, and S. Chohan, Optimization of phasor measurement units placement under contingency using reliability of network components, *IEEE Transactions on Instrumentation and Measurement, 69*(12), 2020, 9893–9906.
[40] A. K. Sinha, R. Kumar, C. Saikia, S. Rudrapaul, and B. Saikia, "An optimal PMU placement technique for the topological observability of a part of the NER grid of India," *Proc. International Conference on Circuits, Power and Computing Technologies*, Nagercoil, 2013, 142–146.
[41] G. C. Patil and A. G. Thosar, Optimal placement of PMU for power system observability using integer programming, *Proc. International Conference on Innovative Research In Electrical Sciences* , Nagapattinam, 2017, 1–6.
[42] K. M. Hassanin, A. A. Abdelsalam, and A. Y. Abdelaziz, Optimal PMUs placement for full observability of electrical power systems using flower pollination algorithm, *Proc. IEEE International Conference on Smart Energy Grid Engineering*, Oshawa, ON, 2017, 20–25.
[43] Z. Lu, Z. Xu, Z. Shi, and H. Yan, State estimation of voltage phasors based on part of voltage and current phasors measurement, *Automation of Electric Power Systems, 24*, 2000, 42–44.
[44] W. S. Meyer and V. D. Albertson, Improved loss formula computation by optimally ordered elimination techniques, *IEEE Transactions on Power Apparatus and Systems, PAS-90*(1), 1971, 62–69.
[45] R. D. Zimmerman, C. E. Murillo- Sánchez, and R. J. Thomas, MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education, *IEEE Transactions on Power Systems, 26*(1), 2011, 12–19.
[46] MATLAB version 9.6.0.1072779 (R2019a), The MathWorks, Inc., Natick, MA, 2019.
[47] "MATLAB Optimization Toolbox," The MathWorks, Inc., Natick, MA, 2019.
[48] S. Mirjalili, Genetic algorithm, in *Evolutionary Algorithms and Neural Networks*, Cham, Switzerland: Springer, 2019, 43–55.
[49] S. Katoch, S.S. Chauhan, and V. Kumar, A review on genetic algorithm: past, present, and future, *Multimedia Tools and Applications,* 80(5), 2021, 8091–8126.

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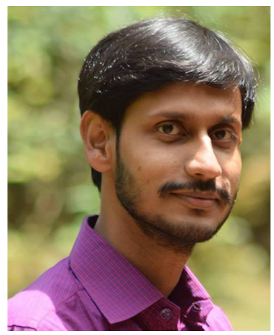

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