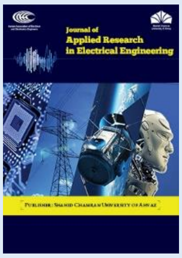
Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Assessing Power System Adequacy and Generation Expansion Planning in the Presence of Wind Power Plants Considering Uncertainties in the DIgSILENT Software Environment

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Abstract: Renewable energy sources are particularly important in clean energy transitions and must be considered in Generation Expansion Planning (GEP) problems due to low cost, ease of installation, and ability to implement Demand Response (DR) programs. However, challenges such as the stochastic nature of renewable energy sources, consumer unawareness regarding participation in DR programs, and difficulties in integrating some resources have posed challenges to the use of these resources in the GEP problem. This paper addresses these challenges by using the Weibull distribution function to model wind power plants' uncertainty and rewards and penalties to motivate consumer participation in the GEP problem. To achieve these objectives, initially, the adequacy assessment of the generation system is performed analytically using the reliability index, which includes Expected Energy Not Supplied (EENS), considering the forced outage rate of generators in the DIgSILENT power factory through Python programming. Subsequently, an optimized GEP model is presented to enhance the generation system's adequacy against short-term demand for the next year. In this model, wind farms and the DR program are integrated and optimized using the genetic algorithm, employing Python programming. The genetic algorithm selects the number of existing turbines in the wind power plant and the level of consumer participation needed to reduce the EENS to the desired value at the minimum cost. Validation of the proposed model is conducted on a 9-bus network. The strength of the presented method lies in its applicability to real-world networks modeled in the DIgSILENT Power Factory.

Keywords: System adequacy assessment, generation expansion planning, wind power plant, uncertainty, demand response, reliability.

Article history
Received 14 February 2024; Revised 10 June 2024; Accepted 23 June 2024; Published online 23 October 2024.

How to cite this article
H. R. Safa, A. A. Ghadimi, and M. R. Miveh, "assessing power system adequacy and generation expansion planning in the presence of wind power plants considering uncertainties in the DIgSILENT software environment," *J. Appl. Res. Electr. Eng.*, vol. 3, no. 1, pp. 99-109, 2024. DOI: 10.22055/jaree.2024.46140.1109

1. Introduction

Electricity as one of the vital energy sources plays a significant role in meeting the daily needs of modern society and ensuring the future development of humanity. Given this issue, the generation segment of the power system must have sufficient capacity to meet the load demand at any given moment to ensure the reliability of the power system [1]. To achieve reliable generation for the demand sector, it is necessary to first assess the adequacy of the generation network to obtain information about its capability to meet the demand load for the desired horizon (e.g., short-term, such as the upcoming year). After obtaining sufficient information, a Generation Expansion Planning (GEP) model is employed to address production shortages [2]. In this regard, it is preferable to utilize renewable energy sources and/or demand response programs in the GEP model, as both are proposed solutions for environmental sustainability in the future [3, 4]. The deployment of renewable resources and demand response (DR) programs, due to their environmental benefits, lower costs, and rapid implementation capabilities in short-term horizons, is a highly suitable solution for balancing generation and consumption. However, it comes with challenges that require special attention. Failure to address or adequately model these challenges may result in additional costs or network outages [4, 5]. Regarding wind energy utilization, wind speed exhibits random and variable behavior. Additionally, people lack the necessary awareness to participate in the generation sector in DR programs. Therefore, the use of these resources in generation development planning faces challenges that must be addressed with appropriate methods [6-8].

Another challenge facing power system planners is the large-scale dimensions of power grids, which complicates the optimization of generation planning considering practical parameters and constraints. In such cases, simplifications are employed, and results are extracted [9]. If a method can be implemented on industrial software where the entire power grid at the national or regional level is fully modeled, more realistic results can be provided, thereby reducing future challenges and additional costs imposed on the network. The efficiency indices of power generation can be calculated using deterministic or probabilistic methods. As renewable energy sources and flexible load demand increase gradually, the priority has shifted from deterministic methods to probabilistic ones [10]. Probabilistic methods for assessing adequacy indices are divided into two main approaches: analytical methods and Monte Carlo simulation. Power system adequacy is determined based on the actual presence of power generation units when they are available and capable of generating electricity, as well as during failures or unplanned outages [11]. For adequacy evaluation, the analytical method, if conducted using precise and appropriate models, can provide accurate results with power generation adequacy indices. On the other hand, the Monte Carlo simulation method requires a large number of iterations to achieve more accurate results and typically demands significant computational time, especially when applied to large-scale systems [12]. Therefore, adequacy assessment and generation expansion planning are vital components of the energy infrastructure for modern society, and if not properly evaluated and planned, society will face serious challenges. In reliability assessment, the study of generation adequacy focuses on the system's ability to meet the requested load demand without considering the transmission line facilities and distribution system [13]. After evaluating the adequacy of the network, any future shortages should be addressed through generation expansion planning. In reference [14], the optimization problem of generation expansion planning has been modeled using the General Algebraic Modeling System (GAMS). The GEP problem involves determining the optimal investment in the generation network with various objectives such as maximizing profits, minimizing production costs, reducing outage costs, and increasing the share of renewable energy resources [15]. In [16], a mathematical model is presented for the optimal measurement of energy storage in GEP for old systems with high penetration of renewable energies to increase production. Also in [17] wind turbine uncertainty and demand response are considered only for the transmission system and the production sector is not considered. Therefore, other suitable approaches can contribute to improving generation planning alongside the use of renewable sources to enhance short-term adequacy. These approaches not only reduce costs but also increase the flexibility in meeting the required load at any given moment. One of these solutions is peak load reduction, where Demand Response (DR) serves as a cost-effective resource, improving system adequacy [18, 19]. Furthermore, in [20], demand response (DR) programs and renewable energy sources have been utilized to enhance network resilience in coping with potential disruptions to input energy carriers, only on a daily basis (one or a few days ahead), optimal planning has been performed. However, in the development of production studies, planning should be done annually (short-term, medium-term, long-term). In [21], thermal generators with similar characteristics are clustered together using clustering techniques. Each cluster shares information among its members and exchanges power, enabling the improvement of power generation adequacy. Furthermore, in [22], energy shifting to periods with lower demand has been utilized to improve adequacy. To achieve this, battery systems are employed to store energy during low-demand periods using the Monte Carlo method.

Based on the above statements, the efforts made by others to improve efficiency indicate that these resources alone are insufficient in increasing efficiency. Therefore, this article simultaneously utilizes two key sources, namely wind power plants and a DR program. To address the stochastic nature of wind speed, the Weibull distribution function has been employed to model the uncertainty of wind power plants. In addition, in the DR program, tools such as rewards are used to encourage consumer participation to participate with the production sector in the proposed GEP model. This model integrates wind power plant and DR program by using a genetic algorithm. The genetic algorithm works in such a way that what percentage of the contribution amount that the consumer can have, along with how many of the existing turbines of the wind power plant, can be chosen so that the EENS is reduced to the desired amount with the minimum cost. The proposed GEP model provides the most optimal mode to the planners so that the planners can make the right decision to increase the network adequacy in the present and short term.

Furthermore, to ensure the practicality of the proposed method, the implementation approach of the proposed method on real-world networks modeled in the DIgSILENT software has been emphasized.

As can be seen in Table 1, past works in the GEP model have not fully evaluated the production adequacy and only renewable resources have been used. But in this article, in the first step, the network adequacy has been investigated. Due to the high importance of Demand Response (DR) due to its cost-effectiveness and zero environmental pollution, it has been added to the GEP model alongside wind power plants. Additionally, in this paper, Python software and DIgSILENT

Table 1: Summary of reviewed articles.

Reference	Adequacy assessment		Consider demand response	Generation Expansion Planning	
	EENS	Solution method		Using renewable energy source	Optimization method
[3]				*	MILP
[4]			*		
[11]	*	Analytical in Python			
[13]				*	MILP
[14]				*	MILP
[15]				*	Gurobi
[16]			*		
[17]	*				
[18]	*				
In this article	*	An Analytical with Python programming in DIgSILENT	*	*	GA

are linked to facilitate computational development. This capability is provided in any real industrial network.

The organization of this paper is as follows: In Section 2, the research methodology is introduced. Section 3 describes the results and simulations. Section 4 discusses the conclusions.

In summary, the innovations and contributions of this paper are as follows:

1- This article evaluates generation adequacy using analytical methods with Python programming in DIgSILENT.

2- Simultaneous use of wind power plant and load response programs to implement the generation expansion planning (GEP) to improve the adequacy of the generation system in the short term.

3- The use of genetic algorithms in GEP.

2. Methodology

In this section, the formulation of indices for evaluating adequacy, uncertainty, and wind power generation capacity, as well as the development planning of the power plant, is presented.

2.1. Modeling the Adequacy Evaluation Index

In [21, 23], the reliability index (EENS), which is used to assess the adequacy of generation, has been examined.

2.1.1. Expected energy not supplied (EENS)

This index indicates the amount of energy that is not supplied by the electricity generation system in the event of a power outage. Energy non-supply can lead to significant damages and losses for customers and even society as a whole. The formula for calculating this index is based on the total expected energy that is not supplied under specific conditions and the probability of occurrence of these conditions, along with the unit of energy measurement and the number of specific conditions. By using this index, the amount of lost energy and the damages associated with power outages can be estimated and analyzed.

$$EENS = T * \sum_{i \in S} c_i p_i \quad (1)$$

In (1), c_i represents the capacity that has a probability p_i of not being met within the time period *T*.

2.2. Wind Power Plant Model

2.2.1. Considering the uncertainty of the wind power plant with the Weibull distribution function

The Weibull distribution is utilized to study and analyze wind characteristics at wind sites. This distribution is well-suited to the wind speed distribution under specific conditions. Therefore, by using the Weibull distribution, the wind power generation at wind sites can be estimated, and wind characteristics can be investigated. The probability density function (PDF) of this distribution is as follows [24, 25].

$$f_v(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \quad (2)$$

In (2), *k* represents the shape parameter, and *c* represents the scale parameter.

2.2.2. The relationship between the output power of the wind power plant and the wind speed

The relationship between the power output of wind turbines and wind speed is depicted in Fig. 1. The mathematical equation can be expressed as follows [26, 27].

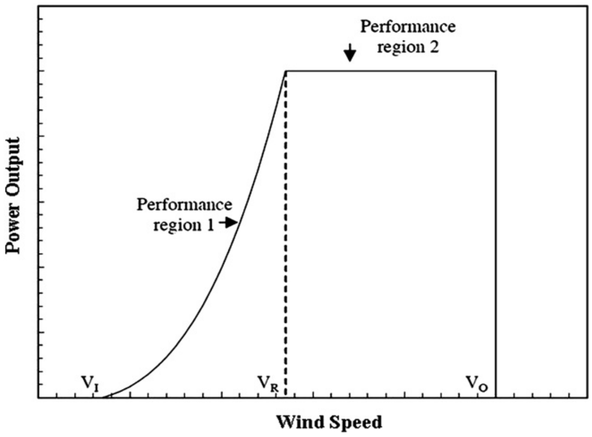

Fig. 1: Power curve vs. wind speed curve showing the overall cost of wind turbines in a wind farm per year.

$$P_T=\begin{cases} 0 & 0 \le V \le V_I \\ (A + BV + CV^2) * P_R & V_I \le V \le V_R \\ P_R & V_R \le V \le V_O \\ 0 & V \ge V_O \end{cases} \tag{3}$$

In (3), V represents the wind speed variable, V_I is the cut-in speed at which the wind turbine begins generating electricity, V_R is the rated speed at which the wind turbine produces maximum power, P_R is the rated power of the wind turbine, and V_O is the cut-out speed, beyond which the wind turbine stops and does not generate any power.

The constants A, B, and C are obtained using the following equations:

$$A = \frac{1}{(V_I-V_R)[V_I+V_R)-4(V_IV_R)(\frac{V_I+V_R}{2V_R})^3]} \tag{4}$$

$$B = \frac{1}{(V_I-V_R)^2}[4(V_I + V_R)(\frac{V_I+V_R}{2V_R})^3 - 3(V_I + V_R)] \tag{5}$$

$$C = \frac{1}{(V_I-V_R)^2}[2 - 4(\frac{V_I+V_R}{2V_R})^3] \tag{6}$$

2.3. Power Plant Development Planning

2.3.1. *Objective function*

The total cost (C_{total}), which is used as an objective function to reduce costs (wind turbine, expected energy not supplied, demand response), is expressed as the main objective as follows:

$$C_{total} = C_{wt} + C_{ENS} + C_{DR} \tag{7}$$

2.3.2. Cost Model for Wind Farm

To calculate the cost of wind turbines in a wind farm, a cost model introduced in [28, 29] is employed. In [28], the model assumes that with an increase in the number of turbines (n_{wt}), the cost per year for the turbines decreases, and the maximum reduction reaches one-third of the turbine cost. ($Cost_y$) represents the cost of one wind turbine per year.

$$\mathrm{Cost}=n_{wt}\left(\frac{2}{3}+\frac{1}{3}\mathrm{e}^{-0.00174n_{wt}^2}\right) \tag{8}$$

$$\mathrm{Cost_{total}} = \mathrm{Cost_y} \times \mathrm{Cost} \tag{9}$$

2.3.3. Energy Not Served Cost

A generating unit may experience outage due to unforeseen failures, referred to as Forced Outage Rate (FOR). This rate represents the percentage of time that a generating unit is unavailable due to unexpected failures. Due to the forced outage rate of generating units and based on demand and available reserves, a portion of the energy demand may not be met. This portion is referred to as Energy Not Supplied (ENS). Its formula is as follows:

$$C_{ENS} = \sum_{t=1}^{T} Cost_{ENS_t} \times ENS_t \tag{10}$$

2.3.4. Demand Response Cost

In the demand response cost formula C_{DR} represent the amount of power that consumers can actively participate in demand response management. This amount is typically expressed as a percentage of the total consumed load. Here, DR_{level} indicates the amount of power that consumers can reduce in a participatory manner, up to 30% of their load or equivalently, the capacity that is saved through consumer participation in demand reduction.

In this context, $Cost_{DR}$ represents the cost per megawatt of reduced power that the electricity producer receives from consumers' participatory reduction. Therefore, the set of costs C_{DR} in this formula represents the expenses related to consumer participation in load management and power reduction.

$$C_{DR} = Cost_{DR} \times DR_{level} \times Load_{peak} \tag{11}$$

2.3.5. *The decision variable*

In this article, the decision variables in power plant development planning include the number of wind turbines (n_{wt}) and the level of consumer participation (DR_{Level}) in the power generation network.

2.3.6. *Constraints in the problem*

The power range of wind turbines (p_{wt}) and the demand response level (DR_{Level}) are constrained by (12) and (13), and the reliability model range in (14) is provided.

$$p_{wt} \le L \times Peak_{Load} \tag{12}$$

$$DR_{Level} \le n \times Peak_{Load} \tag{13}$$

$$EENS \le EENS_{max} \tag{14}$$

2.4. Proposed Methodology Flowchart

The generation of the GEP model's performance flowchart is depicted in Fig. 2. This model, informed by the adequacy assessment data, evaluates the system's capacity to meet the demanded load. Employing a genetic algorithm in Python, it strives to balance generation and demand in the short term (next year) by integrating wind energy and demand response programs.

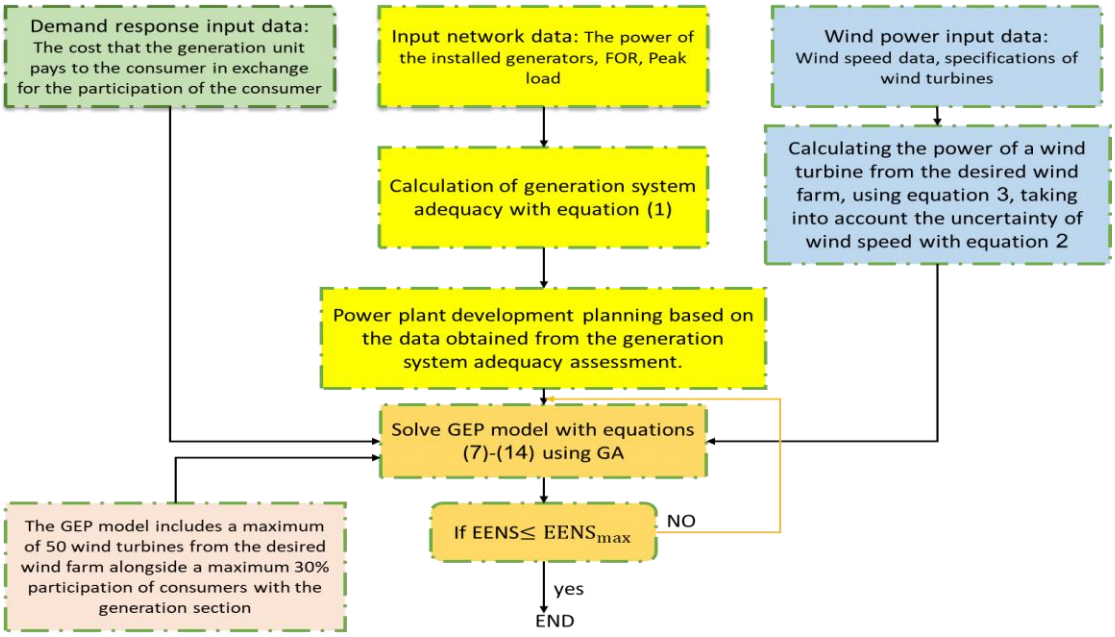

Fig. 2: Flowchart of the proposed GEP model.

3. Results and Simulation

In this section, the examination of the given data (including network type, generators, required software, and system specifications) and simulation for validating the proposed method have been addressed.

3.1. Introduction of Test Network and Production System Model

Using the analytical method, the adequacy of generation units has been evaluated under normal conditions (without forced outages) and based on their forced outage rates. Only generation units and loads are considered in the adequacy assessment, while transmission lines and distribution networks are not taken into account. In this paper, the IEEE 9-bus test system with a peak load of 900 megawatts (Fig. 3) has been utilized in DIgSILENT. The generators in the network under study are listed in Table 2.

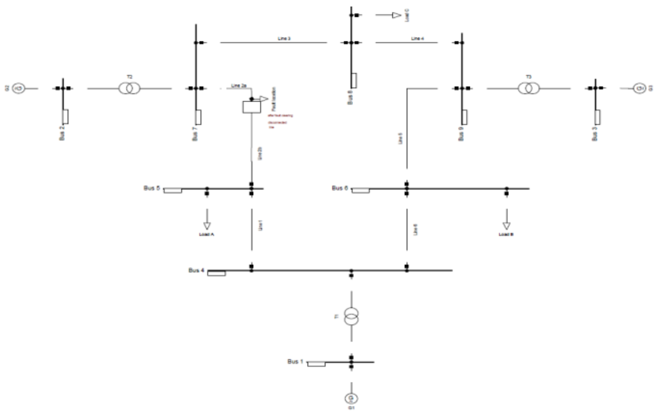

Fig. 3: The 9-bus test network model in DIgSILENT

Table 2: Generator specifications and their forced outage rates

Generating Unit	Generating Capacity (MW)	Forced Outage Rate (FOR)
G_1	202	0.04
G_2	200	0.02
G_3	250	0.01

3.2. Required Software and Systems

Simulations were conducted using Python in the system whose specifications are provided in Table 3 for the short term (one year).

3.3. Simulation Results Related to Adequacy

3.3.1. The value of Expected Energy Not Supplied (EENS)

The load duration curve consists of three parts (base, intermediate, and peak load), as shown in Fig. 4, where all power plants are online but the generation network still has a shortfall of 248 megawatts. The unmet energy is examined in Table 4 for both cases of no generator outages and individual generator outages.

$$ENS = t \times \frac{1}{2}(Load_{Peak} - Power_{level}) = 47.310769$$

$$EENS = ENS * q_1 q_2 q_3 = 44.06487198 \text{ (MWh/Year)}$$

Table 3: System specifications

System Model	P553UJ
Processor	Intel(R) Core (TM) i5-6198DU CPU@ 2.30GHZ (4CPUS), ~2.4GHZ
Memory	819MB RAM

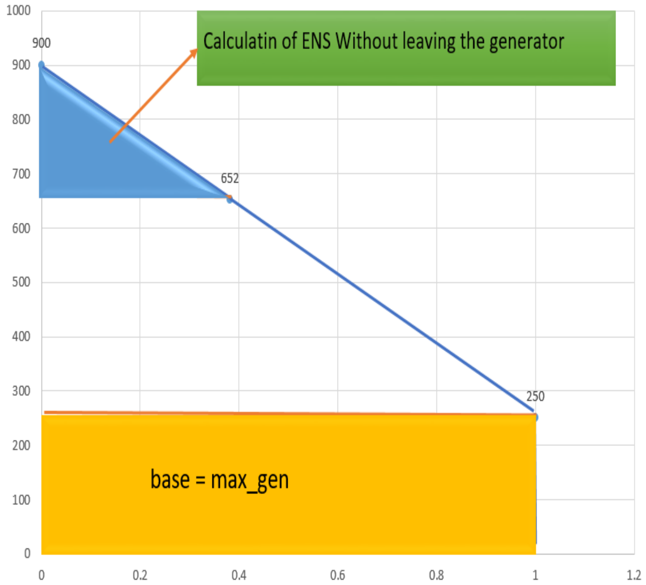

Fig. 4: Load continuity curve in terms of perionite.

Table 4: Results of expected energy not served for the initial network.

Out of capacity (c_i) in MW	Probability (p_i)	t_i	$\text{EENS}_i = t_i * \sum_{i \in S} c_i p_i$
0	$0.96\times 0.98 \times 0.99 = 0.931392$	0.38153546	44.0648719754
202	$0.04 \times 0.98 \times 0.99 = 0.038808$	0.69230769	5.427143327
200	$0.96\times 0.02 \times 0.99 = 0.019008$	0.68923076	2.620179657
250	$0.96\times 0.98 \times 0.01 = 9.408 \times 10^{-3}$	0.76615384	1.801993832
			$\sum \text{EENS}_i = 54.8393514092$

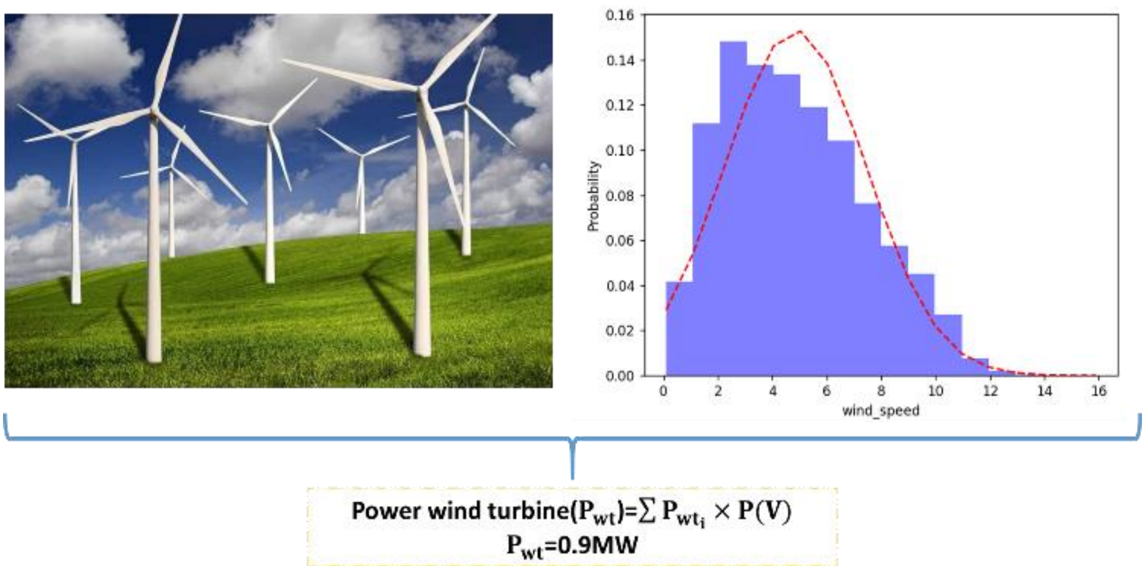

Fig. 5: Average annual power of each wind turbine considering wind speed uncertainty.

3.4. Results of the Wind Power Plant

Wind speed data has been collected by a meteorological station. Considering the specifications of the wind turbine provided in Table 5, the average annual power of each wind turbine (p_{wt}) has been obtained, taking into account the uncertainty of wind speed with the Weibull distribution function as shown in Fig. 5. Its value is equal to 0.9 MW.

3.5. Data Related to the Generation Development

In this section Table 6, the information regarding the wind turbine, including the wind turbine investment cost ($Cost_y$), energy not served cost ($Cost_{ENS_t}$), demand response ($Cost_{DR}$), is provided.

3.6. Simulation Results

Simulation in a 9-node network, as depicted in Fig. 3, has been conducted as follows:

First, the network adequacy in the current state is evaluated in scenarios with and without the generator's exit. Based on this evaluation, the Expected Energy Not Supplied (EENS) is determined. Therefore, after gathering information about the current state of the network, necessary measures have been taken to improve and enhance the network adequacy in the current and short-term periods. These actions have been carried out using the proposed GEP model, as shown in Fig. 2. The model integrates wind power plant and Demand Response (DR) program using the genetic algorithm. The genetic algorithm considers two factors: firstly, Table 6 which includes three costs (the reward cost given to consumers for participation, the installation cost of each wind turbine, and the cost of unsupplied energy); and secondly, the maximum participation power of the consumer, which is 83% higher than the total participation power of wind turbines. In the proposed GEP model, the genetic algorithm operates by determining what percentage of consumer participation, along with how many of the existing wind turbines in the wind power plant, should be selected to reduce the EENS to the desired level with minimum cost. The results in Table 7 show information about various scenarios of consumer participation along with the participation of wind turbines, along with the costs associated with these scenarios. And the reduced EENS values resulting from these participations are displayed in Table 8. In Table 8, the first column indicates the number of generator outputs, where column A represents the amount of power shortage in the current network state without generator outputs, and G_1 to G_2 are the generators removed from the network. The EENS results in Table 8 are presented under two conditions. $EENS_1$ to $EENS_9$ correspond to participation scenarios, and $EENS_{10}$ represents the scenario without participation. In the power generation system, the baseline load is set equal to the capacity of the generator that exceeds that of the other generators. In this regard, the maximum total participation of consumers and wind power plant is set to be greater than or equal to the capacity of the fixed generator G_3, which produces more power compared to generators G_1 and G_2 ($P_{gen_{max}} \leq P_{maximum\ contribution}$). In Table 7, the total power of participations corresponding to scenarios 1 to 5 fails to meet this condition. The results in Table 8 ($EENS_1$ to $EENS_5$) indicate that, considering the participation limits set in scenarios 1 to 5, the combination of maximum consumer participation along with wind turbines by the genetic algorithm within this range does not satisfy the condition ($EENS_i \leq 4$ MWh). However, the total power of participations corresponding to scenarios 6 to 9 satisfies the condition ($P_{gen_{max}} \leq P_{maximum\ contribution}$). The results in Table 8 ($EENS_6$ to $EENS_9$) indicate that, considering the participation limits set in scenarios 6 to 9, the combination of consumer participation with wind turbine participation by the genetic algorithm within these ranges satisfies the condition ($EENS_i \leq 4$ MWh). The costs associated with these participations in Fig. 7 indicate that they are higher compared to the EENS cost in a year without participation. To ensure that participation in the production sector is profitable, considering that the consumer participation cost is significantly higher compared to the wind turbines, it has been reduced by 42.5%. Based on the new cost for consumer participation, Table 9 re-evaluates the participation scenarios corresponding to scenarios 6 to 9 that satisfy the condition ($EENS_i \leq 4MWh$). The proposed model selects the best participation mode for each constraint based on their participation scenarios with the minimum cost, and Table 10 displays the EENS values related to the new participations where the condition ($EENS_i \leq 4MWh$) is satisfied. In Table 9, the participation range (n=46, i=23) determined by the proposed GEP model is the optimal mode. Considering the newly obtained EENS values (shown in Fig. 6 and Table 10), it can be observed that the condition (3.91MWh $\leq$ 4MWh) is satisfied with the minimum cost within this range. In scenario 2, power production is more profitable compared to other scenarios in Table 9. The costs of all scenarios are compared in Fig. 7.

Table 5 : Wind turbine specifications.

Technical specifications of the 2-megawatt Samen (AV928) wind turbines under license of the Avantis Energy Germany.	
Startup speed	3m/s
Rated speed	9m/s
Cut-off speed	20m/s

Table 6: Costs (wind turbine, EENS, and demand response)

$\boldsymbol{Cost_y}$	1624000 ($/MW)/25
$\boldsymbol{Cost_{ENS_t}}$	5.5*1000*8760 ($/MWh)
$\boldsymbol{Cost_{DR}}$	2*1000*8760 ($/MWh)

Table 7 : Comparison table of the results of the participation of the number of wind turbines next to the participation of the consumer, considering the total costs for improving the adequacy of the electricity generation system

Scenario	$P_{gen_{max}}$(MW) $P_{gen_{max}}$(MW) $\leq P_{maximum\ contribution}$	$P_{maximum\ contribution}$(MW) $= (n\times P_{wt}) + (DR_{level_i} \times Load_{peak})$ Acc. to (12) and (13)	The maximum number of turbines (n) and the maximum load participation percentage (i)	Total cost	Number of wind turbines	Consumer participation percentage
1	250	9+90=99	n = 10 i = 10%	2878713513	10	10
2		27+90=117	n = 30 i = 10%	2711209422	30	10
3		18+180=198	n = 20 i = 20%	3541154965	20	20
4		27+180=207	n = 30 i = 20%	3498372560	30	20
5		45+180=225	n = 50 i = 20%	3426020585	50	20
6		27+270=297	n = 30 i = 30%	4041727163	29	24.4
7		45+270=315	n = 50 i = 30%	3933851414	47	23
8		9+270=279	n = 10 i = 30%	4294743428	9	26
9		18+270=288	n=20 i=30%	4295942587	16	26.11

Table 8: EENS results considering wind turbines and demand response.

Generator exited	**Capacity outed (MW) = C_i**	$EENS_1$	$EENS_2$	$EENS_3$	$EENS_4$	$EENS_5$	$EENS_6$	$EENS_7$	$EENS_8$	$EENS_9$	$EENS_{10}$ (MWh) $= t_i * \sum_{i\in S} c_i p_i$	$EENS_i \leq EENS_{max}$
A	A (No exit gen)=248	19.14	16.06	2.92	2.22	1.08	0.056	0	0.0002	0.0016	44.064	
A,G_1	G_1=202	23.51	20.18	5.70	4.88	3.52	2.12	1.96	1.97	1.98	50.109	
A,G_1, G_2	G_2=200	25.62	22.18	7.04	6.17	4.70	3.12	2.9	2.92	2.94	53.044	
A,G_1, G_2, G_3	G_3=250	26.99	23.48	7.99	7.09	5.56	3.88	3.63	3.65	3.67	54.839	$EENS_i \leq 4$MWh

Table 9: Comparison table of the results of the participation of the number of wind turbines next to the participation of the consumer, considering the total costs for improving the adequacy of the electricity generation system (Based on the new cost of consumer participation).

Scenario	$P_{gen_{max}}$(MW) $P_{gen_{max}}$(MW) $\leq P_{maximum\ contribution}$	$P_{maximum\ contribution}$(MW) $= (n\times P_{wt}) + (DR_{level_i} \times Load_{peak})$ Acc. to (12) and (13)	The maximum number of turbines (n) and the maximum load participation percentage (i)	total cost	Number of wind turbines	Consumer participation percentage
1	250	27+270=297	n = 30 i = 30%	2486809821	29	25.4
2		45+270=315	n = 50 i = 30%	2279302873	46	23
3		9+270=279	n = 10 i = 30%	2551641219	9	26
4		18+270=288	n=20 i=30%	2573663747	18	26

Table 10: EENS results considering wind turbines and demand response (Based on the new cost of consumer participation).

Generator exited	Capacity outed (MW) = C_i	$EENS_1$	$EENS_2$	$EENS_3$	$EENS_4$	$EENS_5$ (MWh) $= t_i * \sum_{i \in S} c_i p_i$	$EENS_i \leq EENS_{max}$
A	A (No exit gen)=248	0.0	0.06	0.05	0.0	44.064	
A,G_1	G_1=202	1.93	2.15	2.13	1.92	50.109	
A,G_1, G_2	G_2=200	2.86	3.15	3.13	2.84	53.044	
A,G_1, G_2, G_3	G_3=250	3.58	3.91	3.89	3.56	54.839	$EENS_i \leq$ 4MWh

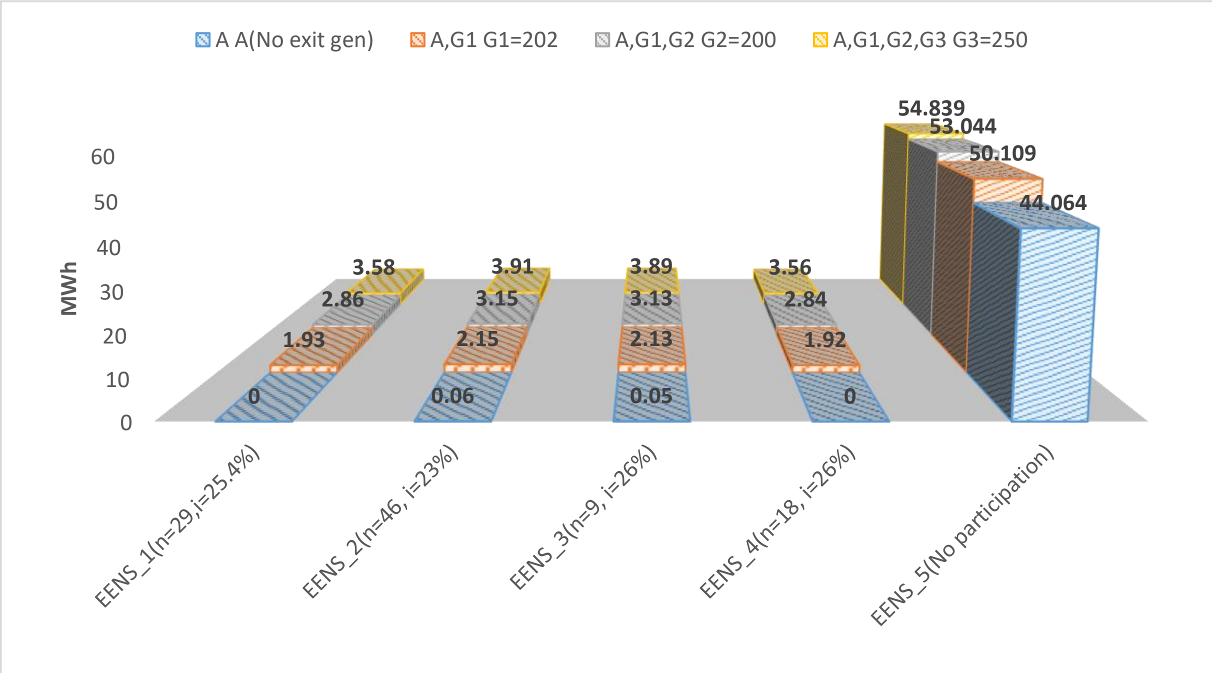

Fig. 6: EENS results for different modes (Based on the new cost of consumer participation).

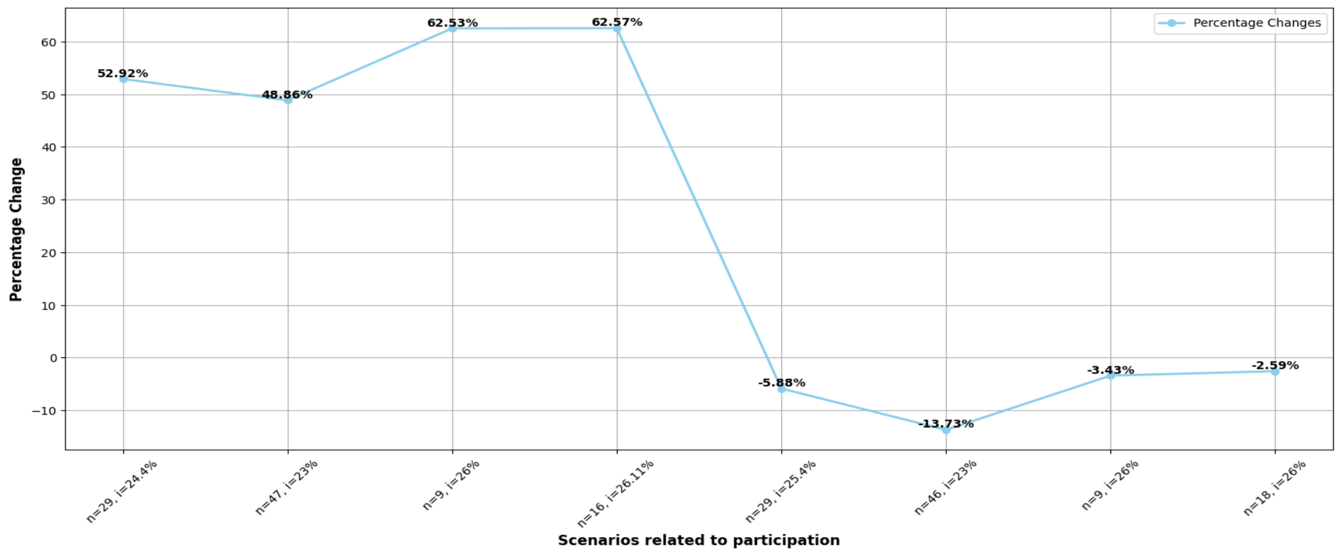

Fig. 7: Comparing the results of the participation costs of the proposed GEP model with the EENS cost in the non-participation mode in a year.

4. Conclusions

In this article, a proposed GEP model has been utilized to enhance network adequacy in the current and short-term periods. Therefore, in this regard, considering Table 6 where the consumer participation cost exceeds the wind turbine installation cost, and furthermore, the maximum power of consumer participation exceeds the total power of wind turbines in the wind power plant by 83%, the results should favor maximal wind turbine participation, given their lower costs, compared to maximal consumer participation. The impact of these higher costs and increased consumer power can be observed in Tables 7 and 8. where scenarios of participation that meet the condition ($EENS_i$ ≤4MWh) are depicted, however, the costs in these participations, as shown in Fig. 7, are high. In order to ensure profitability in the production sector, the consumer participation cost has been reduced by 42.5%. The results obtained in Tables 9 and 10 indicate that the condition ($EENS_i$ ≤ 4 MWh) has been met, as shown in Fig. 6. The associated costs are shown in Fig. 7, which demonstrate a reduction compared to the EENS cost in a year without participation. The optimal participation mode, as determined by the proposed GEP model while considering the condition ($EENS_i$ ≤ 4MWh) with minimum cost within the range (*n*=46, *i*=23%), results in a 13.73% reduction in participation cost compared to the EENS cost in a year without participation.

Credit Authorship Contribution Statement

Hamid Reza Safa: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing - original draft. **Ali Asghar Ghadimi**: Conceptualization, Investigation, Project administration, Supervision, Validation, Writing - review & editing. **Mohammad Reza Miveh**: Conceptualization, Funding acquisition, Resources, Validation, Visualization, Writing – original draft.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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Biography

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