

Placement and Quantitating of FACTS Devices in a Power System Including the Wind Unit to Enhance System Parameters

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Abstract: One of the main concerns of network operators is the enhancement of system parameters; accordingly, a set of different means to this end are posed. However, the use of renewable energies such as the wind could increase the importance of the debate over sustainability and conditions of power system parameters. In this study, the condition of said parameters is examined by placing FACTS (Flexible Alternating Current Transmission System) devices in a 24-bus power system including a wind farm. Research data entailing information on the wind and the amount of consumption load per year are classified by using the K-means classification algorithm; then, the objective function is obtained according to the parameters intended for optimization. This function is optimized by using the Honey-bee mating optimization (HBMO) algorithm followed by obtaining the suitable place and amount for FACTS devices. The results showed that the examined parameters are optimized when using FACTS devices.

Keywords: FACTS devices; HBMO algorithm; K-Means algorithm; system's parameters

1 INTRODUCTION

One of the criteria of industrial countries is their extent of electric energy production. The amount of energy production and consumption is a suitable criterion to assess the welfare level. Subsequently, it is of substantial importance to provide stability and sustainability to the production of this type of energy. The sustainability of the power system and the voltage and reduction of costs are the most significant concerns of operators. A lack of attention to system parameters would impose considerable expenses on the network caused by network unsustainability, voltage collapse and large-scale blackouts in the network; unquestionably, putting an end to this situation is costly, requires time and may result in severe damages. A solution to this problem is to increase the production of the network, which is possible through building new production units, though it requires considerable costs. Another solution is to employ the methods of increasing the network capacity, which not only enhances network parameters, but also prevents spending significant costs on building new production units. In previous studies, FACTS devices were used to reduce system parameters. In [1], the power flow was controlled by using FACTS devices in a 9-bus system. In [2], voltage sustainability and the load-flow were improved. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were employed to increase the sustainability of the power system and to reduce losses [3]. Sustainability increase and production cost reductions were examined by using an innovative optimization algorithm in 9 and 39-bus test systems [4]. In [5], in order to decrease the system losses and improve the voltage profile, the test was performed on a 30-bus system. What is worth pointing out in previous studies is the fact that the majority of inquiries were focused on the optimization of one, or at most, two objectives, while the examined networks did not include wind units. Nonetheless, the network investigated in the present study is an IEEE standard 24-bus test system, intended for the optimization of several parameters simultaneously. The honey-bee mating

optimization algorithm could be considered as a general method of optimization based on the behavior of insects. In this study, the objective function which includes the parameters in question is optimized by using the HBMO method, the results of which would provide thorough information.

2 FACTS DEVICES

FACTS devices is capable of consistently controlling the load-flow, minimizing costs, increasing sustainability, altering the reactive power according to system requirements and increasing transferability. The modelling of FACTS devices is done as a series, parallel, or series-parallel. The FACTS devices used in this study are described in the following text.

2.1 SVC (Static VAR Compensator)

SVC is a compensator controlled by using a thyristor; it is a pioneering element in the area of FACTS controls which became prevalent in the late 1970s. SVC is placed in a circuit as parallels (Fig. 1).

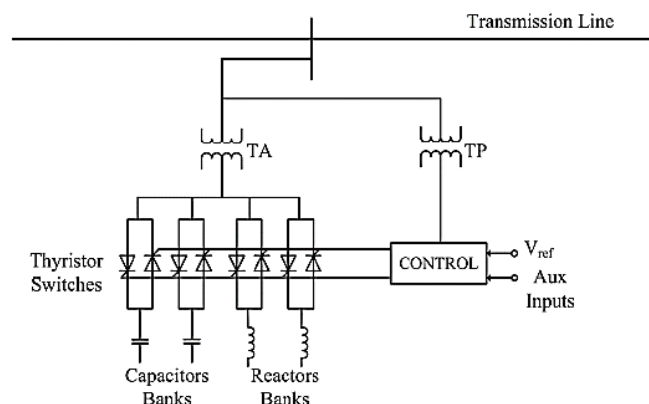


Figure 1 SVC with switchable capacitors with a thyristor and a reactor bank controlled by using a thyristor

2.2 TCSC (Thyristor Controlled Series Capacitor)

Placed in a series inside a circuit, this element offers numerous benefits for the power system. An overall schematic view of TCSC is shown in Fig. (2).

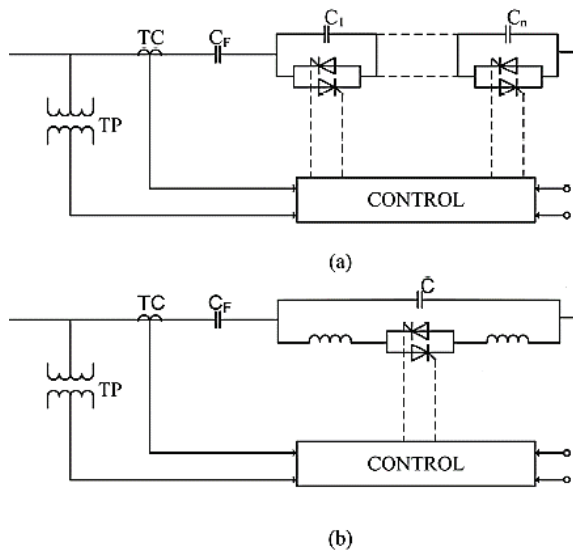


Figure 2 a) TCSC using capacitors controlled via a thyristor
b) TCSC using a capacitor parallel to the reactor controlled via a thyristor

In the first case, the compensator control in series is done separately through increasing or decreasing the number of connected capacitor banks; while in the second case, control is carried out continuously by changing the thyristor’s conduction time and as a result, the reactor flow. It is worth pointing out that a combination of models A and B offers better control and more flexibility [6].

2.3 UPFC (Unified Power Flow Controller)

There are two different type of the UPFC element; coupled model and decoupled model [7].

In the coupled model, UPFC is modeled through a serial connection with a voltage source and impedance on transmission line. In the coupled model, the Jacobian matrix should be formed which becomes much more complicated compared to the decoupled model. In the decoupled model (Fig. 3), the common load-flow algorithms can be implemented easily with no need for complex Jacobian matrices.

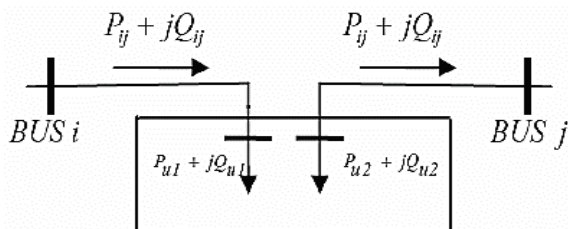


Figure 3 A decoupled UPFC model

3 WIND FARMS

Wind is a type of energy produced by the movement of air due to the heat produced by sunlight. According to meteorologists, almost 1% of the sun’s energy is converted to wind. Every day, 0.1% of the wind’s energy is converted into energy by humans; it means that only 0.01% of the sun’s energy is used. A wind turbine is a device that converts the wind’s energy into electric energy. A wind farm involves using a number of turbines together, which is cost-effective due to increased production capacity. Wind farms are modelled with respect to wind speed and the type of turbine. The wind speed model can be obtained through a variety of means such as using previous data on the time series of the distribution coefficient or Rayleigh’s model usage [8]. The direction of the output power wind turbine model is also important, as it would be proportionate to the wind speed, with a non-linear relation between them.

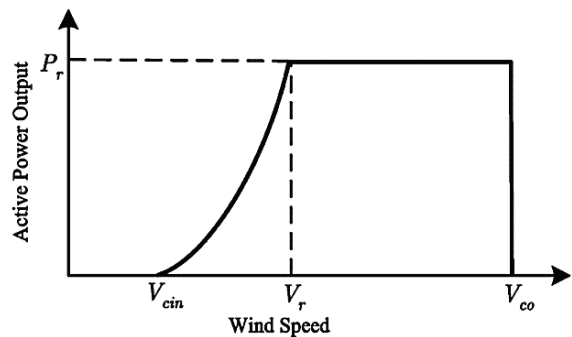


Figure 4 Power characteristic curve based on the speed of the wind turbine

The mathematical relation for the turbine’s power based on speed can be obtained by using the following:

Eq. (1) shows the turbine’s output power. Coefficients *A*, *B*, and *C* are determined by using turbine parameters.

$$P_w = \begin{cases} 0 & x < V_{cin} \\ P_r(A + Bx + Cx^2) & V_{cin} \leq x < V_r \\ P_r & V_r \leq x < V_{co} \\ 0 & x \geq V_{co} \end{cases} \quad (1)$$

4 OBJECTIVE FUNCTION

In order to obtain the objective function, the system parameters intended for optimization should be first selected. In this study, the parameters including cost minimization, increasing voltage sustainability and voltage profile are taken into account [6].

4.1 Production Cost

Production cost is expressed by using Eq. (2).

$$Cost P_G = ap^2 + bp + c \quad (2)$$

In these relations, a , b , and c are determined according to the type of production unit and its specifications.

The total cost is expressed in Eq. (3) as the sum of each of the unit's costs.

$$Cost P_G(Total) = \sum_{i=1}^N Cost P_G(i) \quad (3)$$

4.2 Loss Cost

To obtain the cost of losses, first the cost of a 1 MW loss is calculated and then multiplied by the number of losses according to the MW.

$$Cost loss^{(Total)} = Cost loss^{(1 MW)} \cdot P_{Loss} \quad (4)$$

4.3 Pollution Cost

A modern man is faced with many challenges, such as global warming and CO₂ emissions. Consequently, efforts in line with reducing environmental pollutions and CO₂ absorption are of paramount importance [7].

$$F_{CO_2}(Heat) = \xi P_G \Delta t \delta K_{CO_2} C_p \quad (5)$$

Posed as a penalty for air pollution, Eq. (5) is the penalty imposed on production units according to the extent of CO₂ emission and air pollution within the Δt time interval. In this relation, P_G is the output of the total production of units during the Δt time interval. ξ is the standard Carbon component. K_{CO_2} is the CO₂ oxygenation efficiency and C_p is the penalty factor related to Carbon emissions.

The sum of the total pollution costs of units is based on the Eq. (6).

$$Cost_{CO_2}^{(Total)} = \sum_{i=1}^M F_{CO_2}^{(i)} \quad (6)$$

4.4 Total System Cost

The total system cost is obtained by using the Eq. (7) which should be expressed per unit in the final function.

$$Cost T = Cost PG + Cost Loss + Cost CO_2 \quad (7)$$

4.5 Voltage Sustainability

The lambda parameter is used to examine voltage sustainability in the objective function. Voltage sustainability involves the voltage collapse threshold. In order to obtain voltage sustainability, the network's consumption power voltage is increased via the known coefficients until reaching the collapse threshold. The obtained point indicates the system's voltage collapse onset.

4.6 Voltage Profile of Buses

To calculate this parameter, the voltage for each bus is calculated per unit and then compared with its nominal value; then, its absolute value is calculated in all buses. Finally, the IVP (Indication of Voltage Profile) is obtained through the sum of all parameter values [9].

$$IVP = \sum_{i=1}^N |1 - V_i| \quad (8)$$

4.7 Fitness Function

The fitness function is formed according to the intended objectives.

$$\begin{aligned} Fitness Function = & a_1 \cdot Cost P_G^{(Total)} + \\ & + a_2 \cdot Cost Loss^{(Total)} + a_3 \cdot Cost_{CO_2}^{(Total)} + \\ & + a_4 \cdot \varphi \cdot \frac{1}{\Lambda} + a_5 \cdot IVP \end{aligned} \quad (9)$$

Weight coefficients including a_1 , a_2 , a_3 , a_4 , and a_5 are specified per each objective. The objective here is to minimize the fitness function.

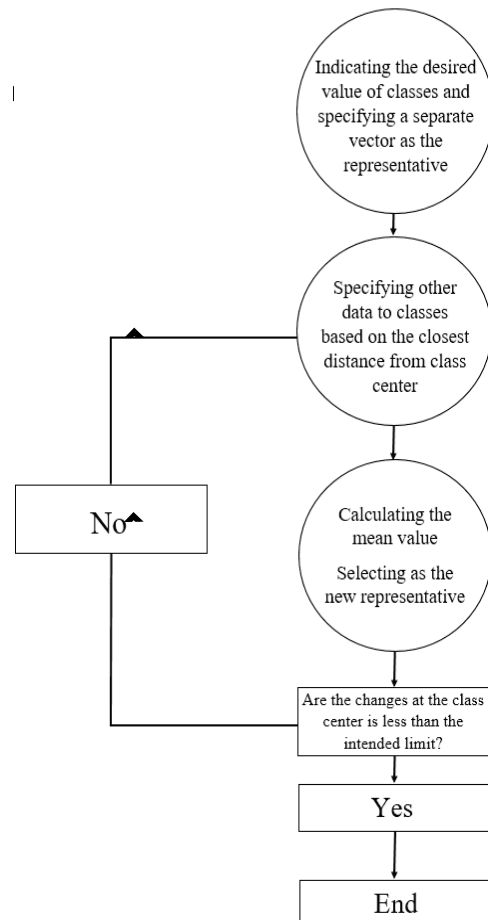


Figure 5 K-means classification performance chart

Minimizing the fitness function results in the minimization of costs and voltage profile; yet, since the intention here is to also maximize voltage sustainability, then a reversed voltage sustainability is considered in the fitness function; accordingly, a minimization of $1/\lambda$ results in an increase in λ , i.e. voltage sustainability.

5 K-MEANS CLASSIFICATION ALGORITHM

The data of the present study include wind shifts and winds during all hours in a year, amounting to 8760 data ($365 \times 24 = 8760$). Such number of data would add to the calculation volume. The K-means classification algorithm is used to reduce the data volume. To this end, the first K vector is selected as the representative; then, other data are classified based on the least distance from the center of classes. Next, the mean value is calculated and then selected as the new representative. When the changes at the center of the class are less than the intended limit, the classification process is finished. Otherwise, data are classified once more based on the least distance [10]. Fig. 5 shows the performance chart of the K-means classification.

6 SYSTEM DATA

Estimations are carried out based on the system data which include wind shifts and winds, both involving the consequential, random nature. In this study, a reliable regimen with respect to the consumption load and wind speed is obtained according to the pattern of previous years which can be seen in Tabs. (1), (2), and (3) and Fig. (6).

Table 1 Peak load percentage in each week of the year compared to the annual peak load

Week	Peak load	Week	Peak load
1	86.2	27	75.5
2	90.0	28	81.6
3	87.8	29	80.1
4	83.4	30	88.0
5	88.0	31	82.2
6	84.0	32	77.6
7	83.2	33	80.0
8	80.6	34	72.9
9	74.0	35	72.6
10	73.7	36	70.5
11	71.5	37	78.0
12	72.7	38	69.7
13	70.4	39	72.4
14	75.0	40	72.4
15	72.1	41	74.3
16	80.0	42	74.4
17	85.4	43	80.0
18	83.7	44	88.1
19	87.0	45	88.5
20	88.0	46	80.9
21	85.6	47	94.0
22	81.1	48	89.0
23	90.0	49	94.2
24	88.7	50	97.0
25	89.6	51	100.0
26	86.1	52	85.2

Table 2 Daily peak load percentage compared to the weekly peak load

Days	Peak load
Saturday	77
Sunday	75
Monday	92
Tuesday	100
Wednesday	98
Thursday	96
Friday	94

Table 3 Hourly peak load percentage compared to the daily peak load

Hour	Week of Winter		Summer		Spring/Autumn	
	Normal day	Holiday	Normal day	Holiday	Normal day	Holiday
12 - 1 am	67	78	64	74	63	75
1 - 2	63	72	60	70	62	73
2 - 3	60	68	58	66	60	69
3 - 4	53	66	56	65	56	66
4 - 5	53	64	56	64	59	65
5 - 6	60	65	58	62	65	65
6 - 7	74	66	64	62	72	68
7 - 8	86	70	76	66	85	74
8 - 9	95	80	87	81	95	83
9 - 10	96	88	95	86	99	89
10 - 11	96	90	99	91	100	92
11 - Noon	95	91	100	93	99	94
Noon - 1 pm	95	90	99	93	93	91
1 - 2	95	88	100	92	92	90
2 - 3	93	87	100	91	90	90
3 - 4	94	87	97	91	88	86
4 - 5	99	91	96	92	90	85
5 - 6	100	100	96	94	92	88
6 - 7	100	99	93	95	96	92
7 - 8	96	97	92	95	98	100
8 - 9	91	94	92	100	96	97
9 - 10	83	92	93	96	90	95
10 - 11	73	87	87	87	80	90
11 - 12	63	81	81	72	70	85

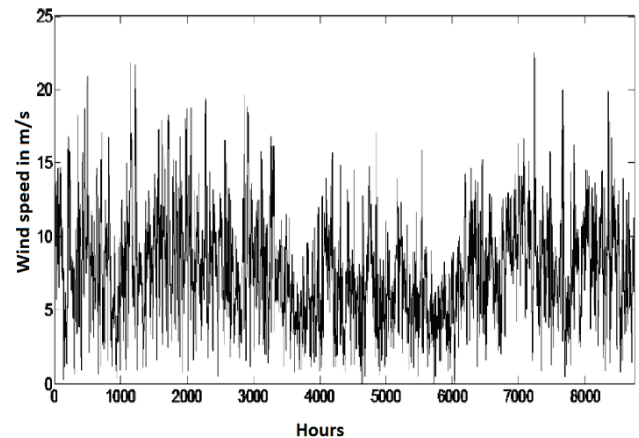


Figure 6 Wind speed model

6.1 Classification Data via the Algorithm

As it has previously been mentioned, there are 8760 data in this study intended for classification using the K-means. 8760 data are classified into 5 classes with specified class centers using the algorithm. It was assumed that the classes specified by the K-means algorithm were suitable representatives for other data, expressing the behavior of the entire data.

Table 4 double data bunch by the K-Means algorithm

Centre of group 1	(109.56, 1472.88)
Centre of group 2	(185.56, 1777.545)
Centre of group 3	(77.84, 2077.08)
Centre of group 4	(21.1, 1379.4)
Centre of group 5	(11.12, 2078.79)

6.2 Honey-Bee Mating Evolutionary Algorithm

One of the evolutionary algorithms is derived from the particular behavior of honey bees when mating. This algorithm was inspired by the special dance between the queen and male honey bees. The algorithm includes the queen, male bee, worker bee and newborns. The queen is the superior response while workers are search functions and newborns are experimental responses; worker bees are responsible for developing the newborn generation. If newborns are developed (experimental response), their superiority over the queen (the superior response) is replaced [12, 13].

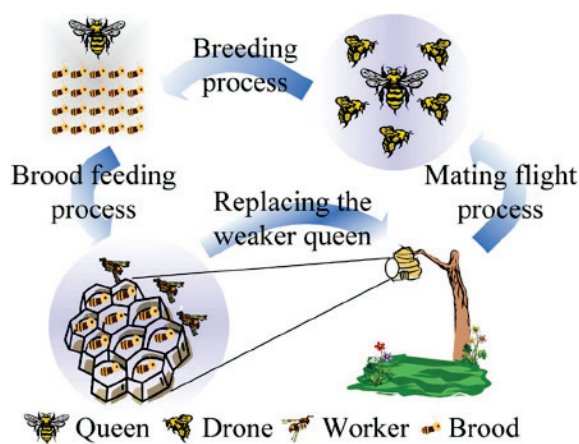


Figure 7 Modelling of HBMO (honey-bee mating optimization)

7 THE SYSTEM UNDER EXAMINATION

The system including 24-bus standard IEEE 38 transmission lines with an annual peak load of 2850 MW and maximum capacity of 3405 MW were installed in 17 buses of a wind farm system with a capacity of 200 MW which involves 100 turbines over 2 MW. The turbines' low and high cut-off speed and the nominal speed are 4 m/s (V_{cin}), 22 m/s (V_{co}), and 10 m/s (V_r), respectively.

7.1 Placement and Quantitating of SVC

When placing the SVC in 3-bus and producing a 100 MVAR Reactive Power, the fitness function will be minimized.

With an initial population of 30, the HBMO evolutionary algorithm reaches its minimum value at 0.933 per unit after 4 repetitions.

7.2 Placement and Quantitating of TCSC

In the bus 22 and the -52/63 MVAR Reactive Power, the fitness function falls to a minimum.

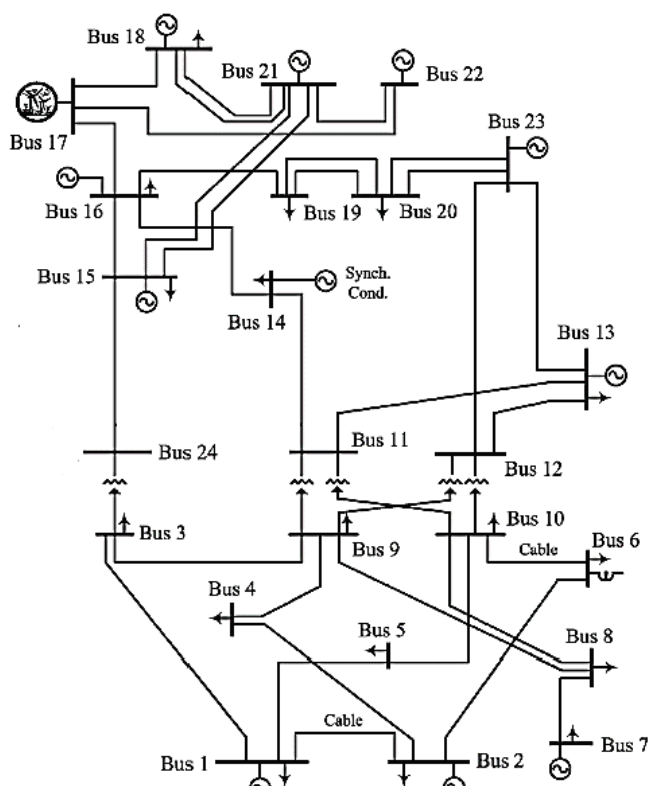


Figure 8 IEEE 24 buses

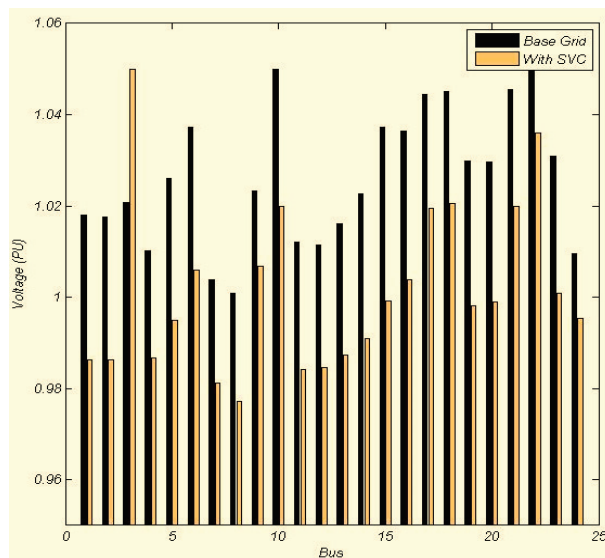


Figure 9 Bar chart on the voltage of buses in a IEEE 24-bus test network

Following 7 repetitions of the population of 30, the fitness function is reduced to its minimum number of 0.936 per unit.

7.3 Placement and Quantitating of UPFC

The fitness function is minimized in bus 17 and the reactive power of -70 MVAR (consumed reactive power).

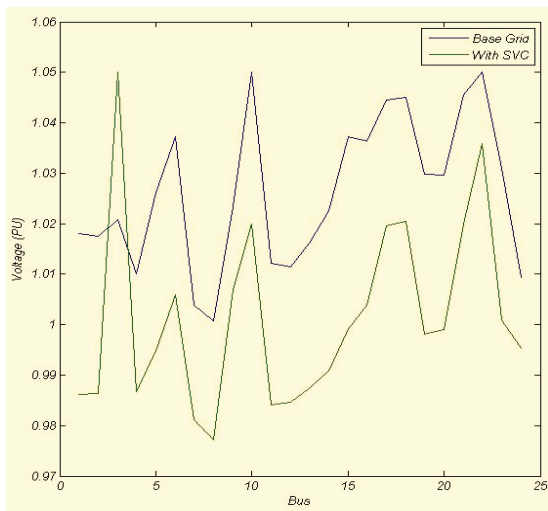


Figure 10 Continuous chart on the voltage of buses in a IEEE 24-bus test network

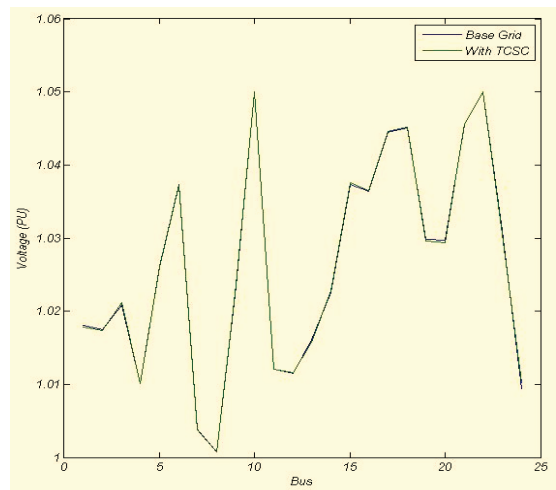


Figure 13 Continuous chart on the voltage of buses in a IEEE 24-bus test network

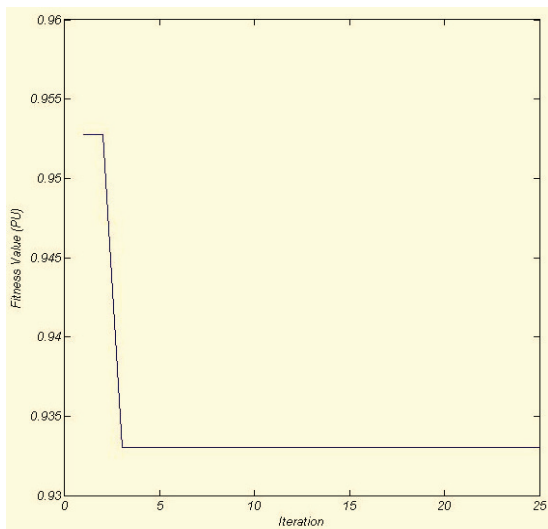


Figure 11 Fitness function chart according to the number of repetitions

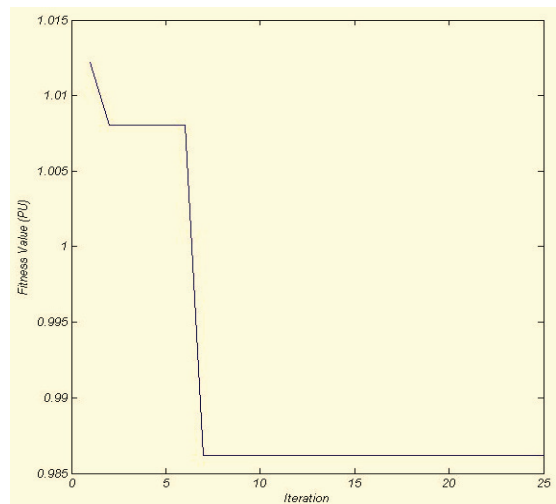


Figure 14 Fitness function chart based on the number of repetitions

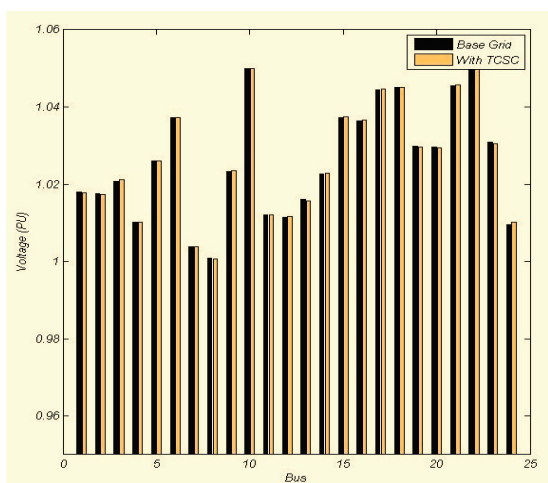


Figure 12 Bar chart on the voltage of buses in a IEEE 24-bus test network

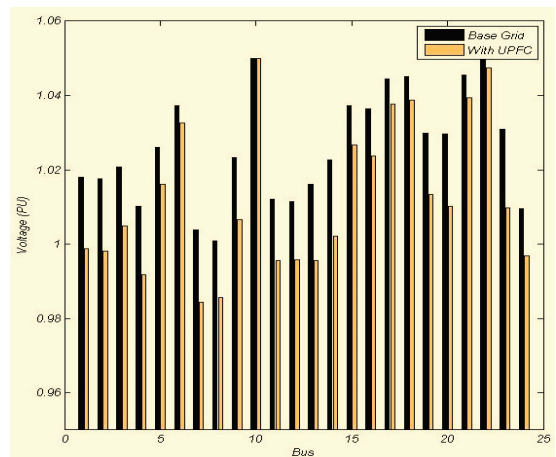


Figure 15 Bar chart on the voltage of buses in a IEEE 24-bus test network

Following 4 repetitions of the initial population of 30, the fitness function reaches its minimum number of 0.942 per unit.

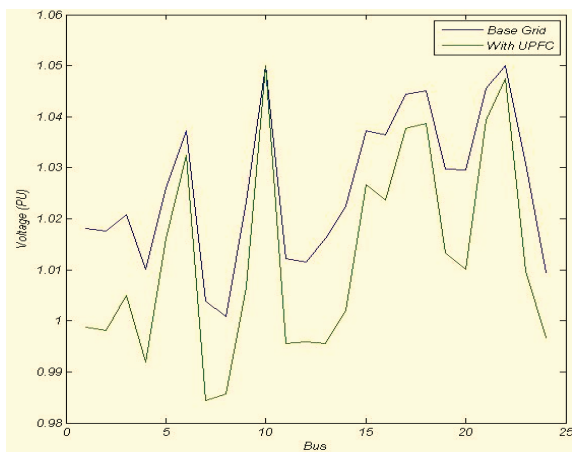


Figure 16 Continuous chart on the voltage of buses in a IEEE 24-bus test network

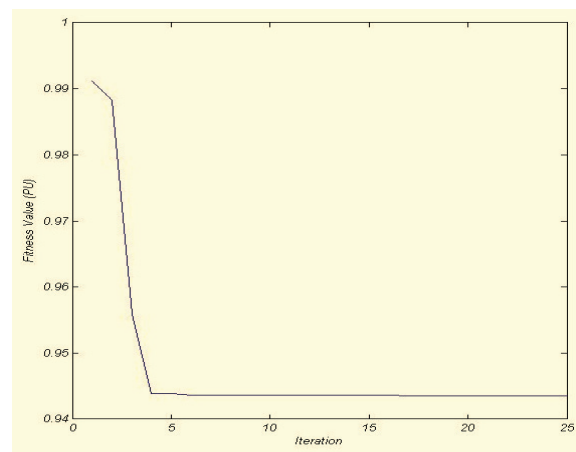


Figure 17 Fitness function chart based on the number of repetitions

Table 5 Comparison between parameter changes when applying different FACTS devices compared to the base mode.

Case	Cluster	Lambda	IVP	Cost CO 2 1.0e+004 *	Cost L 1.0e+003 *	Cost T 1.0e+005 *	Cost Facts
Base	1	1.2437	0.5431	4.1905	1.9988	0.8406	----
	2	1.3389	0.6652	4.9299	3.5377	0.9409	----
	3	1.2849	0.7322	6.2084	5.0168	1.1184	----
	4	1.1754	0.4860	4.1656	1.6763	0.8345	----
	5	1.2843	0.7395	6.4098	4.8207	1.1458	----
	mean	1.2655	0.9332	5.1808	3.4100	0.97606	----
SVC	1	1.2993	0.3852	4.1967	2.2024	0.9976	1013.7042
	2	1.5530	0.4045	4.9372	3.7783	1.0874	998.5123
	3	1.5994	0.5265	6.2142	5.2072	1.2381	1001.4415
	4	1.2160	0.4388	4.1713	1.8646	0.9917	991.3891
	5	1.5988	0.5113	6.4157	5.0175	1.2589	989.1147
	mean	1.4533	0.4532	5.1870	6.6140	1.1147	998.83236
TCSC	1	1.6930	0.5402	4.1910	2.0126	0.8970	173.1322
	2	1.5898	0.6685	4.9307	3.5642	0.9865	180.7538
	3	1.4329	0.7332	6.2099	5.0673	1.1384	193.7340
	4	1.7086	0.4812	4.1659	1.6868	0.8912	170.8361
	5	1.4319	0.7394	6.4114	4.8749	1.1592	195.4379
	mean	1.5712	0.6325	5.1818	3.4412	1.0144	182.7788
UPFC	1	1.2695	0.3789	4.1951	2.1485	0.8991	211.0130
	2	1.3693	0.4908	4.9344	3.6863	0.9884	202.1254
	3	1.3231	0.5497	6.2122	5.1433	1.1396	219.3256
	4	1.1999	0.3452	4.1700	1.8225	0.8934	201.9658
	5	1.3226	0.5560	6.4136	4.9479	1.1604	200.0556
	mean	1.2969	0.4641	5.1851	3.5497	1.0162	206.89706

8 CONCLUSION

The entire values of examined parameters at the base mode, SVC, TCSC, and UPFC are listed in Tab. 4. Given the Lambda or sustainability, the number of values in the base mode was 1.2655, which was increased to 1.4533, 1.5712, and 1.2969 after using SVC, TCSC, and UPFC, respectively. Figures show that the TCSC mode involved a better performance in enhancing voltage sustainability compared to the two previous modes. As it can be seen in Tab. 5 regarding the voltage profile (IVP), the value at the base mode was 0.9332 which was increased to 0.4532, 0.6325, and 0.4641 after using SVC, TCSC, and UPFC, respectively. Figures show that the SVC element had a better performance in line with enhancing the voltage profile parameter compared to the other two elements. It should be noted that the weight coefficients considered in the fitness function are a_1 , a_2 , a_3 , a_4 , and a_5 . Considering the importance of the voltage profile and sustainability, their coefficients include higher values compared to those of cost coefficients. Consequently, when

using FACTS devices, a more suitable and more tangible performance was observed with respect to the enhancement of these two parameters, while the performance was more insignificant regarding the costs. Another important point to mention is the cost of the FACTS devices themselves, which will definitely affect the total cost. The costs of each FACTS device are listed in the last row of the table. As a result, using Facts devices leads to improved system parameters such as sustainability and the voltage profile (IVP) and pollution. Depending on each of the Facts devices and the cost and plan that we have for the system, we can choose the best Facts devices.

The objectives set in the present study regarding system parameters were achieved. A number of studies can be conducted through increasing the power of the wind farm or by using multiple wind farms in the examined system. Furthermore, the use of other FACTS devices such as STATCOM would yield interesting results. Additionally, simultaneous use of several FACTS devices in the system

and the examination of results can be of great help to the operators when choosing the correct mode.

Nomenclature

P_w	Active power output, kW
V_{cin}	Cut-in speed, m/s
V_r	Rated speed, m/s
V_{co}	Cut-out speed, m/s
P_r	Rated power, kW
P_G	Production units
Δt	Time interval, sec
ξ	Standard Carbon component
K_{CO_2}	CO ₂ oxygenation efficiency
C_p	Penalty factor related to Carbon emissions.
F_{CO_2}	Penalty for air pollution
IVP	Indication of Voltage Profile
Λ	Voltage Sustainability

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