Reactive Power Control Using New Grey Wolf Optimizer Algorithm to Minimize Power System Loss

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Abstract: In this paper, optimization of reactive power flow of IEEE 6 bus standard system is used with parallel capacitors with the aim of minimizing the system active power losses. Generators voltage, status of transformers tap and switchable parallel capacitors banks are considered as variables of reactive power dispatch. The new Grey Wolf Optimizer algorithm is used to optimization of IEEE 6 bus standard system with the aim of the minimizing the system active power losses. The results showed that system losses after optimization is decreased 25%. It was determined that when the control and state variables of reactive power optimization problem are optimally determined with the aim of minimizing the system losses, all of the state and control variables are in their determined range. The simulation results showed that by optimal injecting the reactive power into system, the voltage profile at system buses is improved.

Key words: distribution network, reactive power optimization, losses, voltage profile, Grey Wolf Optimizer

1. Introduction

Optimization of reactive power flow improves the voltage profile and minimize the active power losses [1]. Reactive power flow is controllable in a power system through generators voltage, transformers tap and switchable VAR resources [1]. Certain combinations of generators voltages, location of transformers tap and reactive power of capacitor banks can optimize the reactive power flow [1]. The reactive power optimization problem is a nonlinear combined optimization problem. Search space due to the large number of control variables is multidimensional. However, complexity of reactive power optimization is increased by increasing the size of the power system. Therefore, due to complexity of reactive power optimization, use of optimization algorithm is essential to solve the problem. In [1], the optimization algorithm based on biogeography (BBO) as a nonlinear multi-objective optimization problem is used to solve the optimal reactive power dispatch problem in power system. Minimizing the power losses and system buses voltage deviation are considered as the problem objective function. In [2], the genetic algorithm is used to determine the optimal values of required switchable fixed parallel capacitors to locate in a radial distribution network under the conditions of the load status variation and with the aim of losses reduction.

In [3], a method is presented to control the reactive power of capacitor bank using the changes in the reactance of the connecting reactor. In this method, the soft control of reactive power of capacitor banks can be guaranteed and leads to higher quality of power. In [4], the effect of distributed generation (DG) on the distribution system losses in medium voltage networks is studied. The purpose of this study was to minimize losses and operation cost. In [5], the multi-objective optimal reactive power dispatch problem solution is presented using the Teaching Learning Based Optimization algorithm to minimize the active power losses, voltage deviation and voltage stability indice. In [6], the Differential Evolutionary Algorithm (DEA) is proposed to solve the optimal reactive power dispatch problem and voltage control in power system. In [7], the reactive power distribution problem is presented with the aim of minimizing the lines active power losses and deviations of all buses voltages in range, using the improved genetic algorithm. In [8], genetic algorithm with local search is used to solve a multi-objective reactive power compensation problem. In [9], the reactive power distribution problem solution is proposed by considering the voltage stability using dynamic optimization problem. In [10], an approach is presented with the aim of reduction of the number of tap changes and tuning the capacitors in reactive power control in distribution networks. In this paper, the reactive power dispatch optimization of IEEE 6-bus standard system [11] is presented with the aim of minimizing the system active power losses using the parallel capacitors with the new optimization algorithm of Grey Wolf Optimizer (GWO).

In Section 2, reactive power control and its importance is presented. The problem formulation including the objective function and optimization constraints are presented in section 3 and the proposed optimization method of reactive power dispatch and its implementation is explained in section 4.

2. **Reactive Power Control in Power System**

Reactive power control is traditionally considered as an important factor in the design and operation of electrical power systems. Since the impedances of power system components are dominantly reactive, active power transmit requires phase angle difference between beginning and end of the line [1]. While, to transmit the reactive power, it is necessary that the amplitude of this voltages to be different. Not only most of the system components consume reactive power, but also most of electrical loads are reactive power consumer. Therefore, the consumed reactive power should be supplied from a location. If reactive power is not easily transferable, it must be produced where it is needed.

A fundamental and important relationship is between reactive and active power transfer so that active power transfer requires to voltage and phase displacement. However, the amount of voltage to the same extent is important. They not only have a high enough level to be able to support loads but it should be low enough which is not to defeat equipment insulation [3-4]. Therefore, voltages should be controlled at key points or support or restrictions should be applied upon them. This control can be widely by the generation or consumption of reactive power at key points. Today has at least two very important reasons. The first reason is due to the increasing pressure to operate the maximum possible from transmission systems. Second reason is that, a variety of controllable reactive compensators have been developed. In the year so far, in the growth trend of electrical power networks the synchronous condensers are used to support and improve the ability of power transfer. At the same time, in the distribution system, the parallel capacitors are used to improve the voltage profile and line loading reduction and the losses (with power factor correction) [11].

A part of reactive power is consumed by series elements of network such as reactance of lines and transformer. Hence, one of the direct ways of increasing transmission power in the transmission system and reduction of voltage drop in distribution system, is compensation of a part of series inductive reactance by capacitors. Despite the development of direct current transmission technology in many of these projects, alternating-current transmission is preferred. Stability and control problems of voltage is related to reactive power control problems and many solutions have been proposed that begins from parallel reactors and capacitors and continues until series capacitors, synchronous condensers and new static compensators [11]. Reactive power control is an essential tool in maintaining supply quality.

3. Problem Formulation

In this paper, the reactive power dispatch optimization of IEEE 6-bus standard system [11] is presented with the aim of minimizing the system active power losses using the parallel capacitors. Generators voltage, status of transformers tap and switchable parallel capacitors banks are considered as variables of reactive power dispatch. The new optimization algorithm of Grey Wolf Optimizer (GWO) is used to optimize the reactive power dispatch.

3.1 Problem Objective Function

In this study, minimizing the losses of IEEE 6-bus standard system is considered as the objective function of optimization problem [11].

$$F = \min P_{loss} \qquad (1)$$

Where P_{loss} is the system losses.

3.2 Problem Constraints

- Real power constraint

$$P_{Gi} - P_{Di} - V_i \sum_{j\neq 1} V_j (\mathrm{G}_{ij}\sin\theta_{ij} + \mathrm{B}_{ij}\sin\theta_{ij}) = 0 \qquad (2)$$

In the above equation, $i \in n$ expresses the number of buses apart from floating bus, P_{Gi} is the active power generated by bus i, P_{Di} is the load active power in bus i, θ_{ij} is the phase angle difference between bus i and j, G_{ij} is the mutual electrical conductivity between bus i and j, B_{ij} is the mutual susceptance between bus i and j, G_{ii} is the self-electrical conductivity between bus i and j and B_{ii} is the self susceptance between bus i and j.

- Reactive power constraint

$$Q_{Gi} - Q_{Di} - V_i \sum_{j\neq 1} V_j (\mathrm{G}_{ij}\sin\theta_{ij} - \mathrm{B}_{ij}\sin\theta_{ij}) = 0 \qquad (3)$$

Where Q_{Gi} is the reactive power generated in bus i and Q_{Di} is the load reactive power at bus i.

- Amplitude of buses voltage constraint

$$V_{i-\min} \le V_i \le V_{i-\max} \qquad (4)$$

- Generator Bus Reactive Power constraint

$$Q_{Gi-\min} \le Q_{Gi} \le Q_{Gi-\max} \qquad i \in \{\mathrm{N}_{pv}, \mathrm{N}_o\} \qquad (5)$$

Where $Q_{Gi-\min}, \mathrm{Q}_{Gi-\max}$ are the minimum and maximum limit of generator reactive power at bus i, N_{pv} is the number of PV buses and N_o is the floating bus.

- Reactive power capacity constraint

$$q_{ci-\min} \le q_{ci} \le q_{ci-\max} \qquad i \in \mathrm{N}_c \qquad (6)$$

Where q_{ci} reactive power is source at bus i and $q_{c-\min}, \mathrm{q}_{c-\max}$ are limits of reactive power source and N_c is the number of reactive power resources.

4. Proposed Optimization Method

Reactive power optimization problem is a nonlinear optimization problem and due to the large number of control variables has a multi-dimensional search space. Complexity of reactive power optimization is increased by increasing the size of the power system. Generators voltage, status of transformers tap and switchable parallel capacitors banks are considered as variables of reactive power dispatch. The new optimization algorithm of Grey Wolf Optimizer (GWO) is used to optimize the reactive power dispatch.

4.1. Grey Wolf Optimization Algorithm

Grey wolf optimization algorithm is presented for the first time in 2014 by Mr. Seyed Ali Mir Jalili [12].This algorithm has been established based on modeling the social behavior of the gray wolf and its prey mechanism. Then the algorithm is presented.

Gray wolf hunting techniques and social hierarchy in order to design and optimize GWO algorithm is modeled mathematically.

4.2 Mathematical Models and Algorithm

In order to mathematically model the social hierarchy of wolves when designing GWO, the best way to solve what we consider as the alpha, α (one female who are called alpha, group leader). Thus, the second and third best solution would be to beta, β (The second level in the hierarchy of gray wolves, advisor to Alpha and a disciplinarian to the group) and delta, δ (delta wolves should be submitted to the alpha and betas, but they must dominate the Omega). The rest of the solutions are assumed to Omega, ω (lowest ranking, omega plays the role of the scapegoat and should always submit to all other dominant wolves). In the GWO algorithm, hunt (optimization) is guided, with α, β and δ. The ω wolves follow the α, β and δ.

As mentioned above, Gray wolves surround the prey during hunting. The following equations are proposed for mathematical modeling of prey surround behavior [12]:

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \tag{7}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{8}$$

Where t represents the current iteration $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ is the position vector of the prey, and $\vec{X}$ shows the position vector of a grey wolf. The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows [12]:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{9}$$

$$\vec{C} = 2.\vec{r}_2 \tag{10}$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 during iterations and r_1, r_2 are random vectors in [0, 1]. To see the effect of Eq. (7) and (8), a two-dimensional position vector and some neighbors may have been shown in Figure 1-a. As seen in this figure, a gray wolf in the position of (X, Y) is able to update its position with respect to the position of prey (X^*, Y^*). Various places around the best operator can reach the current position, by setting the vectors $\vec{A}$ and $\vec{C}$. The possible updated position of a gray wolf in 3-dimensional space is shown in Figure 1-b. Note that the random vectors r_1 and r_2 to allow wolves to reach any position between points is shown in Figure 3. So a gray wolf can update his/her location in the space around the prey at any random location using Eqs. (7) and (8). The same concept can be extended to a search space of n dimensions and the grey wolves will move in hyper-cubes (or hyper-spheres) around the best solution obtained so far.

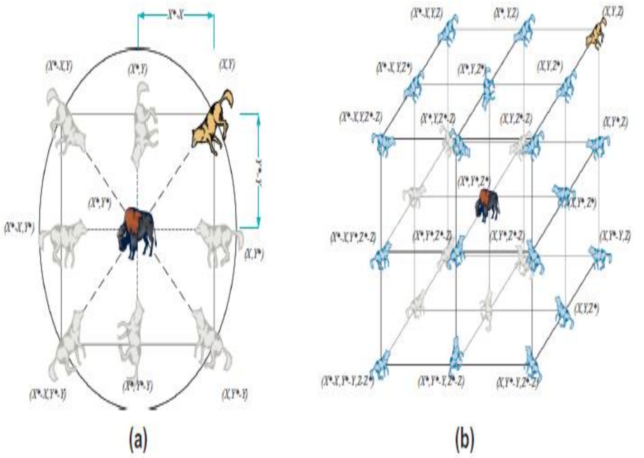

Fig. 1. 2 and 3 dimensional position vectors and their other possible locations [12]

Gray wolves are able to identify the location of prey, and surrounded them. Hunting is usually driven by alpha. Beta and Delta may also sometimes participate in the hunt. However, in an abstract space, we have no idea about the proper location (prey). In order to mathematically simulate hunting behavior of gray wolves, Suppose that alpha (best candidate), Beta and Delta have better knowledge about the location of potential prey. So we'll save three best solutions obtained so far for the first time. We force the other search factors (including Omega) to update their positions with respect to the position of the best search factors. The following formula has been proposed in this field [12]:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{11}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{12}$$

$$\vec{X}(t+1)=\frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \qquad (13)$$

Figure 2 shows how a search agent updates its position according to the alpha, beta and delta in a two-dimensional search space. It can be seen that the final position in a random location is inside a circle that is defined by the position of the alpha, beta, delta in the search space. In other words, alpha, beta, delta estimate prey position and other wolves are updating their positions randomly around the prey.

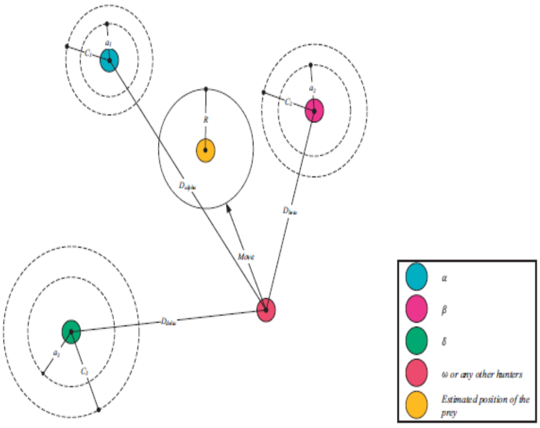

Fig. 2: Position Update in GWO [12]

As mentioned above, Gray wolves end the hunt by attacking prey when the prey stops moving. In order to mathematically modeling the approach to the prey, the amount $\vec{a}$ is decreased. Note that the oscillation amplitude $\vec{A}$ is reduced by $\vec{a}$ In other words, $\vec{A}$ is a random value between $[-2a,2a]$, which is a decrease from 2 to 0 during the iterations. When random values of $\vec{A}$ are in the interval [-1, 1], the next position of a search agent can be in any position between the current position and the position of the prey. Figure 3- a shows that $|A|\prec 1$ forcing the wolves to attack towards prey. With operators that have been proposed so far, the GWO algorithm allows that its search agents update its position based on the location of alpha, beta, and delta and attack toward prey. However, the GWO algorithm in local solutions with this operator is at risk of recession. It is true that the proposed surround mechanism shows some extent the exploration, But GWO requires more operators are to emphasize exploration.

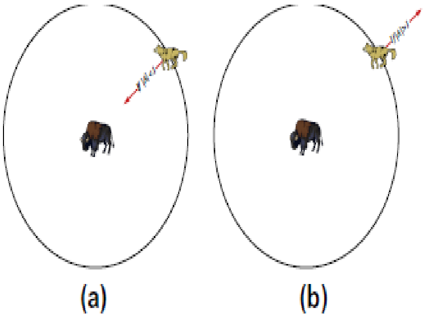

Fig. 3: Attack Prey in the Search for Prey [12]

The gray wolf searches mainly due to the position of alpha, beta, and delta. They are split and separated from each other, to search for prey and converge to attack prey. In order to model mathematically divergence, we will use $\vec{A}$ with random values greater than 1 or less than -1 to help the search agent, to split from prey. This emphasis on exploration and will allow that GWO algorithm to do an extensive search. Figure 3-b, also shows that $|A| > 1$ force gray wolves to diverge from prey that hopefully they find a prey. One other component of GWO, which is beneficial to explore is $\vec{C}$. As in Eq. (10) can be seen, $\vec{C}$ vector contains random values in [2, 0]. This component provides random weights for prey in order to stochastically emphasize (C > 1) or deemphasize (C < 1) the effect of prey in defining the distance in Eq. (7). This helps GWO to illustrate the random behavior throughout desire explore optimization and local optima avoidance. It should be noted here is that C compared with A does not decrease linearly. We need deliberately to C to provide random values at all times in order to emphasize exploration not only in the early iterations, but the final iterations. This component is very useful in case of recession, local optimization, especially in final iterations. Vector C can be also considered as an effective barrier to get closer to hunting in the wild. In general, barriers appear in nature in the course of hunting wolves and actually prevent them from approaching the prey is quick and easy. This is exactly what the vector C does. Depending on the position of a wolf, it can accidentally give weight to the prey and make it harder to get away from the wolves, or vice versa. To sum up, the search process starts by creating a random population of gray wolf (candidate solutions) in the GWO algorithm. During the course of the iterations, the wolves Alpha, Beta, Delta estimate the probable location of the prey. Each candidate solution updates its distance from the prey. Parameter a, is reduced from 2 to 0 in order to emphasize exploration and exploitation. Candidate solutions tend to diverge the prey if $\left|\vec{A}\right| \succ 1$ and Converge to the prey if $\left|\vec{A}\right| \prec 1$. Finally, the GWO algorithm is terminated by satisfying of a final criterion.

4.3 Implementation of GWO in Problem Solution

The GWO steps in reactive power dispatch problem solution are considered as follows:

First step) Minimum and maximum values for the control variables and state variables are adjusted. First, the location of transformer tap is determined. Gray wolves select variables randomly.

2nd step) Counter starts repeating from 1 iteration and count each iteration.

3rd step) power flow constraints are confirmed.

4th step) power flow is run for each grey wolf. So the amount of active power losses or amount of objective function or the competence for the gray wolf is determined.

5th step) best position is updated for better competence amount of grey wolves.

6th step) after updating the all of best positions of grey wolves, the best the general position is also updated.

7th step) based on the best position of grey wolves, the best general position and random velocity of each particle is referred to a new position.

8th step) convergence qualifying condition is checked. If satisfied, the search process has been stopped and the results will be shown, otherwise, the search for the next iteration, continues.

5. Simulation

5.1 Studied System

In this paper, optimization of reactive power flow of IEEE 6-bus standard system is used based on the Figure 4, with the aim of minimizing the system active power losses using the parallel capacitors [11]. Bus 1 is considered as the reference bus and bus 2 is a PV bus. While the buses 3, 5 and 6 are the load bus. The switchable parallel capacitor banks are on buses 4 and 6. The transformers are connected between buses 3-4 and 5-6. The load is connected at each bus. The information of IEEE 6-bus standard system including buses order, impedance of buses connecting branches and transformers tap are presented in TABLE I. Generators voltage, status of transformers tap and switchable parallel capacitors banks are considered as control variables of reactive power dispatch. The constraints of control variables are presented in TABLE II-IV. In the TABLE II, T_{65} expresses the transformer tap between bus 5 and 6 and T_{43} is the tap of transformer between buses 3 and 4. V_1 is the generator voltage at bus 1 and V_2 is the generator voltage at bus 2 in terms of per unit. Q_4 is the capacity amount of capacitor installed at bus 4 and Q_6 is the capacity of capacitor installed at bus 6 in terms of MVAR. State variables constraints are presented in TABLE III.
TABLE IV and V show the system initial state values and initial values of control variable. In this state, the losses of studied system based on the [11] is obtained equal to 11.61 MW.

5.2 Simulation Results

TABLE VI and VII show the simulation results of the studied system after optimization by GWO algorithm. The value of system losses after optimization is decreased from 11.61 MW to 8.7 MW (i.e. 25% reduction). The obtained results showed that all state variables and control variables are in their determined ranges.

According to TABLE IV and VI, it is clear that by injecting the reactive power into system, the system buses voltage are improved after optimization. So the reactive power dispatch optimization has improved the system voltage profile. In [11], the optimization of reactive power dispatch of IEEE 6-bus standard system is used by PSO algorithm with dynamic factors. The minimizing the system losses is considered as the objective function of optimization problem. The results obtained from proposed GWO method is compared with [11]. The obtained results showed that the system losses are significantly reduced after optimization of reactive power dispatch of IEEE 6 bus standard system using the GWO method and the GWO method as well as the PSO method with dynamic factors has the same results that proves the ability of proposed method

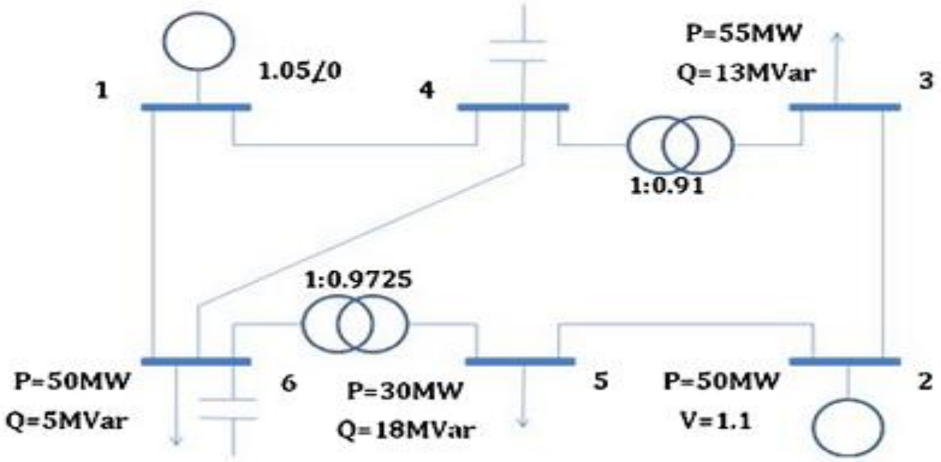

Fig. 4: The IEEE 6-bus standard system [11]

TABLE I: The information of IEEE 6-bus standard system [11]

Sending end	Receiving end	Impedance of Branch	Transformer tap
1	6	0.518 *J* + 0.23	
1	4	0.37 *J* + 0.08	
4	6	0.407 *J* + 0.097	
5	2	0.64 *J* + 0.282	
2	3	1.05 *J* + 0.723	
6	5	J0.3	1.025
4	3	J0.133	1.1

TABLE II: Control variables constraints [11]

	Transformet TAP	Generator Bus Voltage		VAR (MVAR)	
	T_{65} , T_{43}	V_1	V_2	Q_4	Q_6
Min	0.91	1	1.1	0	0
Max	1.11	1.1	1.15	5	5.5

TABLE III: State variables constraints [11]

	Bus Voltage *PQ*	*PVBus* (MVAR)
Min	0.9	-20
Max	1.1	100

TABLE IV: system initial state values and initial values of control variable [11]

Bus	(p.u)	voltage	(p.u)	load	(p.u)	Power supply
	V	θ	P_1	Q_1	P_G	Q_G
1	1.05	۰	0	0	0.966	0.381
2	1.1	-6.139	0	0	0.5	0.348
3	0.855	-13.83	0.55	0.13	0	0
4	0.953	-9.92	0	0	0	0
5	0.901	-13.42	0.3	0.18	0	0
6	0.933	-12.65	0.5	0.05	0	0

TABLE V: Control variables (initial state) [11]

V_1	V_2	Q_4	Q_6	T_{43}	T_{65}
1.05	1.1	0	0	1.1	1.025

TABLE VI: System initial state values and initial values of control variable after optimization

Bus	(p.u)	voltage	(p.u)	load	(p.u)	Power supply
	V	θ	P_1	Q_1	P_G	Q_G
1	1.1	0	0	0	0.952	0.466
2	1.15	-4.656	0	0	۰/۵	0.243
3	0.899	-12.187	0.55	0.13	0	0
4	0.999	-8.77	0	0	0	0
5	1.027	-11.841	0.3	0.18	0	0
6	0.964	-11.222	0.5	0.05	0	0

TABLE VII: Control variables after optimization

V_1	V_2	Q_4	Q_6	T_{43}	T_{65}
1.1	1.15	5	5.5	1.1	0.91

6. Conclusion

In this paper, the new optimization algorithm of Grey Wolf Optimizer (GWO) is used to optimize the reactive power dispatch. Generators voltage, status of transformers tap and switchable parallel capacitors banks are considered as control variables of reactive power dispatch. The GWO algorithm is used to optimization of IEEE 6 bus standard system with the aim of the minimizing the system active power losses. The obtained results from GWO was compared to other algorithms. The results showed that system losses after optimization is decreased from 11.61 MW to 8.7 MW (i.e. 25% reduction). It is determined that when the control and state variables of reactive power optimization problem are optimally determined with the aim of minimizing the system losses, all of the state and control variables are in their determined range. The simulation results showed that by optimal injecting the reactive power into system, the voltage profile at system buses is improved.

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