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ENHANCEMENT OF VOLTAGE STABILITY IN THE POWER SYSTEM USING GENETIC ALGORITHM

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Abstract**—**The power system should ensure safe and consistent power to the customer. For secure operation, the voltage should be within the desired limits, or else it will result in voltage collapse and power losses. The power system will be more competent, economic, reliable, and reduce power losses if the voltage stability is enhanced. Since the voltage stability is determined by the reactive power of the network, a reactive power source should be provided to safeguard the stability of the power system. This paper presents the enhancement of voltage stability in the power system using a Genetic Algorithm (GA). The GA approach is used to find the optimal value of control variables such as generator bus voltage, shunt capacitance, and transformer tap setting which are the source of reactive power. The GA was executed via MATLAB programming with MATPOWER. The propounded method was tested on the western grid of Bhutan to minimize the real power losses. The results demonstrate improved voltage stability in the power system and a significant reduction in power losses. The results will help Power System Operators to make a better decision while encountering voltage issues in their power lines. Moreover, this research will guide future research in dealing with similar research especially in calculating the optimal location of FACT devices for reactive power compensation.

Keywords—Optimization, Genetic Algorithm, Voltage stability, Active power loss

I. INTRODUCTION

1.1 Brief Introduction

The potential of an electrical system to sustain appropriate voltages through all busses under the system under both usual and abnormal conditions is known as voltage stability. The voltage of a power grid is constant in the normal state, but the voltage becomes unstable if a malfunction or a disruption occurs, resulting in a gradual and uncontrollable drop in tension [1]. To provide the customer with a reliable supply of power, the power system needs to maintain the voltage within the practicable range [2]. The reactive power mismatch is the primary cause of voltage problems. It means the demand for reactive power is not equal to the supply of reactive power. In the power system, the load demand is never steady. The change in the demand for electricity results in voltage variation that will make the grid vulnerable and unstable. Power grids must be able to manage various disruptions and contingencies safely and sufficiently to guarantee a consistent, efficient, and secure grid. Voltage instability is caused not only by the change in load demand but also due to system disturbance. This issue can be solved by absorbing or injecting the reactive power. Therefore, the installation of reactive power compensation systems on the grid such as condenser banks or various types of advanced Flexible Alternating Current Transmission System (FACTS) devices is an important way of increasing transmission capability. It will inject the reactive power into the grid to keep the bus voltages close to their nominal values, reduce line currents, and minimize the line losses [3]. If the voltage is not regulated correctly, there will be transmission loss. And these power transmission losses will result in voltage breakdown and power failure. Therefore, it is vital to minimize these power transmission losses so that the power system operation will be reliable and economic [4].

The variation in the load and generation profiles in the power systems can result in over voltage and under voltage. The overvoltage will result in insulation failure of equipment and under voltages will affect the system voltage stabilization margin. So, the system stability can be improved by injecting the reactive power into the system [5]. Various methods are used for improving the voltage stability of the power system. Some researchers have used conventional methods such as FACTS devices, Non-linear Programming, Newton method, Gradient method, and Linear Programming. These methods have certain drawbacks such as not being able to determine the global optimum, problem with handling many variables, and huge computations [6], [8]. All these drawbacks can be overcome using a non-conventional method or metaheuristic methods such as genetic algorithm [9], [10], Particle Swarm Optimization (PSO), and Eagle strategy (ES). These methods are found to be more efficient and have less computation time. The optimization method used in this research is a genetic algorithm that is inspired by biological processes and the survival of fittest.

1.2 Problem statement

All over the world, there are many problems related to the power flow such as voltage fluctuations, blackouts, and power losses while transmitting the power from the generation side to the consumer side. Similarly, in a Western grid of Bhutan, on doing a survey it was found that there is a significant power loss occurrence, the voltage at the consumer end is not within the acceptable limit, and the no existence of voltage fluctuations throughout the network. Such problems can lead to damage to insulation, household, and electrical appliances, and lead to power outages in the worst-case scenario.
Researchers have used conventional methods to solve voltage irregularities problems such as by use of FACTs devices, Gradient Method, Non- linear programming, Quadratic Programming, linear programming, and interior point method which have many drawbacks. FACTS devices are expensive to provide a smooth and fast response to a secure power system. The conventional methods contain derivative and gradient that makes it difficult to obtain optimal value and the time taken to compute such methods are huge. To overcome all these drawbacks, an efficient algorithm such as a genetic algorithm, particle swarm optimization, and other artificial intelligence techniques can be used as it is an efficient and effective technique thus, taking less time to perform the task. However, there were only a few numbers of research being carried out about the application of GA to the voltage irregularities problem.

1.3 Proposed methodology

The methodology that was proposed follows the following flow chart in which a literature review was carried out to get an idea about how to proceed with the main topic with the concept of Problem Based Learning (PBL) since the inception of a problem statement. After getting a good idea to proceed with the project, data collection, familiarization with software, and load flow analysis that was carried out. After that Genetic Algorithm coding was done in MATLAB using MATPOWER and analyzed the result.

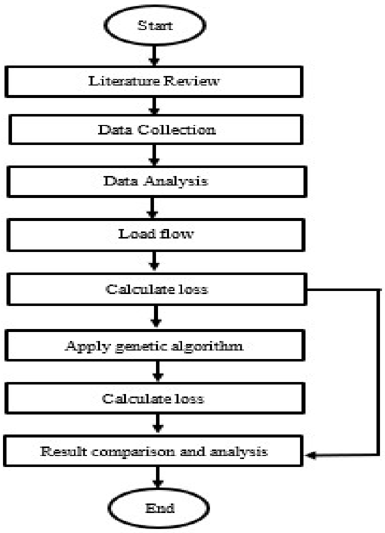

Fig. 1. Methodology flow chart

1.4 Scope of Research

This research is devoted to using the Genetic Algorithm to find the optimal value of the control variable to minimize the power losses in the system. It studies the role of reactive power in keeping the voltages within the specified value for generators, capacitor banks, and transformers. This study limits to inspection only the single objective function which is to minimize the active power transmission loss. The validation of the active transmission power loss was simulated for the western grid of Bhutan on a MATLAB platform using MATPOWER.

II. METHOD

2.1 Problem formulation

Optimization is the method of finding maximum or minimum values of a function of many variables subjected to a set of constraints. The optimization works on a collection of data that are subject to limitations. The function that is to be optimized is known as the objective function. The process starts with the need for optimization and the requirement for optimization helps to recognize the potential problem in optimization. A single method or multi-method optimization can be used to solve many problems in an application. After problems are selected, the variables are selected that decide the main objective of employing a suitable optimization method. Optimization must be carried out under certain limits [9]. In this paper, the single optimization problem is used where the minimization of active power loss is tackled.

2.1.1 Objective function

The problem can be formulated as follows

$Minimize\ f(x, u)$ (1)

subject to $g(x, u) = 0$ (2)

$h(x, u) \leq 0$ (3)

Where

$f(x, u)$ is the objective function to be optimized

$g(x, u)$ is the equality constraint

$h(x, u)$ is the inequality constraint

x is a vector of state variables u is a vector of control variables [4]. If x is not within the limit, the adjustment can be made to u to bring the x within the limits. In this paper, line losses are considered for optimization because losses can be regulated at various nodes with varying voltages. The given problem is a non-linear constraint optimization problem.

- The objective function of this paper is to find the control variables that minimize the active power loss in the system as stated below [4].

$$\mathrm{f(x,u)} = Min\ P_{loss}(x,u) = \sum_{K=1}^{N_L} g_k[V_i^2 + V_j^2 + 2V_iV_j\cos(\theta_i - \theta_j)] \quad (4)$$

Where,

$Ploss$ is the active/real power loss

k is the branch between bus i and j

N_L is the total number of transmission lines

gk is the mutual conductance of branch k

Vi, Vj are voltage magnitude at bus i, j

$\theta_i - \theta_j$ is the voltage angle difference between buses i and j

- Augmented Objective Function is given by,

$$F = Min\ P_{loss}(x, u) + \lambda_V \sum_{N_V^{lim}} \Delta V^2 + \lambda_T \sum_{N_T^{lim}} \Delta T^2 + \lambda_S \sum_{N_Q^{lim}} \Delta Q^2 \tag{5}$$

Where, λ_V, λ_T, and λ_Q are the penalty factors. If there is any violation of the constraint limit the penalty factor will take care of by adding the penalties to the objective function. For this quadratic penalty, the function is used [4].

Where,

$$\Delta V = V_i - V_i^{lim} \tag{6}$$

$$V_i^{lim} = \begin{cases} V_i^{min} & if\ V_i < V_i^{min} \\ V_i^{max} & if\ V_i > V_i^{max} \\ V_i & else \end{cases} \tag{7}$$

$$\Delta T = T_i - T_i^{lim} \tag{8}$$

$$T_i^{lim} = \begin{cases} T_i^{min} & if\ T_i < T_i^{min} \\ T_i^{max} & if\ T_i > T_i^{max} \\ T_i & else \end{cases} \tag{9}$$

$$\Delta Q = Q_i - Q_i^{lim} \tag{10}$$

$$Q_i^{lim} = \begin{cases} Q_i^{min} & if\ Q_i < Q_i^{min} \\ Q_i^{max} & if\ Q_i > Q_i^{max} \\ Q_i & else \end{cases} \tag{11}$$

2.1.2 Objective constraint

Equality constraint

- Real power constraints

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_{ij} - \theta_j) \tag{12}$$

- Reactive power constraints

$$Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_{ij} - \theta_j) \tag{13}$$

Inequality constraint

- Voltage constraints:

$$V_i^{min} \le V_i \le V_i^{max}\ i \in N_B \tag{14}$$

- Transformer tap-setting limit:

$$T_k^{min} \le T_k \le T_k^{max}\ k \in N_T \tag{15}$$

- Generator reactive power capability limit:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} i \in N_G \tag{16}$$

- Capacitive reactive power capability limit:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max} i \in N_C \tag{17}$$

Where,

PGi is the active power generations at bus i

PDi is the active power load demands at bus i

QGi is the reactive power generations at bus i

QDi is the reactive power load demands at bus i

Bij is the mutual susceptance of the branch ij

2.2 Genetic Algorithm

2.2.1 Introduction

Genetic Algorithms (GAs) were invented by John Holland in the year 1975. Holland proposed GA as a heuristic method based on "Survival of the fittest". GA is one of the branches of evolutionary computation. Natural selection theory states that today's plants and animals are the product of millions of years of adaptation to the demands of the environment. A variety of different species can coexist and compete for the same resources in an ecosystem at any given time. The species that are most capable of accumulating energy and successfully reproducing would have a large number of descendants in the future. For any cause, fewer competent organisms would have little to no offspring in the future. It is said that the offspring produced over time will fit better than the former offspring because they are selected over the characteristics of the former offspring. Over time, the ecosystem's entire population is said to evolve to have species that are, on average, more suited than previous generations of the population and they possess more of the traits that foster longevity [9].

GA was found to be a useful search and optimization tool for solving complex technical problems and machine learning. Genetic algorithms are based on the principle of genetics and evolution [9]. A new group of approximations at each generation are generated by choosing individuals based on their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. As a result, populations of individuals that are more adapted to their environment than the individuals from which they were produced evolve. This mechanism results in the emergence of species of people that are more adapted to their environment than the individuals themselves that they were created from. The "best fit" offspring who are more fit than their parents will survive. Species change naturally over generations and become more and more suited to their surroundings [10]. The benefits of the GA include the fact that it does not need any derived knowledge, that it is simpler and more effective than conventional approaches, that it can simplify continuous functions, discrete functions, and multi-objective problems, and that it offers a variety of good solutions and limiting to just a single solution [11]. The huge amount of variables and constraints can be handled by GA. It was used to solve complex optimization problems such as traveling salesman problems, machine intelligence, Network design and routing job shop scheduling, and gameplay.

2.2.2 Genetic operators

GA has three main operators which are selection, crossover, and mutation and they should work together for the algorithm to work. The details of the genetic operators used in the GA are presented below:

- Tournament selection

It is the process where the best chromosomes are selected from the initial population based on their fitness to make it as parents. According to Darwin's evolution theory, the best one of all which can survive is to be selected and be able to create new offspring. Methods such as Roulette Wheel Selection [12], [13], Rank selection, and tournament selection were used to select the chromosomes. However, in this study, the tournament selection was used for selecting the best chromosomes and they are taken as a parent. In tournament selection, k individuals are selected randomly from the larger population, and the selected individuals compete against each other. The individual with the highest fitness will be selected and included as one of the populations for the next generation. Tournament selection is also very popular in literature because of its efficiency, easy implementation, and the fact that it can even work with negative fitness value [12]-[14].

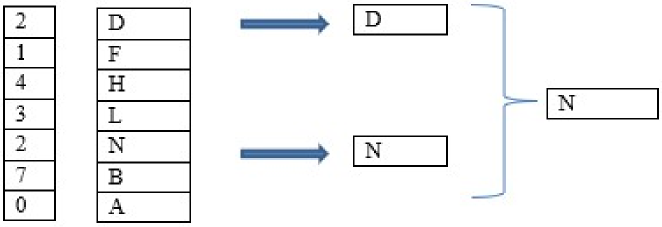

Fig. 2. Selection of chromosomes using tournament selection

- Single point crossover

In the crossover, more than one parent is chosen, and then one or more offspring are created using the parents' genetic material. Two main approaches to crossover development are parent-centric and mean-centric operators. The parent-centric approach generates offspring near each of the parents whereas the mean centric generates offspring solutions near the centroid of the parents. The crossover will combine genetic material from the selected parents. Crossover is usually finding its application in a GA with high probability. In this research, the single-point crossover also known as one-point crossover was used. Here, one crossover point is randomly detected before splitting the parents thereby producing offspring by exchanging tails.

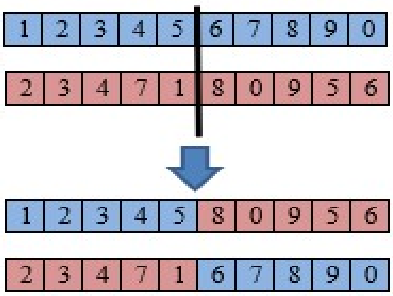

Fig. 3. Single point crossover

- Uniform Mutation

The mutation is defined as the small random tweak in the chromosome used for the production of the new chromosomes. It is part of the genetic algorithm more related to the exploration of the search space and is used for maintaining and introducing diversity in the genetic population [11]. As a result, using a mutation in a genetic algorithm will lead to a better solution [13]. Some of the most mutation operators used are Bit Flip Mutation, Random Mutation, Swap Mutation, Scramble Mutation, and uniform Mutation [11], [14]. In this case, a random gene is given a random value between the upper and lower limits.

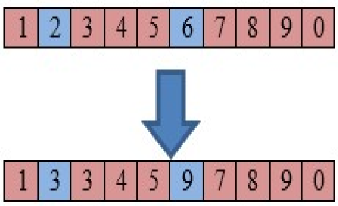

Fig. 4. Random change in genes using uniform mutation

2.2.3 Flowchart of Genetic Algorithm

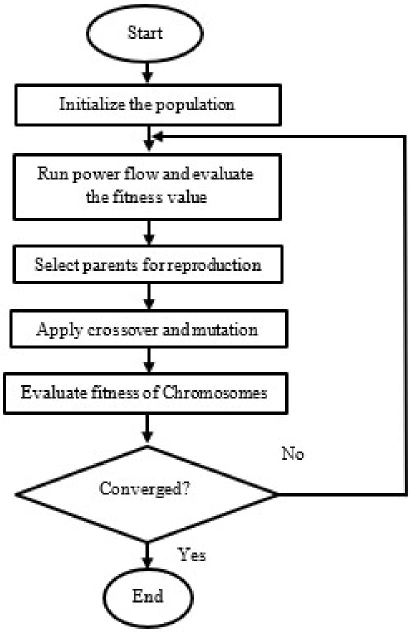

Fig. 5. Flowchart of GA based algorithm

III. Results and Discussion

3.1 Result

3.1.1 Load flow analysis of Western Grid of Bhutan

The western grid of Bhutan is a 36-bus system with 5 generator buses, 31 load buses, and 41 transmission lines of which ten branches are with a tap setting transformer. The load flow analysis was carried out in MATPOWER taking the Tala bus as a slack bus because it is the largest generating bus. Newton Raphson Method was used for the analysis of Load Flow and the voltage profile is graphically shown in fig. 6.

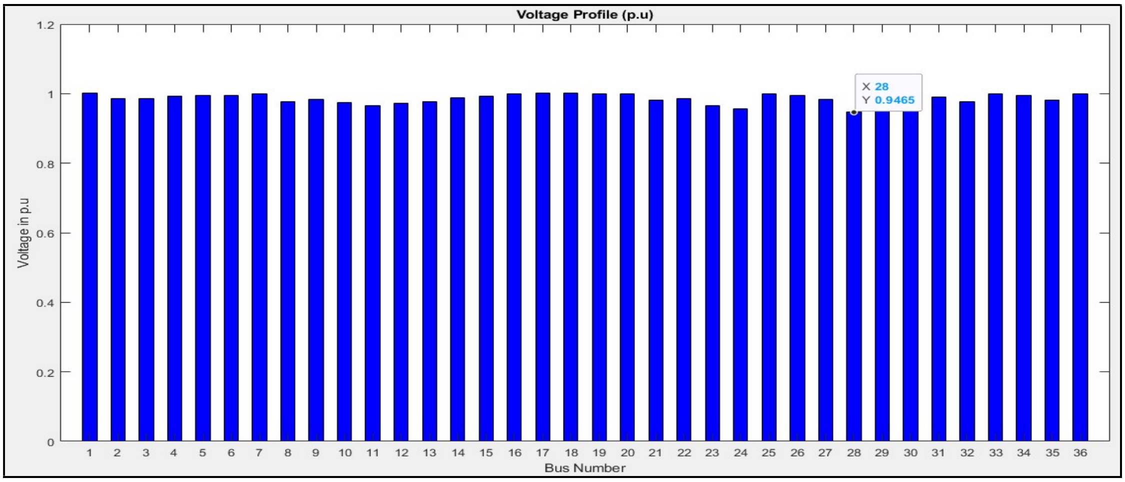

Fig. 6. Voltage profile for different buses in p.u of Western Grid

After the load flow analysis, it was found that the voltage at bus 28 (Malbase, 66 kV bus) is below the specified limit i.e., 0.9465 p.u. It is mainly because of the presence of factories at Pasakha, Bhutan. While other buses were found to be within the specified limits. The initial control variables were found as shown in table 5, with a total real power loss of 21.775 MW.
The GA algorithm was coded in MATLAB R2020a incorporating MATPOWER 7.0. The limits of the control variables that were used to solve the objective function of minimizing the active power transmission loss are shown in table 1. To demonstrate the efficacy of the proposed approach, two separate cases were considered. In case 1, the GA was implemented for one generation and maximum generation in case 2.

TABLE 1. Limits of a control variable

Control variables (p.u)	Quantities	Minimum	Maximum
Generator voltage	5	0.95	1.05
Transformer tap setting	10	0.90	1.10
Shunt capacitor	1	0	0.20

3.1.2 Case 1: GA for one generation

In the first case, the Genetic Algorithm is implemented for only one generation to give a glimpse of how it works. Firstly, the initial population were generated randomly within the given limits of control variables. The best chromosome was selected and taken as a parent. In the next step, crossover takes place between the parent with the crossover point 13. Offspring1 gives the best fitness and it is taken as a final Child which will undergo the mutation process. The genes that need to be mutated were found to be 15. As a result, the initial value of gene 15 is changed from 0.9414 to 0.9519 which is within the specified limit. This mutated child is considered as an optimal setting of the control variables. The initial active power losses were 21.775 MW but after applying GA for one generation the active power loss was found to be 20.3863 MW showing a 6.37 % reduction in the losses. The voltage profile graph before and after GA for one generation is compared in fig. 7. The voltage at bus 28 has reached the acceptable limit with the optimized control variable given in table 5. The minimum voltage of the power system is increased from 0.9465p.u to 0.961p.u. However, the losses are found to have decreased by only a few percent. The voltage at buses is within the limit, proving that GA can help in enhancing the voltage stability.

TABLE 2. Comparison of losses obtained before and after GA for one generation

Sl.no		Initial losses	Losses after GA	% reduction in losses
1	Active power loss (Ploss in MW)	21.775	20.3863	6.37

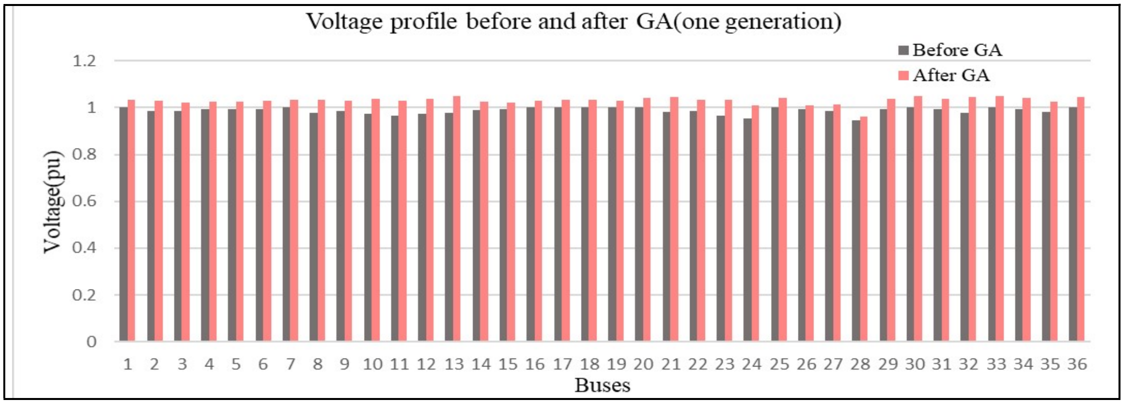

Fig. 7. Voltage profile obtained before and after GA for one generation

3.1.3 Case 2: GA for maximum generation

For the second case, GA was applied for a maximum generation. GA gives different results for every simulation as it is a stochastic optimization method. Therefore, several simulations were carried out and one of the best results was considered. The parameters taken during the implementation of GA are given in table 3.

TABLE 3. Parameters used in GA algorithm.

Parameter	Symbol	Value
Population size	N	50
Max. number of iterations	$miter$	100
Penalty factor	$\lambda V, \lambda c\ , \lambda T$	10

To obtain the best result, the maximum number of iterations was taken and the losses found after optimization is 17.3753 MW with a 21.07 % reduction of losses from the initial loss. With every iteration, the losses were found to be decreasing as shown in fig. 8.

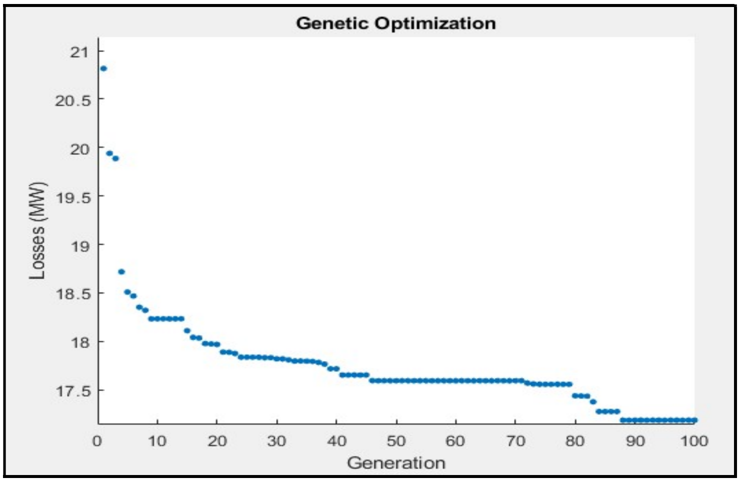

Fig. 8. Loss reduction using GA optimization

The optimized control variables obtained using a genetic algorithm are given in Table 5. The control variables are within their restricted desired limit, as seen in the table. With the use of these optimized control variables, the active power transmission loss decreases thus maintaining the voltage profile of the power system as shown in figure 9. With the use of a genetic algorithm, it is observed that the voltage at bus 28 has improved and reached within the specified limits as well as voltages at the other buses. The minimum voltage of the power system is increased from 0. 9465 p.u to 1.0124 p.u. Thus, enhancing the system's voltage.

TABLE 4. Comparison of losses obtained before and after genetic optimization

Sl.No.		Losses before Optimization	Losses after Optimization	% Reduction in losses
1	Active Power Loss (Ploss in MW)	21.7750	17.1862	21.0700

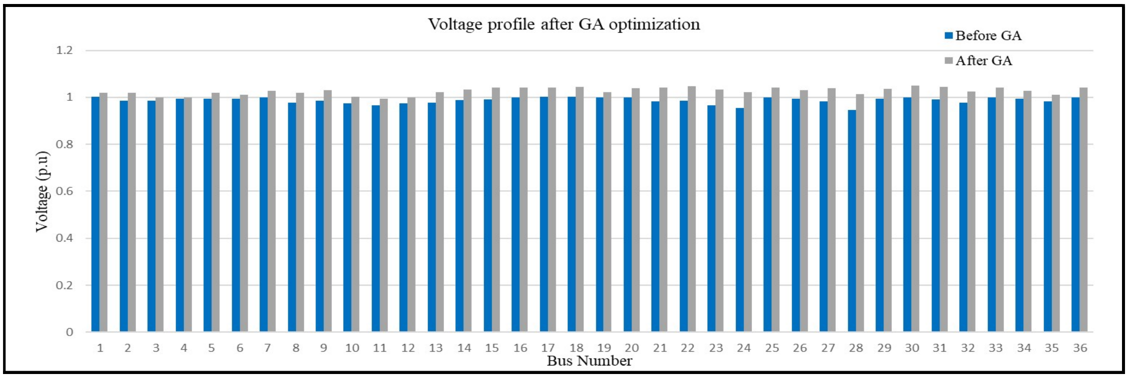

Fig. 9. Voltage profile after genetic optimization

3.2 Discussion

Figure 10 shows the comparative studies of losses before and after the implementations of the Genetic Algorithm. Before performing the optimization, the initial loss was calculated to 21.7750 MW. Genetic optimization was carried out in two cases: Taking one generation in the first case and maximum generations in the second case. In the first case, the losses are reduced to 20.3863 MW and 17.186MW in the second case. Thereby improving the voltage stability of the system because with the decrease in losses, there will be less voltage deviation and the voltage will be within the specified limit.

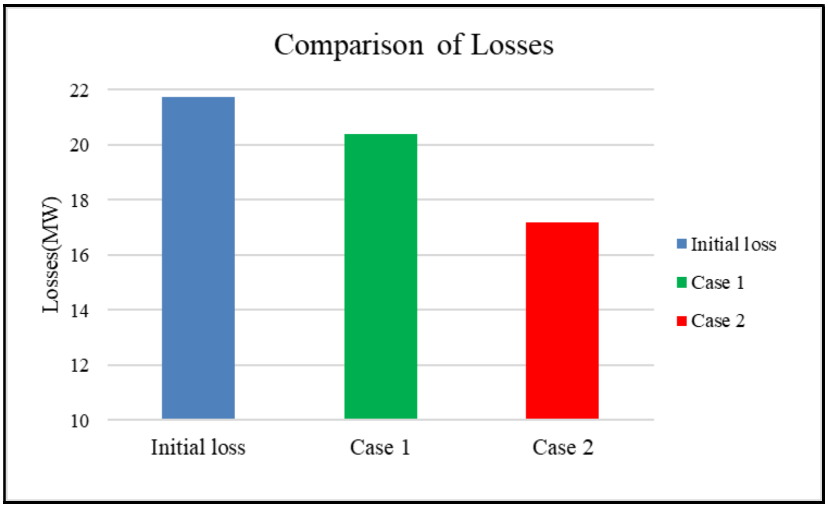

Fig. 10. Comparison of losses before and after GA

Fig. 11 shows the comparison of control variables before and after GA. Every control variable is an optimized value that is within the specified limit. The minimum losses were obtained when using these optimized control variables which help in the enhancement of voltage stability as discussed earlier. The generator voltage and transformer taps are found to be decreasing. It is because the voltage tends to go beyond the limit. As the result, the generator and transformers bring the voltage near the rated value by absorbing the reactive power. Similarly, the generator voltage and transformer tap setting increase to inject the reactive power in the system to increase the voltage if it goes below the limit. The shunt capacitance was found to have increased 2.95 times the initial values. The increase in the value of shunt capacitance indicates the injection of reactive power to increase the voltage.

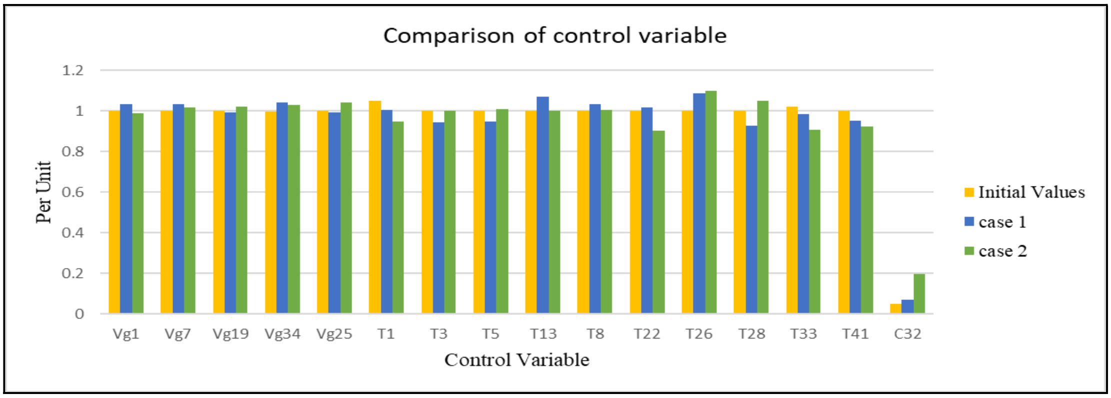

Fig. 11. Comparison of control variables before and after GA

TABLE 5. Values of control variables after genetic optimization

Control Variables	Initial value	Optimize value or case 1	Optimize value for case 2
Vg1	1.0023	1.0346	0.9874
Vg7	1.0000	1.0331	1.0169
Vg19	1.0000	0.9938	1.0212
Vg34	0.9954	1.04268	1.0281
Vg25	1.0000	0.9942	1.0404
T1	1.0500	1.0060	0.9474
T3	1.0000	0.9456	1.0033
T5	1.0000	0.9487	1.0107
T13	1.0000	1.0720	1.0002
T8	1.0000	1.0322	1.0050
T22	1.0000	1.0176	0.9052
T26	1.0000	1.0874	1.0983
T28	1.0000	0.9267	1.0486
T33	1.0200	0.9843	0.9091
T41	1.0000	0.9519	0.9230
C32	0.0500	0.0713	0.1976

IV. CONCLUSION

In this paper, a genetic algorithm is used for the minimization of active power loss of transmission lines with equality and inequality constraints. The proposed GA is conducted on a western grid of Bhutan to validate its effectiveness by taking Generator voltage, transformer tap setting, and shunt capacitance as a control variable. A genetic algorithm, a stochastic optimization technique was used in the MATLAB environment using MATPOWER to find the optimal value of the control variables. GA operators such as selection, crossover, and mutation are used for the voltage deviation problem. The load flow analysis of the western grid of Bhutan was carried out using Newton Raphson's method in which the losses obtained were 21.7750 MW. The proposed algorithm was used to reduce such losses to have stable voltage in the power system. The simulation was taken for a single and maximum generation. For a single generation, the active power losses were reduced to 20.3863 MW with a 6.37 % reduction in losses from the initial loss. While simulating for maximum generation, the simulation reveals that successful power transfer loss has been decreased from 21.7750 MW to 17.1860 MW (21.07 % reduction in losses). With the proposed approach, the abnormal bus voltage was corrected and was observed to be within the desired limit. At the same time reducing the transmission losses and satisfying the constraint. Furthermore, the PBL methodology can be always handy to strategically pick up the problem that needs attention and work on to study the problems with possible recommendations.

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