OPTIMAL POWER FLOW ANALYSIS AND TRANSMISSION SYSTEM WITH JAYA ALGORITHM FOR REDUCING POWER LOSS

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ABSTRACT:

The objective function of the Optimal Power Flow (OPF) problem is addressed in this study by the use of two metaheuristic optimisation methods, the JAYA algorithm and the Teacher Learning Based Optimisation (TLBO) algorithm. Since TLBO and Jaya have no parameters, they are less complex than other algorithms. This paper's major goal is to minimise real power losses while keeping the voltages and tap placements within safe ranges. Data from the IEEE-39 bus system is taken into account when applying the algorithms. The outcomes of the JAYA algorithm demonstrate improved development in objective function reduction. The entire project was carried out in the MATLAB environment.

Keywords: Optimal Power Flow, JAYA Algorithm, TLBO algorithm, Active power loss.

I. INTRODUCTION

J. Carpentier was the one who first proposed the Optimal Power Flow (OPF) problem [1]. Running electric power networks requires the use of solutions for Optimal Power Flow (OPF) [11,12]. It is a power flow that, while addressing various constraints, appropriately modifies power grid management parameters [2].

The OPF problem has been addressed using a variety of conventional optimisation techniques, including non-linear programming, the Newton algorithm, and Decomposition algorithms [13,14]. In-depth analysis is provided of the prior deterministic optimisation approaches used. Although these methods can occasionally find the globally optimal solution, they have a number of disadvantages, such as being stuck in local optima (i.e., having insecure convergence qualities) (3), being unable to handle goal functions that are not differentiable, and having a high sensitivity to beginning search sites.

As a result of recent advances in computing, new algorithms known as "nature-inspired algorithms" were used to solve OPF problems [12]. Many developments in the previous century led to the suggestion of nature-inspired algorithms, which were beneficial in addressing real-time problems while avoiding minute errors. The OPF is a convex problem, and while no algorithm has been successful in solving it up to this point, nature-inspired algorithms are capable of offering the best answers. The many meta heuristic methods, including the Particle Swarm Optimisation algorithm [15], Gravitational Search algorithm [3], BAT algorithm [4,6], Artificial Bee Colony algorithm [16], and Cuckoo Search algorithm [8], are used to tackle the OPF problem. These algorithms lessen the complexity of the issue and offer the best answer. Unfortunately, despite their advantages, each of these population-based optimisation strategies requires correctly created regulating parameters that are specific to the underlying algorithm, as improper tuning of these variables will either make the problem harder to solve [7] or increase the computational load.

One of the most recent population-based optimisation strategies is the Jaya algorithm, which Rao proposed in 2016 to address the aforementioned problem [5]. In contrast to other population-based strategies, the Jaya algorithm's optimisation procedure does not include adjusting any algorithm-specific regulating factors. As was already mentioned, controlling these aspects is not always simple. The Jaya algorithm benefits greatly from this feature since it removes the difficulty of controlling these parameters and reduces the time required to complete the optimisation process. Both the method's development and application are quite simple. The optimisation method of this technique is motivated by the notion that the response to a particular problem must advance towards the ideal answer and avoid suboptimal ones.

The two specific parameter-less algorithms, TLBO [10] and JAYA [5], are examined. They are used in electrical engineering to address issues involving restricted and unconstrained type parameters. These algorithms are part of the meta-heuristics algorithm class, which is extremely common in this period. The TLBO algorithm is given more consideration than the Jaya algorithm since it uses a two-step process that is more similar to a classroom setting. Teacher and student are the two phases.

The particular algorithm parameters, such as population size and iterations, are necessary for the meta heuristic algorithms. Jaya and TLBO, in contrast, merely need population size and iterations. Thus, the algorithms Jaya and TLBO are special parameter-free algorithms.

The New England power system, often known as the IEEE-39, is the bus system that was used in this study. Ten generators and a 46-line transmission line system make up this bus system. Energy function analysis for power system analysis stability is the book from which the bus system's parameters were extracted.

The appealing and straightforward nature of the Jaya algorithm served as the inspiration for this paper. The organisation of the paper is briefly discussed, the problem formulation is covered in detail in the second chapter, followed by the detailed explanation of the two algorithms in the following chapters, and the conclusion is covered in the final chapter.

II. PROBLEM FORMATION

This essay focused on OPF problems with a single objective function. Minimising active power losses is the objective function. With the equality and inequality constraints, an optimised objective function is created.

A. Objective function

By determining the ideal values for the control variables, such as voltage (V) and the tap values of transformers, which sink the active power loss, the objective function is attained. Equation (1) shows the formula for this objective function.

$$P_{li} = \frac{1}{Y_{ij}}\left(V_i^2 + V_j^2 - 2 * V_i * V_j * \cos\left(\theta_i - \theta_j\right)\right) \quad \ldots \quad (1)$$

The system's overall losses are stated as:

$$P_{LOSSES} = \sum_{i=1}^{br} P_{li} \quad \ldots \quad (2)$$

Voltages from the sending and receiving ends are represented by the letters V_i, V_j, and Y_{ij}, respectively.

voltage angle = i, j.

Constraints

The OPF problem involves two types of constraints

- Equality constraints
- Inequality constraints

Equality constraints

Real and reactive power restrictions are the equality restraints.

Limits to actual power generation

$$P_{Gi} = P_{di} + P_{Li} \quad \ldots \quad (3)$$

P_{di}=real power demand (Pd) at i th bus; P_{Gi}=real power generation (PG) at i th bus.

P_{Li} stands for real power losses (PL) at the i th bus.

Limits on reactive power generation

$$Q_{Gi} = Q_{di} + Q_{Li} \quad \ldots \quad (4)$$

Reactive power generation at i-th-bus equals Q_{Gi}, while reactive power demand there equals Q_{di}.

Q_{Li} stands for reactive power losses at the bus.

Inequality constraints

a) Limits on actual power generation

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \quad \ldots \quad (5)$$

Real power restrictions that are allowed must fall within the range that is depicted above.

Where i is the number of generators (1, 2, 3, etc.);

P_{gi}^{min} is the minimum real power level (Pg) at bus i; and P_{gi}^{max} is the highest real power level (Pg) at bus i.

b) Limits on bus voltage

The voltage levels must be kept within certain bounds.

$$V_i^{min} \leq V_i \leq V_i^{max} \quad \ldots \quad (6)$$

Where i is 1, 2, 3, etc., V_i^{min} is the minimum voltage level at bus i.

V_i^{max} is the bus i's maximum voltage level.

c) Limits on tapping

Transformer tap locations were consistently kept within acceptable ranges.

$$t_i^{min} \leq t_i \leq t_i^{max} \quad \ldots \quad (7)$$

Where i is 1, 2, 3, etc., t_i^{min} is the minimal tapping position level at bus i.

t_i^{max} is the highest level of tapping at bus i.

It is vital to emphasise that the afore mentioned mathematical formulation of the modified objective function is only used when one or more dependent variables violate the upper/lower restriction. The main goal is to locate and eliminate any impractical solutions that may be discovered during the optimisation process.

Depending on the application and the designer's experience, the penalty variables may change. Different aspects of the punishment have different effects. In order to solve this issue, this study takes into account a high unity penalty of 10,000 on each dependent variable in the event that the upper/lower boundary is violated.

III. GENETIC ALGORITHM

A basic understanding of the following terms will aid in your comprehension of the basic Genetic algorithm [19] and its operation. Below is a description of them.

• Genetic operators: Genetic operators are employ –ed in genetic algorithms to modify the genetic makeup of the following generation.

• Chromosome/Individual: This term describes a group of genes that can be represented as a string consisting of one bit for each gene.

• Population: A group of chromosomes/person constitutes the population, and each chromosome represents an individual.

• Fitness function: In genetic algorithms, this function yields a better result for a given input.

Let's now examine how genetic algorithms function in machine learning.

The complete process of how this algorithm operates is broken down into five steps.

3.1. Initialization

Genetic algorithms function by first generating a population, or set of individuals, during the initialization procedure. It has a collection of instructions known as genes, which are bundled into a string to create chromosomes. The problem that is solved by the random binary string technique is represented by these chromosomes.

3.2. Assignment of fitness

A person's capacity to compete with others is determined by the genetic algorithm's fitness function. It gives each person a score that indicates how likely they are to be chosen for the reproduction process.A person is more likely to be chosen for reproduction if they have a higher fitness score.

3.3. Selection

During this stage of the genetic algorithm, individuals are paired off and chosen to have children out of all the phases. The following list includes the three sorts of selection methods that are used in this process.

• Selection depending on rank

• Selection of the tournament

• Choice of roulette wheels

3.4. Reproduction

The genetic algorithm uses two variation operators in the reproduction step. The parent population is the target of these. The two operators in question are:

• Crossover

A crossover point is arbitrarily chosen within the genes throughout this process. In order to create an offspring, this operator then switches the genetic makeup of the two chosen parents, or, alternatively, of those living in the present generation. One-point crossover, two-point crossover, livery crossover, and inheritable algorithms crossover are the several crossover styles between the parents.

Up until the crossover point is reached, the genes of the selected parents who are the fittest are switched. An offspring with genes from both parents is created when the procedure is complete.

• Mutation

To preserve the population's diversity, a random gene is injected into the progeny throughout this process. Flip bit mutation, gaussian mutation, and exchange or swap mutation are the three available mutation styles.This operator improves population diversification and aids in the resolution of the premature convergence problem.

3.5. Closing

After the progeny is generated, a stopping criterion is applied to end the reproduction face. When the threshold fitness solution is met, the algorithm comes to an end. Additionally, it finds the population's ultimate but optimal solution.

The Voltage and Tap positions of the transformer serve as the control variables in this methodology. The objective function is accomplished by modifying the control variables. The control variable graphs shown in Fig. 1 show the values at which the ideal solution is achieved. The voltage profiles of the system under the genetic algorithm is shown in the below.

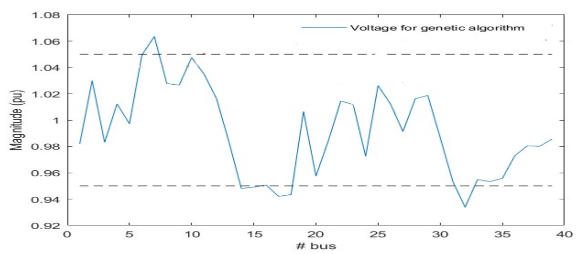

Fig.1. Voltages of IEEE-39 Bus system with Genetic Algorithm

A Tap value of Genetic Algorithm is displayed below. The Tap value of Genetic Algorithm is placed in the value of 1. The Tap value is represented in per unit.

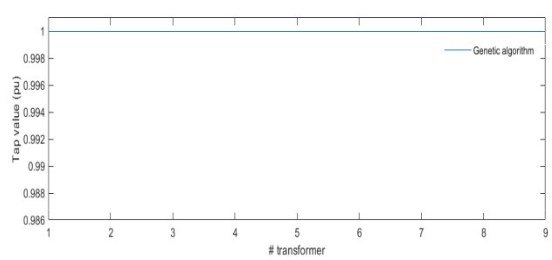

Fig.2. Tap value of Genetic Algorithm

The function values of the Genetic algorithm are shown in the diagram below. The function value will vary with each repetition. The function value becomes constant after a few repetitions for every iteration.

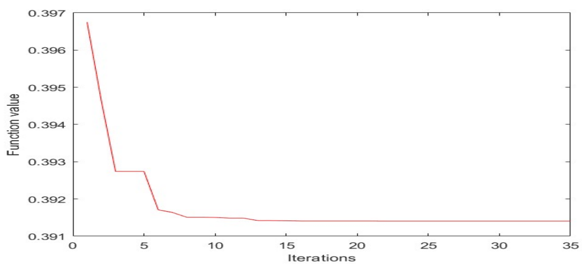

Fig.3. Function values for Genetic Algorithm

IV. TLBO ALGORITHM

R.V. Rao et al. introduced teaching learning-based optimisation (TLBO) in 2011 [9]. It is a population-based meta-heuristic optimisation technique that optimises a given objective function by simulating a classroom setting.In a classroom, the instructor works diligently to ensure that every student in the class is educated. The students then engage in self-interaction to refine and enhance the knowledge they have acquired.

This algorithm is predicated on how a teacher's influence affects the work that students produce in a classroom. The instructor works diligently to ensure that every student in the class is educated. The students then engage in self-interaction to refine and enhance the knowledge they have acquired. The key sources of inspiration for the TLBO algorithm are the interactions and effects that learners have on one another, the teacher-student connection in a learning environment, and the teacher's impact over learners or pupils. The two main parts of the algorithm are, respectively, the instructor phase and learner phase. Rao [6] has proposed this algorithm.

This algorithm is divided into two stages:

1) Teacher stage

Every student gains information and learns from the teacher.

2) Learner stage

Students engage in conversation with one another in order to exchange knowledge.

The TLBO algorithm's step-by-step process is described below.

A. First, set the parameters.

B. Describe the goal function.

C. Produce a population.

D. Calculate T_f, mean, andX_{best}.

Where X_{best} stands for the class's top performer.

Mean is the average of all marks.

T_f stands for the ability-based teacher factor (random variable).

E. Teacher phase

• Calculate the difference (X_{di}) between the top and average marks.

$$X_{di} = r_i(X_{best} - T_f \times Mean) \quad ... \quad (8)$$

r_i= random integer in the range (0, 1)

• Find the answer produced by student interaction between students i and j using the (X_{di}).

$$X_{j,i,x} = X_{i,j} + X_{di} \quad ... \quad (9)$$

$X_{i,j}$= the marks that j received during iteration i.

• If $X_{best} > X_{i,j}$, X_{best} moves on to the learner phase.

Otherwise, the learner phase receives $X_{i,j}$.

• The new answer must fall within the bounds when compared to the old one.

F. Greedy selection

• Create a fresh solution for the specified objective function.

•Save the variables for the aforementioned solution.

J. Learner phase

Create populations for both couples (A, B) after randomly choosing two students to be partners (A, B).

- If $X_{i,j,A} < X_{i,j,B}$

$$X_{j,i\,new} = X_{j,i-A} + rand \times (X_{j,i-A} - X_{j,i-B}) \quad ... \quad (10)$$

Otherwise

$$X_{j,i\,new} = X_{j,i-A} - rand \times (X_{j,i-A} - X_{j,i-B}) \quad ... \quad (11)$$

K. Repetition of step F with greedy selection.

L. End

The Voltage and Tap positions of the transformer serve as the control variables in this methodology. The objective function is accomplished by modifying the control variables. The control variable graphs shown in Fig. 4 show the values at which the ideal solution is achieved. The voltage profiles of the system under various algorithms are shown in the below. In the most basic scenario, the voltage profiles go above the constraints placed on the system. Using TLBO algorithm, the voltage profiles are within the permitted ranges, the active power losses have not significantly decreased.

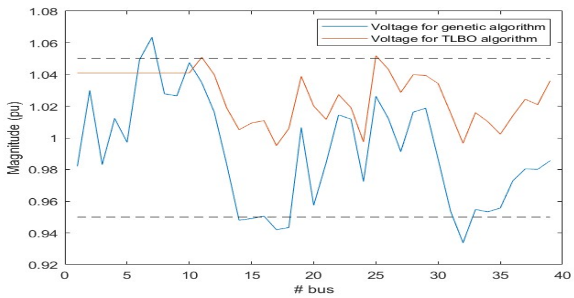

Fig.4. Voltages of IEEE-39 Bus system with TLBO

A comparison of tap values is displayed below. The tap value of TLBO algorithm lies in 0.987 p.u. Tap value is represented in the per unit (p.u). In TLBO algorithm the tap value is decreased to the value of 0.987 p.u.

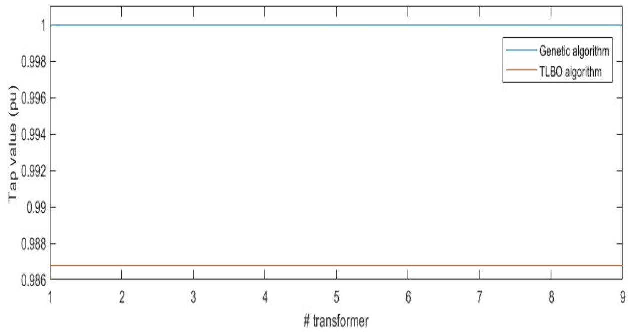

Fig.5. Tap value comparision

A comparison of active power losses is displayed in the image below. It has made comparisons between the TLBO and Genetic algorithms. The TLBO algorithm will minimise active power losses.

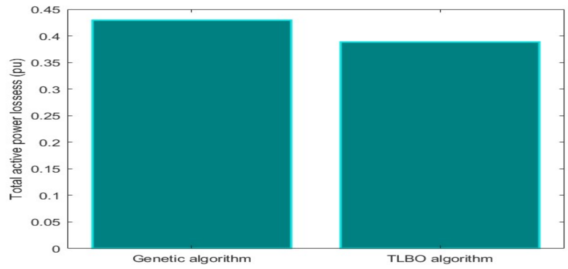

Fig.6. Comparision of Active power losses

The function values of the TLBO algorithm are shown in the diagram below. The function value will vary with each repetition. The function value becomes constant after a few repetitions for every iteration.

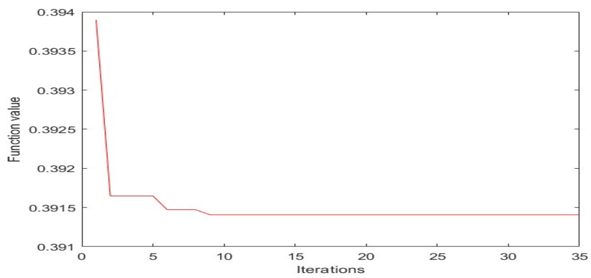

Fig.7. Function values for TLBO algorithm

V. JAYA ALGORITHM

The optimisation algorithm Jaya Algorithm [5] does not require gradients. It can be applied to either function minimization or maximisation. It is a population-based technique that can solve both limited and unconstrained optimisation problems by continuously modifying a population of individual solutions.

Rao created the cutting-edge Jaya population-based optimisation method to achieve the best outcomes for both limited and unconstrained optimisation problems. Jaya only uses the two common regulatory factors of population size (n) and the number of iterations (i), in contrast to other population-based heuristic algorithms. The principle behind this technique's optimisation strategy is that the solution selected for a particular problem must err towards the ideal answer while avoiding the less desirable one. The basic Jaya algorithm is a simple optimisation approach since it just comprises one step, in accordance with the aforementioned notion. The steps for putting the Jaya algorithm into practise are covered here. Rao has proposed this algorithm.

Therefore, simplicity, efficiency, and having no algorithmic-specific parameters can be considered as advantages of the Jaya algorithm. The main advantage of the JAYA algorithm compared to further evolutionary algorithms is that it is unrestricted to algorithm-specific parameters and utilizes only two common parameters, that is, population size and the number of iterations.

According to the related literature, the JAYA algorithm has a unique orientation characteristic of striving for the best and avoiding the worst. It has the advantages of few control parameters, a simple structure, and a flexible mechanism, which make it be suitable for solving diverse optimization problems.

1. Initialise the algorithm's necessary parameters, such as population size and iterations.

2. Specify the goal function.

3. Produce the populace.

4. Among the population size, determine the best and worst solutions.

5. Use the best and worst solutions to update the candidate solution.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - |X_{j,k,i}|\right) - r_{2,j,i}\left(X_{j,worst,i} - |X_{j,k,i}|\right) \quad \dots \quad (12)$$

6. Verify that the old solution ($X_{j,k,i}$) is preferable to the new one ($X'_{j,k,i}$).

Update the old solution if necessary, otherwise update the new solution.

7. Verify the modified solution still fits the parameters.

8. End.

The voltage and tap positions of the transformer serve as the control variables in this methodology. The objective function is accomplished by modifying the control variables. The control variable graphs shown in Fig. 8 show the values at which the ideal solution is achieved. The voltage profiles of the system under various algorithms are shown in the image below. In the most basic scenario, the voltage profiles go above the constraints placed on the system. Although the Later TLBO algorithm has been used and the voltage profiles are within the permitted ranges, the active power losses have not significantly decreased. The Jaya algorithm is thought to better achieve the programme's goal by minimising losses and ensuring that voltage limitations are met. The voltages have upper and lower bounds of 1.05 and 0.95, respectively.

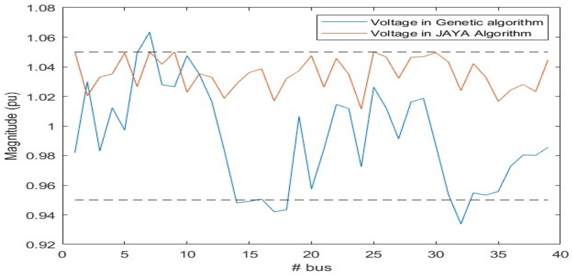

Fig.8. Voltages of IEEE-39 Bus system with TLBO and JAYA algorithm

A comparison of tap values is displayed below. The tap value of JAYA algorithm lies in between 1.01 and 0.95.

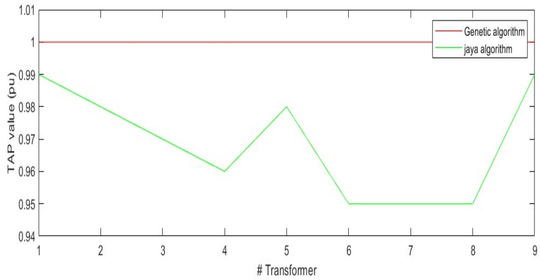

Fig.9. Tap value comparision

A comparison of active power losses is displayed in the image below. It has made comparisons between the JAYA and Genetic algorithms. The JAYA algorithm will minimise active power losses.

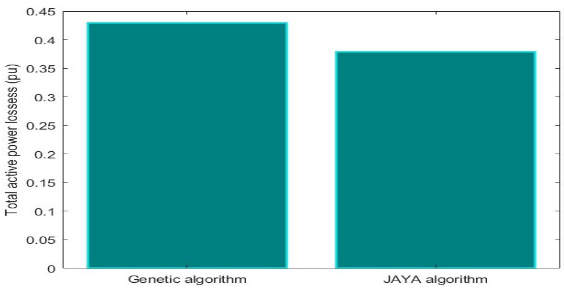

Fig.10. Comparision of Active power losses

The figure below displays the JAYA algorithm's function values. Every iteration will see a change in the function value. Every iteration of the JAYA algorithm has enhanced their function value in comparison to the TLBO.

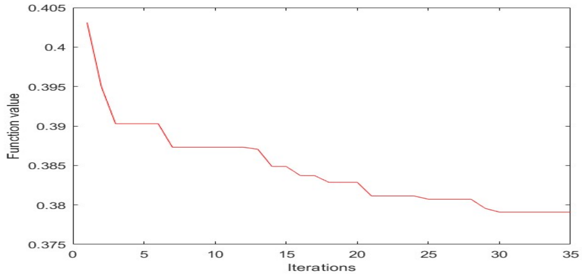

Fig.11. Function values for JAYA algorithm

VI. RESULTS AND DISCUSSION

Using the JAYA and TLBO algorithms, this paper's primary goal is to reduce active and reactive power losses in order to evaluate the algorithms' effectiveness. The IEEE-39 bus system, often known as the New England power system, uses these algorithms. The population size and the maximum number of iterations are set to 210 and 35 respectively for the IEEE-39 bus system. There are 46 lines and 10 generators in the IEEE-39 bus system.

The OPF problem is a convex form of problem, and it is difficult to solve complex difficulties. Therefore, it requires specialised algorithms in order to produce superior results. Figure 13 below illustrates the process for applying algorithms to the formulated OPF problem. Transformer tap positions and bus voltages are the algorithm's control variables. These factors must carefully stay within the bounds. Figure 13 shows the step-by-step procedure for solving this OPF problem using several algorithms while taking into account the optimal solution in the graphical representation.

The procedure of applying the Jaya algorithm is depicted in the flowchart below. Equation 12 demonstrates how the population is formed at random, the best and worst candidates are chosen, and the candidates are updated. When compared to the TLBO algorithm listed in Table 1, the active power losses in the Jaya algorithm decrease. Fig. 12 below displays the IEE-39 one line diagram.

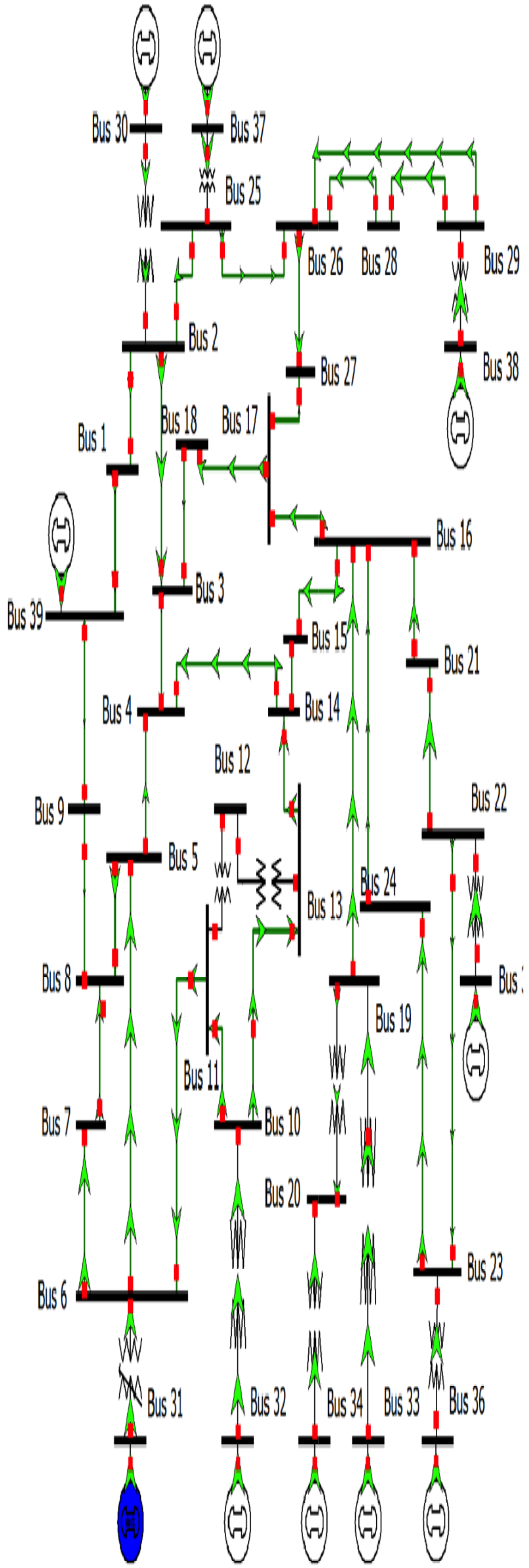

Fig.12. Simulink diagram of IEEE-39 bus system

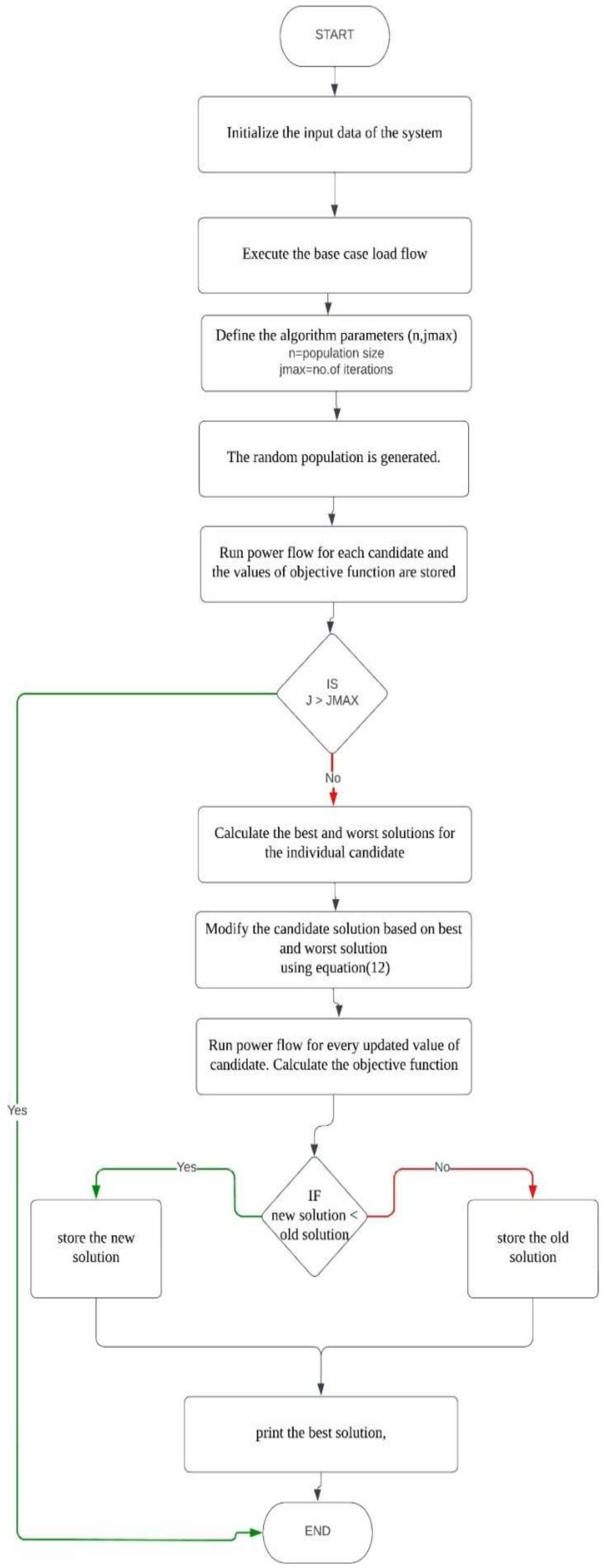

Fig.13. Flowchart of the algorithm applied to OPF problem

The active power loss reduction values are represented in fig. 14 below. Active power loss minimization is the goal of this work while adhering to the established limits. In order to get the required result, various types of algorithms are developed with the active power losses observed as 0.4284 p.u. in the genetic algorithm case. When the TLBO method is used, losses of 0.3895 p.u. are noticed. Additionally, the Jaya algorithm is used to carry out the set goal; losses are recorded at 0.3702 p.u.

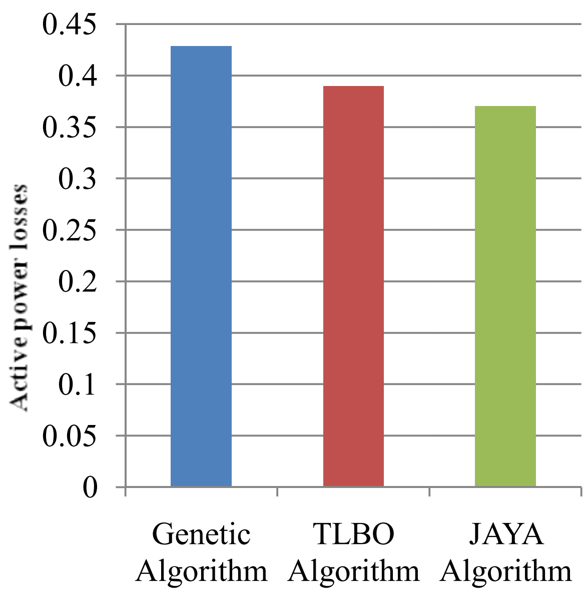

Fig.14. Active power loss reduction of algorithms

When the IEEE-39 system is used with various algorithms, the active and reactive power loss reduction is shown in table 1 below. System losses in the genetic algorithm case are 42.84 MW, while reactive power losses are 54.30 MW. The losses, which are shown in the table below, are decreased by using the TLBO and JAYA algorithms. When the system is used with the Jaya algorithm, the losses are relatively small. Reactive power losses are likewise impacted as active power losses are decreased.

Table 1: Active and Reactive power losses

Types of Algorithms	Active power loss (MW)	% Loss reduction	Reactive power loss (MVAR)	% Loss reduction
Genetic Algorithm	42.84	-	54.30	-
TLBO Algorithm	38.95	9.08	49.71	8.4
JAYA Algorithm	37.02	13.9	48.02	11.71

VII. CONCLUSION AND FUTURE SCOPE

In this study, the optimal active power flow problem is solved using the TLBO and Jaya algorithms. The two algorithms' efficiency is demonstrated using the IEEE-39 bus system. The test results unequivocally demonstrate that Jaya outperforms other algorithms in terms of solution quality. The proposed Jaya method's advantage for big systems is more obvious, as shown by the IEEE-39 bus system. Finally, it can be inferred from all of the findings of the aforementioned test cases that the Jaya algorithm is capable of resolving large-scale issues and is effective in resolving issues with power system optimisation.

In this we are only discussed with single objective functions. By using advanced optimization techniques to overcome this problem.

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