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Genetic algorithm-based optimization for power system operation: Case study on a multi-bus network

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Abstract
The use of genetic algorithm (GA) optimization in power system operation presents a compelling case study for dealing with the complexities inherent in multi-bus networks. This study examines the intricate dynamics of power distribution networks and emphasizes the importance of adaptive approaches in effectively managing modern power systems. As the energy landscape moves towards intelligent grids and advanced network architectures, optimizing the operation of multi-bus networks becomes crucial in ensuring the reliability and efficiency of power supply. By utilizing GA, this research showcases the algorithm's impressive ability to systematically approach optimal solutions for minimizing power loss. Through extensive analysis, GA emerges as the preferred method, demonstrating superior performance in achieving optimal solutions with high objective values and efficient convergence. This underscores the effectiveness of GA in addressing the specific challenges of multi-bus networks, establishing it as a valuable tool for power system optimization. To conclude, the application of GA proves advantageous in achieving desired outcomes in the context of power system operation within multi-bus networks. This research contributes to advancing our understanding of effective strategies for managing complex power systems, paving the way for more resilient and sustainable energy infrastructure.

Keywords: Bus system, convergence, genetic algorithm, optimization, power loss

Introduction
The traditional electrical grid, which is commonly known as the "dumb grid," has served as the fundamental infrastructure for the distribution of electrical power for numerous generations, spanning several decades. This intricate system is distinguished by its centralized generation and unidirectional distribution approach, wherein power flows from the centralized sources to the end-users. The "dumb grid" has been the steadfast pillar of the power sector, enabling the seamless delivery of electricity across vast distances and accommodating the ever-increasing demand for power consumption [1]. The concept of the "smart grid" is a truly transformative and visionary idea that marks a momentous departure from the conventional and antiquated model of electricity distribution, as it sets out to establish a highly innovative and cutting-edge system that fosters an unprecedented level of dynamism, interconnectivity, and adaptability within the electrical grid. The astoundingly smart grid, with its extraordinary level of intellect, has been meticulously constructed to possess an unparalleled level of responsiveness and adaptability in the face of fluctuations in the supply and demand of electricity. This ingeniously crafted grid has been expertly designed to flawlessly integrate a vast array of energy sources, including, but certainly not limited to, the renewable sources of solar and wind power, which are well-known to exhibit a certain degree of variability [2].

The notion of the smart grid symbolizes a transformative shift in the traditional electrical grid, as it encompasses a comprehensive and profound metamorphosis. By leveraging state-of-the-art technologies, advanced data analytics, and two-way communication, the smart grid aspires to establish a highly optimized, resilient, and environmentally conscious energy distribution system. This ground-breaking system not only enhances the overall efficiency of energy transmission but also plays a significant role in mitigating the environmental impact. Furthermore, the smart grid serves as a platform for the seamless integration and utilization of renewable energy sources, thereby paving the way for a more sustainable and ecologically friendly energy future [3]. The IEEE bus system serves as a uniform technique for illustrating and exploring power systems in the domain of electrical engineering.

It is essentially a streamlined representation employed for the purpose of examination and investigation. The IEEE has established multiple standardized bus systems, including but not limited to the IEEE 14-bus system, IEEE 30-bus system, and so forth, where each system uniquely comprising a designated quantity of buses, branches, and generators. These models greatly assist researchers and engineers in scrutinizing the performance of power systems, examining diverse phenomena like load flow, voltage stability, and fault analysis, as well as experimenting with novel algorithms and control strategies. The interlink between the IEEE bus system and the intelligent grid can be found in the utilization of universally accepted frameworks for examining and evaluating the efficiency of energy systems, encompassing the intelligent grid [4].

The process of creating and refining algorithms and control strategies for the smart grid commonly commences by conducting thorough testing and validation procedures, which involve the utilization of IEEE bus systems. By employing these systems, researchers are able to effectively implement and fine-tune control algorithms within simplified power systems, thereby providing a preliminary evaluation of their efficacy and reliability before they are eventually applied to real-world smart grids. This sequential approach allows for a controlled and methodical progression towards the ultimate goal of optimizing the performance and functionality of the smart grid, ensuring its seamless integration and operation within the existing power infrastructure [5].

Genetic algorithms (GAs) represent a kind of optimization methods employed within the realm of the intelligent power grid to tackle an array of predicaments concerning energy administration, arrangement, and regulation. GAs possess the ability to enhance the organization and management of power supplies encompassed within an intelligent grid. This involves the arrangement and coordination of electricity production and dispersal from diverse origins, taking into account elements such as expenditure, necessity, and ecological repercussions. GAs demonstrate exceptional aptitude in addressing intricate and ever-changing scheduling predicaments. GAs has the remarkable capability to unravel the complexities of the smart grid, specifically when it comes to tackling optimal power flow (OPF) predicaments. These predicaments entail the meticulous optimization of power generation distribution, aiming to minimize expenses while strictly adhering to a myriad of constraints, including line capacities, voltage limits, and the intricate web of network topology [6].

Literature review

The IEEE 14 bus system, which serves as a highly regarded benchmark model for power system optimization studies, is widely utilized in the field. Due to its relatively small scale, the system offers a practical yet complex environment which is ideal for the purpose of testing and comparing various optimization algorithms. The genetic algorithm (GA) is a highly regarded and robust evolutionary optimization technique that receives considerable attention and admiration from both researchers and practitioners when addressing the optimal power flow (OPF) challenge in the IEEE 14 bus system. The GA technique is frequently utilized in practice for tackling the OPF problem, thereby demonstrating its efficacy and reliability in this context. Literature review is based on minimizing power losses and reactive power dispatch and voltage control, optimal placement and sizing of distributed generation, and optimal capacitor placement for power factor improvement.

Minimizing power losses and voltage control

The GA has demonstrated remarkable effectiveness in optimizing power loss in the extensively studied power system network of the IEEE 14 bus system. Numerous studies have showcased its potential in significantly decreasing power losses, with outcomes displaying a noteworthy range of enhancements varying from 5% to 15% when compared to reference scenarios. A research conducted by Deb *et al*. in [7] demonstrated that GA can reduce power losses by 5.26%, while another study by Goswami and Chakrabarti in [8] indicated a decrease of 7.1%, emphasizing the positive influence of GA on power system efficiency. The utilization of GA presents vast potential for enhancing power grid operations and ensuring optimal utilization of resources. Hence, power system operators and planners should seriously consider implementing it in power loss reduction strategies to maximize the efficiency and sustainability of power networks.

Optimal capacitor placement and power factor improvement

In a study published in 2012, Kumar and his colleagues undertook an investigation to examine the implementation and utilization of GAs in the particular context and environment of optimal capacitor placement [9]. Their research aimed to achieve two important objectives: significant improvement in power factor and reduction in power loss. By employing GA as a tool, the researchers successfully showcased its effectiveness in the development of network reconfiguration strategies for the purpose of minimizing power losses. This innovative investigation not only elucidated the potential of genetic algorithms in the realm of power systems engineering, but also exhibited their proficiency in optimizing the positioning of capacitors, leading to improved power factor and diminished losses.

Optimal placement and sizing of distributed generation

In their study, Moradi and his fellow researchers effectively utilized the GA as a valuable tool for the purpose of optimizing not only the precise placement but also the proportions of the distributed generation (DG) units, thus ensuring their maximum efficiency and functionality [10]. This implementation yielded significant decreases in power losses and enhanced voltage stability. This highlights the potential of GA as a valuable solution for addressing challenges in DG integration and emphasizes its efficacy and dependability as a powerful tool in power system optimization, thus promoting further research in power systems engineering. This investigation emphasizes the noteworthy role that GA can assume in the incorporation of renewable energy sources, while concurrently optimizing power losses. The outcomes of this study underscore the vast possibilities and opportunities that GA possess in revolutionizing the field of renewable energy integration. The study showcases the extensive capabilities of GA in transforming the integration of renewable energy. By effectively utilizing DG units, GA contributes to the advancement of sustainable and reliable power systems.

Reduction in power losses of IEEE 14 bus system

The research conducted on the effectiveness of the GA in mitigating power loss in the IEEE 14 bus system has unequivocally shown empirical evidence, unequivocally demonstrating a notable decrease in power loss ranging from 5% to 15% when compared to the reference scenarios. It has been reported in [7-8] that power losses have been reduced up to the extent of 5.26% and 7.1%, respectively, highlighting the positive impact of GA on power system efficiency and resource utilization. Additionally, GA has shown effectiveness in achieving improved power factor and reduced power loss in optimal capacitor placement and network reconfiguration strategies, as demonstrated in [9]. The scholarly research in [10] brought to the forefront the significance and effectiveness of GA in the process of optimizing the positioning and measurements of distributed generation entities. This optimization process leads to significant reductions in power losses and enhanced voltage stability. The noteworthy discoveries shed light on the capacity of GA to transform the domain of power systems engineering and the assimilation of renewable energy. Furthermore, GA's effectiveness in addressing challenges and encouraging further research in this area further solidifies its importance in the field.

Motivation

The motivation of GA in power system optimization is driven by the significance of minimizing power losses and enhancing optimal solution, particularly within the well-studied IEEE 14 bus system, where there is a recognized need for comprehensive and integrated approaches to address power losses and improve system efficiency by leveraging the potential of GA as a holistic solution.

Contribution

The contribution of this study establishes Genetic Algorithms as a powerful tool for power system optimization. GA effectively reduces power losses in the IEEE 14 bus system, enhancing power system efficiency. It offers practical insights for power grid operators and planners. GA also improves power factor and reduces power loss in optimal capacitor placement. This insight improves the efficiency of power distribution systems. Investigating location and size of distributed generation units is a significant contribution. The research conducted by Moradi and colleagues provides evidence for the efficacy of GA in optimizing unit placement and proportions, leading to decreased power losses and improved voltage stability. This addresses the challenges in integrating distributed generation and establishes GA as a valuable tool for advancing power systems. In this paper, we leverage Genetic Algorithms to enhance the efficiency of the IEEE 14-bus system by seeking optimal solutions for minimizing line losses, thereby contributing to the overall improvement of the system's performance

System model

The IEEE bus systems, such as the IEEE 14 Bus System, are widely recognized as standard test cases that are employed to evaluate the performance of optimization algorithms in power system analysis. These algorithms, which are specifically developed for power systems, are aimed at determining the most optimal operational configurations. Such configurations encompass a wide range of tasks, including load distribution, generation planning, and network restructuring. The overarching objectives of these optimization algorithms are to minimize power losses, maximize system reliability and show optimal solution of power system. These benchmark systems serve as a well-defined and universally accepted platform for researchers and practitioners to assess and compare the efficacy of various optimization strategies in tackling the intricate challenges encountered within power systems. The most common optimization algorithm is genetic algorithm and can be explained as below.

Genetic algorithm

GAs has exhibited their efficacy as highly proficient instruments within the domain of power system optimization. By capitalizing on the fundamental tenets of natural selection and genetics, GAs facilitate a swift and efficient exploration for the most favorable amalgamation of generator outputs, thereby achieving the minimization of the aggregate generation cost, while concurrently ensuring the full adherence to all system constraints. This ability to simultaneously consider multiple objectives and constraints makes GAs a powerful tool in tackling the complex optimization problems encountered in power systems. GAs can minimize active and reactive power losses in the system, leading to improved overall system efficiency.

The mathematical modeling of genetic algorithm for IEEE 14 bus system comprised of model parameters, chromosomes representation, objective function, constraints, fitness function, genetic operator, and termination criteria.

Model Parameters

The model parameters for GAs consist of bus data, and line data. Bus data is comprised of number of buses, types of buses, active and reactive power for buses, and voltage set-points for buses. Line data comprised of number of lines, line resistance, line reactance and line flow limits.

Chromosomes representation

Chromosomes representation for GA comprised of binary representation and real-valued representation. In binary representation, each gene represents a binary decision variable (1 or 0). In context of IEEE 14 bus system, a gene can represent bus type. As this project is dealing with five types buses that are slack bus (denoted by S_i), PV bus (denoted by P_i), PQ bus (denoted by Q_i), load bus (denoted by L_i), and generator bus (denoted by G_i). If $S_i = 1$, then bus type will be slack otherwise the bus type will be other than slack bus. Similar interpretation is also used for PV bus, PQ bus, load bus and generator bus. Mathematically, chromosome X is represented as given in equation 1.

$$X = [\, S_i \,, P_i \,, Q_i \,, L_i \,, G_i] \tag{1}$$

Objective function

The objective function within the framework of a genetic algorithm applied to the IEEE 14-bus system would customarily pertain to the performance or efficacy of the power system. Within the realm of power systems, the overarching goal is centered on the endeavor to diminish the cumulative dissipation of power within the intricate network, while simultaneously aiming to mitigate the amplitude of voltage fluctuations in the IEEE 14 bus system. The real power losses of IEEE 14 bus system can be given in equation 2. Where the current flowing in lines of power system is denoted by I_{line} and resistance of the line is denoted by R_{line} is the total resistance of the line of power system.

$$P_{losses} = I_{line}^2 R_{line} \quad (2)$$

The objective function for minimization of line losses are given in equation 3, where objective function for IEEE 14 bus system is denoted by f(X).

$$f(X) = \sum_{i=1}^{N} I_i^2 R_i \quad (3)$$

Where N represents lines of IEEE 14-bus system, I_i is the current in the i^{th} line of the IEEE 14 bus system, and R_i is the resistance of the line of i^{th} line of the power system. In order to express, the line current in term of decision variable of chromosome X, we have to write the current in term of voltage at sending and voltage at receiving end along with reactance of the line of power system. where, V_{si} is the sending end voltage of i^{th} bus and V_{ri} is the receiving end voltage of the i^{th} bus of the IEEE 14 bus system and X_{Li} is the reactance of the IEEE 14 bus system. Equation 4 shows the mathematical form of the line current I_i.

$$I_i = \frac{V_{si} - V_{ri}}{X_{Li}} \quad (4)$$

By putting equation 4 in equation 3, the final form of objective function of IEEE 14 bus system is given in equation 5.

$$f(X) = \sum_{i=1}^{N} \left(\frac{V_{si} - V_{ri}}{X_{Li}}\right)^2 R_i \quad (5)$$

Minimizing the deviation in voltage is a widely pursued aim in the realm of power system optimization quandaries. Voltage deviation denotes the disparity that arises between the actual voltage present at a given bus and the voltage value that is deemed desirable for that specific bus. The primary intention is to diminish these deviations across the entirety of the buses that comprise the system. The voltage deviation at bus "i" is denoted by ΔV and objective function f(X) for voltage deviation is given in equation 6.

$$f(X) = \sum_{i=1}^{N} (\Delta V)^2 \quad (6)$$

Where ΔV is the absolute difference between actual voltage and desired voltage and $\Delta V = V_{actual} - V_{desired}$ and by putting the value of ΔV in equation 6, the objective function f(X) for voltage deviation is given as in equation 7.

$$f(X) = \sum_{i=1}^{N} \left(\left|V_{(actual)i} - V_{(desired)i}\right|\right)^2 \quad (7)$$

For slack bus $V_{(actual)i}$ is fixed, for PV bus, for PV bus $V_{(actual)i}$ is controlled and deviation is penalized based on control setting and for PQ bus $V_{(actual)i}$ is part of optimization.

Different constraints of IEEE 14 bus system

In the realm of a genetic algorithm that has been created with the primary objective of improving the functionality of the IEEE 14-bus power system, it becomes absolutely crucial to take into account an extensive range of constraints and prerequisites so as to guarantee that the results produced by the algorithm, which are commonly known as chromosomes, are not only viable but also accurately mirror the prevailing circumstances that exist in the tangible realm. The constraints of IEEE 14 bus system are power balance constraints, bus voltage magnitude constraints, line flow constraints, generator output constraints, voltage angle difference constraints, generator voltage constraints and load shedding constraints.

Power balance constraints

According to the power balance constraints, it becomes crucial to guarantee that the cumulative amount of active power being infused at every bus station remains equivalent to the cumulative quantity of active power being retrieved, thereby maintaining a harmonious equilibrium between the two opposing actions of power injection and withdrawal. Correspondingly, the aggregate amount of reactive power being injected at every bus must be equivalent to the aggregate amount of reactive power being drawn. Power balance constraints for real and reactive power at each bus "j" are given in equation 8 and 9 respectively.

$$\sum_{k \in N(i)} (P_{jk} - P_{kj}) + P_{dj} = P_{gj} \quad (8)$$

$$\sum_{k \in N(i)} (Q_{jk} - Q_{kj}) + Q_{dj} = Q_{gj} \quad (9)$$

Where, P_{jk} and Q_{jk} are the real and reactive power flow from bus j to bus k. Similarly, P_{kj} and Q_{kj} are the real and reactive power flow from bus k to j. where, P_{dj} and Q_{dj} are the demand power at bus j and P_{gi} and Q_{gi} are the real and reactive power generated at bus j. k ε N(j) is used to represent the neighboring buses of bus j.

Bus voltage magnitude constraints

According to the voltage magnitude constraints pertaining to buses within the electrical power system, it is imperative to establish a range of voltage magnitudes that both adhere to the principles of system stability and remain within the boundaries of acceptable operational limits. The voltage magnitude range for each bus is crucial in establishing the system's resilience and dependability, highlighting its significance in power distribution networks. The careful consideration and implementation of such constraints play a pivotal role in ensuring the smooth and efficient functioning of the entire power network, thereby minimizing any potential disruptions or adverse consequences that may arise from voltage instability or deviations from acceptable operational thresholds. Equation 10 shows the relationship among minimum voltage, actual voltage and maximum voltage.

$$\left(V_{(\min)j}\right)^2 \le V_j \le \left(V_{(\max)j}\right)^2 \quad (10)$$

Line power flow constraints

Line flow constraints are utilized in order to impose certain limitations on the active and reactive power flows that occur within each transmission line, thereby effectively averting the possibility of overloading. Mathematically line flow constraints for active and reactive line flow for line "j" are shown in equation 11 and 12 respectively.

$$(S_j)^2 \leq (S_{(max)j})^2 \quad (11)$$

$$(Q_j)^2 \leq (Q_{(max)j})^2 \quad (12)$$

Where, S_j is the complex power flow in line "j" and Q_j is the reactive power flow in line "j". On the other hand, S_{maxj} is the maximum complex power at line "j" and Q_{maxj} is the maximum reactive power flow at line "j".

Voltage angle constraints

The constraints on the difference in voltage angles between the connected buses are necessary in order to ensure the stability of the overall system. These constraints are put in place to regulate the variations in voltage angles and prevent any potential disturbances or fluctuations that may arise. By closely monitoring and controlling the voltage angle differences, it becomes possible to maintain a reliable and secure operation of the entire system. These constraints act as a safeguard against any undesirable effects that may occur due to excessive voltage angle differences, thereby ensuring the smooth functioning of the interconnected buses. The pair of buses is denoted by j and k and the voltage angle difference for pair of buses is given in equation 13.

$$\theta_{(\min)jk} \leq \theta_j - \theta_k \leq \theta_{(\max)jk} \quad (13)$$

Where, $\boldsymbol{\theta}_{(\min)jk}$ is the minimum angle difference for pair of buses "j" and "k", and $\boldsymbol{\theta}_{(\max)jk}$ is the maximum angle difference for pair of angles j and k and $\boldsymbol{\theta}_j$ is the voltage angle at bus j and $\boldsymbol{\theta}_k$ is the voltage angle at bus k.

When we integrate the aforementioned constraints into the genetic algorithm, they play a crucial role in directing the search towards feasible and realistic solutions for the IEEE 14-bus system. This incorporation ensures that the optimization process revolves around identifying a chromosome X that not only meets these constraints but also minimizes or maximizes the defined objective function. By doing so, we are able to navigate the complex landscape of possibilities and arrive at an optimal solution that aligns with the desired outcomes of the system.

Algorithm Implementation

The algorithm implementation provides a comprehensive and methodical framework for carrying out optimal solution of IEEE 14-bus system, taking into account the application of genetic algorithm. It is dealing with the implementation of genetic algorithm in the context of IEEE 14 bus system.

Initialize the Power system

1. Selecting suitable tool for software base analysis
2. Importing bus data and line data of IEEE 14 bus system

Power flow analysis

1. Formulation of bus admittance matrix (Y matrix)
2. Solving power flow equation in order to solve bus voltage, angle and power values.

Genetic algorithm optimization

1. Implementing genetic algorithm to optimize power system parameters.
2. Define the genetic algorithm parameters (e.g., population size, crossover rate, mutation rate).
3. Formulate the objective function based on the IEEE 14-bus system characteristics.
4. Apply genetic operators (selection, crossover, mutation) to evolve the population.
5. Evaluate the fitness of individuals using the objective function.
6. Repeat until convergence or a specified number of generations.

The overall methodology can be shown with help of algorithm given in table 1. It provides a comprehensive approach to evaluating the performance of this algorithm.

Table 1: Algorithm for optimal solution of IEEE 14 bus system using genetic algorithm

Algorithm: Summary of the algorithm for optimal solution of IEEE 14 bus system using Genetic algorithm
1. Start 2. Initialize the system: ▪ Load necessary libraries and tools in MATLAB. ▪ Import bus data and line data for the IEEE 14-bus system. 3. Load Flow Analysis: 3.1 Use the MATLAB code for power flow analysis: a. Formulate Y-bus matrix. b. Solve power flow equations to obtain bus voltages, angles, and power values. 4. Genetic Algorithm Optimization: 4.1. Implement a genetic algorithm to optimize power system parameters: a. Define the genetic algorithm parameters (e.g., population size, crossover rate, mutation rate). b. Formulate the objective function based on the IEEE 14-bus system characteristics. c. Apply genetic operators (selection, crossover, mutation) to evolve the population. d. Evaluate the fitness of individuals using the objective function. e. Repeat until convergence or a specified number of generations. 5. End

Results and Discussions

The result and discussion of the study is divided into two sections. First section is dealing with single line diagram of IEEE 14 bus system and second section is dealing with implementation of genetic algorithm.

Single line diagram of IEEE 14 bus system

Single line diagram in figure 1 shows IEEE 14 bus system, including one slack bus (bus 1), four PV buses (bus 3, 4, 10, 13), four PQ buses (bus 6, 7, 11 , 14), two are load buses (bus 5 , 9) and three are generator buses (2, 8, 12). These buses are labeled with their name and lines drawn are shown.

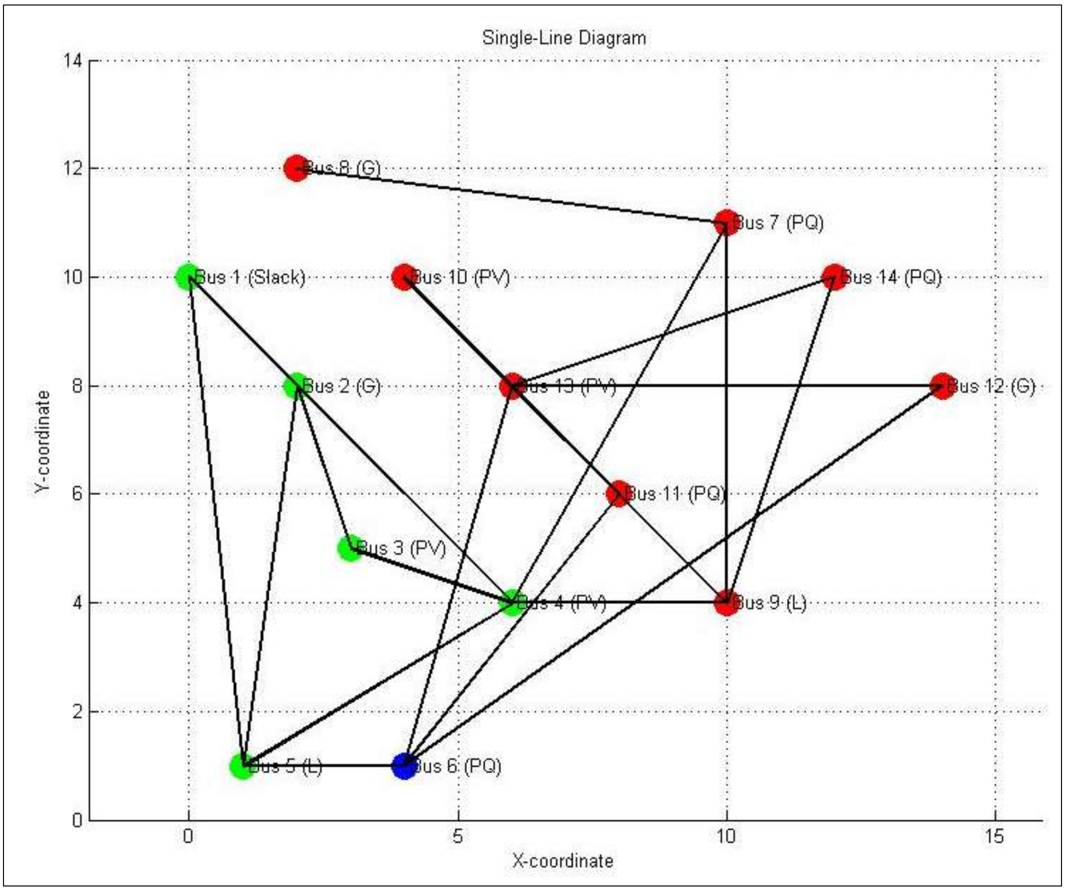

Fig 1: Single line diagram of IEEE 14 bus system

Table 2: Bus type, voltage and power specification of IEEE 14 bus system

Bus type	Voltage specification	Power specification
Slack bus	Specified	Active and reactive power are determined by the system load
PV bus	Specified	Reactive power is determined by the system load
PQ bus	Specified	Active and reactive power are specified
Generator bus	Active power is specified	Voltage is determined by system load
Load bus	Reactive power is specified	Voltage is determined by the system load

Table 2 shows the voltage, power specification, and bus type of IEEE 14 bus system. The single-line diagram depiction clearly illustrates the existence of a system imbued with a notably intricate configuration, replete with manifold loops and a multitude of interconnections between buses. This heightened level of intricacy has the potential to render the operation and control of the system a more demanding endeavor, thereby posing a considerable challenge. However, it is crucial to acknowledge that this very complexity can also serve as a catalyst for the system's enhanced reliability and resilience, as it fosters a robust framework capable of withstanding various potential disruptions and contingencies. The subsequent elucidations proffer a myriad of pivotal insights derived from the single-line diagram, which serves as a graphical representation encapsulating the essential components and interconnections within a given electrical power system. The slack bus, which is also referred to as Bus 1, stands out as the solitary bus within the power system that possesses the unique ability to regulate both the voltage and angle. Notably, this distinctive characteristic of the slack bus renders it an indispensable reference point for the entire system, effectively enabling it to serve as a benchmark against which the remaining buses can be measured. Thus, the slack bus plays a pivotal role in maintaining the stability and reliability of the power system, as it ensures that all other buses adhere to a predetermined standard set by its controlled voltage and angle. The PV buses namely bus 3, 4, 10, and 13, have their operations regulated in order to uphold a predetermined voltage level. The primary function of these PV buses is to offer electrical potential assistance to the remaining components of the system. The generator bus, which includes bus numbers 2, 8, and 12, is skillfully manipulated in order to generate a predetermined quantity of actual power within the system. It is crucial to note that the generator bus serves as the primary supplier of power within the entire system. The single-line diagram exhibits that Bus 5 and Bus 9 function as load buses, indicating that their voltage is determined by the load of the system and their reactive power consumption is predetermined. It is imperative to closely monitor the system load. When the system experiences a significant load change, it is crucial to thoroughly assess the voltages and power flows to maintain its stability and reliability.

Implementation of genetic algorithm: The Genetic Algorithm (GA) functions through a process of iteration, systematically honing and enhancing a population of potential solutions over a multitude of generations, in order to achieve optimal outcomes. This process involves continuously improving the quality of solutions through a combination of selection, crossover, and mutation operations. As the algorithm progresses, it identifies the best solution discovered thus far, along with its corresponding objective value, which in this case is the minimum power loss. The Genetic Algorithm (GA) is a highly sophisticated computational method that exhibits the extraordinary ability to identify, with utmost precision, the remarkably optimal solution for a specified problem, thereby determining the accompanying objective value in a manner that is characterized by meticulousness and precision. To enhance analysis and understanding, the power losses and best objectives achieved at each generation are meticulously recorded. This meticulous documentation ensures that the evolution of the GA can be effectively monitored and scrutinized.

Optimal solution

The optimal solution, also known as the solution that leads to the utmost level of effectiveness and efficiency, can be regarded as the preeminent solution that has been unraveled and obtained during the entirety of the evolutionary process, encompassing various stages and iterations. This optimal solution has been derived by evaluating and comparing all the potential solutions generated across various generations, ultimately identifying the one that exhibits the greatest degree of optimality. Likewise, the optimal objective value, which refers to the quantitative measure of the solution's effectiveness, is characterized by the minimum power loss attained. This signifies that the optimal objective value represents the outcome wherein the power loss is minimized to its lowest possible extent, signifying a highly desirable and efficient solution. Table 3 shows the optimal solution for IEEE 14 bus system along with optimal solution found at generation level, and optimal objective value. Bus 8 possesses the most superior solution among all the buses, while bus 14 exhibits the most substandard optimal solution. The attainment of the optimal solution occurred during the 15 generation level, with a total of 100 generations and a population size of 50. Furthermore, according to table 3, it is evident that the application of genetic algorithm has resulted in optimal objective values reaching 0.28220. Figure 2 shows the optimal solution of genetic algorithm.

Genetic operation

The GA employs a combination of two essential operations, namely crossover and mutation. These operations are employed with the primary objective of exploring the vast solution space. Crossover, being the first operation, plays a crucial role in amalgamating information from two distinct parents. By combining the genetic material of these parents, it aims to generate offspring that possess desirable traits inherited from both sources.

On the other hand, the second operation, namely mutation, introduces random alterations to the genetic makeup of the population. This injection of randomness is pivotal in ensuring the preservation of diversity within the population. By allowing for occasional random changes, the mutation operation guarantees that the population does not converge prematurely to suboptimal solutions. Consequently, the combination of crossover and mutation in the GA serves as a powerful mechanism for navigating the solution space effectively. Table 4 shows the MATLAB algorithm for genetic operators in order to implement genetic algorithm on IEEE 14 bus system. The algorithm for GA operation consist of two steps, first one is related to crossover operation whereas second step is related mutation. Crossover is initialized by random number and mutation is compared with mutation rate. The mutation rate in this project is only 10% and it is equal to 0.1.

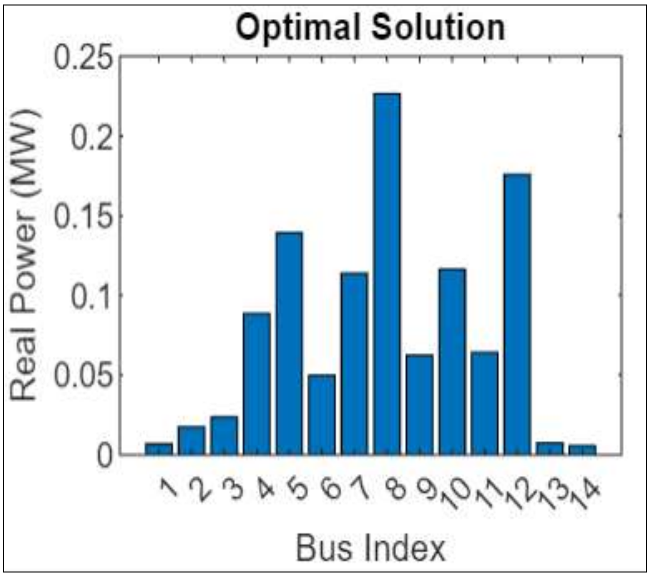

Fig 2: Optimal solution of IEEE 14 bus system using genetic algorithm

Table 3: Optimal solution of IEEE 14 bus system using genetic algorithm

S. No	Optimal solution Real power in (MW)
1	0.0066
2	0.0174
3	0.0236
4	0.0887
5	0.1400
6	0.0500
7	0.1140
8	0.2270
9	0.0623
10	0.1164
11	0.0643
12	0.1800
13	0.0074
14	0.0055
Generation at which optimal solution found	15
Optimal objective value	0.2270

Table 4: Algorithm used for genetic operation

Algorithm for Genetic operation

% Crossover Operation
function offspring = crossover(parent1, parent2)
% Randomly determine crossover point
crossoverPoint = randi(length(parent1));
% Create offspring by combining parents at and after crossover point
offspring1 = [parent1(1:crossoverPoint), parent2(crossoverPoint+1:end)];
offspring2 = [parent2(1:crossoverPoint), parent1(crossoverPoint+1:end)];
% Combine offspring into a matrix
offspring = [offspring1; offspring2];
end
% Mutation Operation
function mutatedPopulation = mutate(population, mutationRate)
[populationSize, nVariables] = size(population);
mutatedPopulation = population;
% Apply mutation for each individual in the population
for i = 1:populationSize
% Check if mutation should be applied
if rand() < mutationRate
% Randomly determine mutation point
mutationPoint = randi(nVariables);
% Replace the value at the mutation point with a random value
mutatedPopulation(i, mutationPoint) = rand();
end
end
end

Algorithm convergence and best objective value

The visualization of the convergence behavior can be effectively demonstrated through the utilization of two distinct figures plots. In the figure 3, a comprehensive representation of the power losses over the power line of the IEEE 14 bus system is presented, allowing for a profound exploration of how the algorithm gradually converges towards an optimal solution. This particular visual aid serves as a valuable tool in comprehending the intricate intricacies of the convergence process. Moreover, the figure 4 showcases the best objective values attained throughout the optimization process, thereby providing a clear indication of the progress made towards achieving the desired optimization outcome. By observing and analyzing these objective values, one can gain valuable insights into the effectiveness and efficiency of the optimization algorithm employed. Consequently, the utilization of these two plots in tandem facilitates a comprehensive understanding of the convergence behavior and the optimization progress.

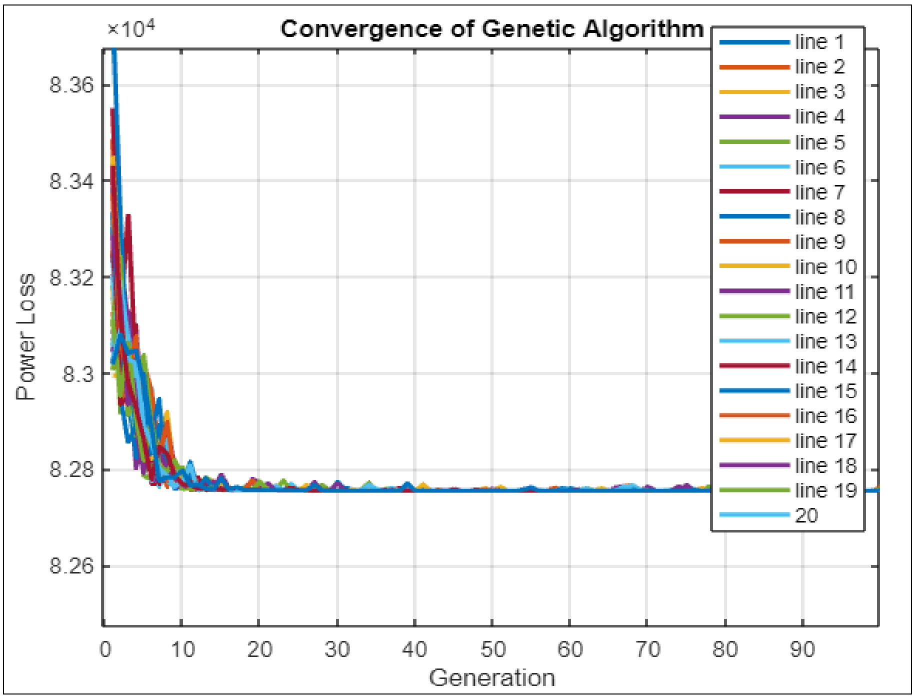

Fig 3: Convergence of genetic algorithm of IEEE 14 bus system

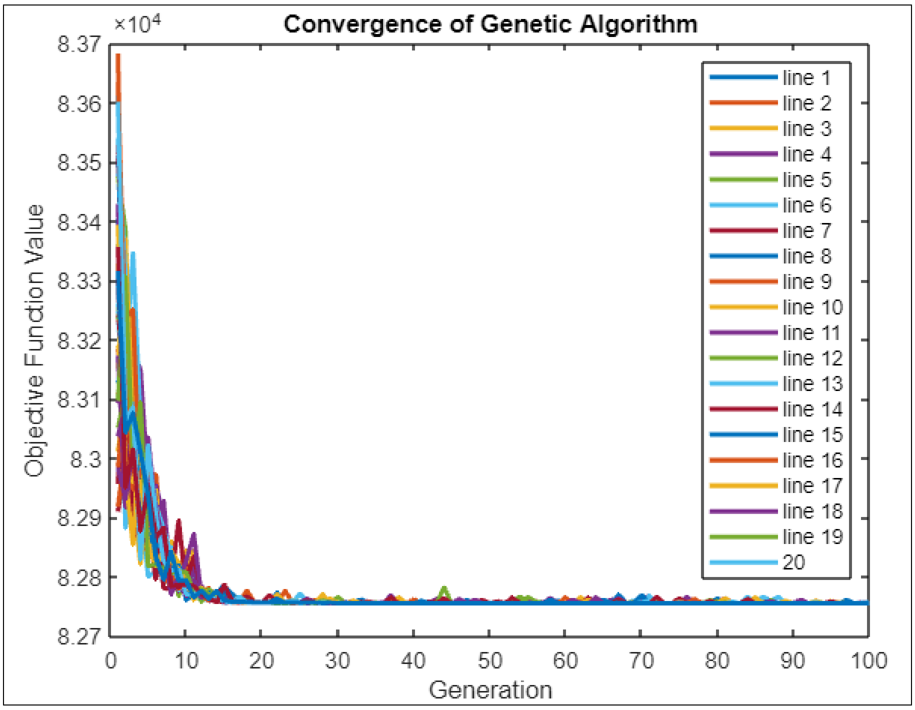

Fig 4: Best objective value of convergence of IEEE 14 bus system

The visual representation of the overall process of minimizing power loss in the IEEE 14 bus system can be observed in Figure 3, wherein the depiction of the convergence of a genetic algorithm (GA) is presented. This figure provides a comprehensive insight into the execution of the GA, with the horizontal axis serving as a means to represent the number of generations that have transpired during the execution, while the vertical axis is effectively employed to display the total power loss experienced within the system. By examining this graph, one can gain a deeper understanding of how the GA operates and its impact on power loss reduction in the IEEE 14 bus system. This plotted curve, which serves as an effective visualization of the GA's progression, initially starts with a significant power loss and gradually decreases as the algorithm continues to iterate. This particular pattern that emerges from the graph is a clear indicator of the GA's effectiveness in successfully identifying and selecting solutions that ultimately lead to a substantial reduction in power loss within the system. As the generations progress, the curve begins to exhibit a plateau-like shape after approximately 15 generations, suggesting that the GA has reached a solution that is approaching optimality. Consequently, it can be inferred that the GA has successfully converged towards a solution that offers a significant reduction in power loss within the IEEE 14 bus system. Ultimately, Figure 4 serves as a valuable representation of the objective function value, which essentially encapsulates the convergence of the optimal solution within the complex structure of the IEEE 14 bus system.

Conclusion

The Genetic Algorithm (GA) has proven to be highly effective in power system optimization by systematically seeking optimal solutions to minimize power loss. Its methodical approach, supported by thorough documentation, visual aids, and the strategic use of controlled randomness, greatly enhances the GA's ability to handle complex optimization tasks. This effectiveness is clearly demonstrated in Figure 3, which shows how the GA steadily converges towards an optimal solution, highlighting its potential to effectively address the numerous challenges inherent in power system optimization.

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