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Optimization of Power Flow using GA Fuzzy Approach

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Abstract: The optimal power flow (OPF) issue is a critical optimization job in the operation and planning of power systems. It entails establishing the best settings of control variables to minimize generating costs while meeting operational restrictions. Traditional optimization techniques often struggle to handle the complexities and uncertainties inherent in power systems. This paper introduces fuzzy systems' concepts and their integration with genetic algorithms. It then delves into the many possibilities for power system optimization problems. The first section introduces the fundamental ideas of fuzzy, while the second section explores its structure and components. The third section explores the genetic algorithm's synergism with the fuzzy technique. The suggested technique was evaluated on an upgraded IEEE 30-bus system, with an optimal solution indicating fuel cost reduction under various linear and non-linear constraints. The suggested methodology's results were compared to all those mentioned in the literature. The outcomes of the offered methodologies are encouraging, demonstrating the efficacy and resilience of the proposed procedures. The synergism of the fuzzy system with the genetic algorithm offers several advantages, including flexibility in handling uncertainties, adaptability to complex systems, and the potential for discovering innovative solutions. However, it is important to carefully design the fuzzy system's rule base and appropriately set the genetic algorithm's parameters for optimal performance.

Keywords: Fuzzy System, Genetic Algorithm, Optimization, Knowledge base, optimal power flow.

1. Introduction

The o*p*timum power flow control in electrical power systems directly affects the security and economic dispatch of the system. Early OPF approaches relied on traditional scientific programming strategies and successfully demonstrated their capability. Various mathematical programming approaches, including quadratic and linear and nonlinear programming, were employed to address the OPF issue, and their capabilities were proven. Daily, numerical programming-dependent OPF systems are used to handle vast OPF issues. However, while there is some evidence from observation on the distinctive characteristics of the OPF arrangement within the region of interest, they are not expected to merge with the most effective global solution of the specific non-convex power flow problems. On-going endeavours to beat the constraints of the scientific programming approaches incorporating genetic algorithm techniques. The synergism of fuzzy with genetic algorithm approaches the optimum solution of OPF problem.

Lotfi Aliasker Zadeh proposed fuzzy logic in the year 1965. He was a mathematician, computer scientist, AI researcher, and professor emeritus at the University of California, Berkeley's computer science engineering department. A fuzzy set hypothesis and fuzzy logic generate non-linear mapping rules or norms. A reason for efficient courses for using indeterminate and uncertain models is accomplished by utilising fuzzy sets. Fuzzy control depends on fuzzy logic. Fuzzy logic is called a logical system, much like human reasoning and ordinary language, than customary coherent systems. In the modern era, fuzzy logic is used in almost every sector of science and production.

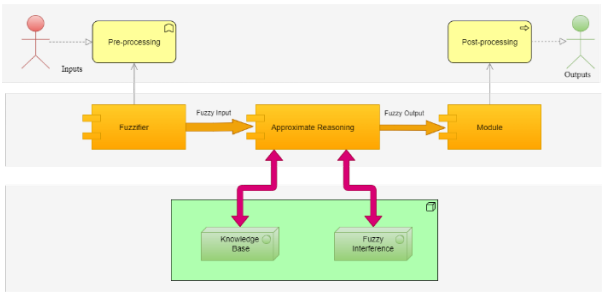


Figure 1:System of Fuzzy Body of Knowledge

A common definition that incorporates most knowledge-based system (KBS) implementations into the closed-loop control system. A KBS for close-loop control improves execution, consistency, and control intensity by incorporating information or learning that cannot be incorporated in the expository model on which a control algorithm plan is based and is generally handled by conventional methods of operation or any other well-being and sub-ordinate logic methodologies[1)-6)].

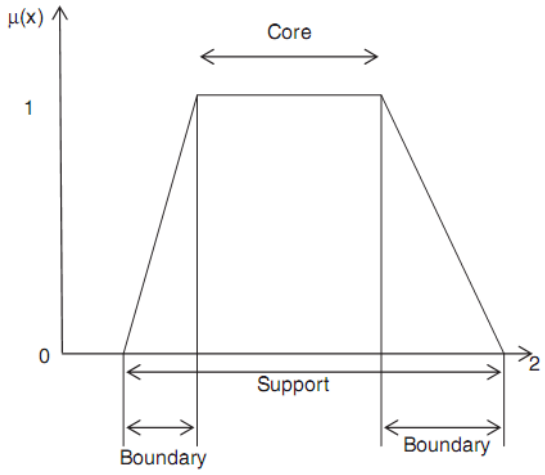


Figure 2: Trapezoidal Membership function characteristics

The objective of the Fuzzy Logic Controller (FLC) is to fuzzify the controller's inputs further and infer the proper fuzzy control decision based on set standards. Figure 1 depicts the schematic diagram of the Fuzzy knowledge-based system. The performance of the fuzzy controller is then obtained by defuzzifying the fuzzy control decision. Therefore, the systems of the fuzzy controller consist of the aforementioned key elements:

1. Fuzzification
2. Rules Definition
3. Inference Engine
4. Defuzzification

2. FLC Structure

2.1 Fuzzification

Fuzzification is the way to relate fuzzy factors to the controller's tangy input factors. Choosing control parameters depends on the system's actions and required performance. The process error and output components are often employed as controller inputs[7)]. The fuzzy variables are mapped from crisp values using the membership function.

2.1.1 Categorization of Fuzzy Sets

Membership functions can be used to classify fuzzy sets. They are listed below:

1. Normal fuzzy set
2. Non-normal fuzzy set
3. Convex fuzzy set
4. Non-convex fuzzy set

2.1.2 Characteristics of Membership Function

The following are the membership function's characteristics:

1. Support
2. Core
3. Boundary

The characteristics of the membership function appear in Figure 2.

2.1.3 Category of memberships functions

Figure 3 depicts the many forms of membership functions. To anticipate and quantify the fuzzy process performance, commonly triangular membership function is used because of its simplicity. Another reason to choose the triangular membership function is that the greater crispness provided by fuzzy perceptual sets and requiring more computing effort is not always reflected in the performance efficiency of a fuzzy model. Be that as it may, the decision on the membership function has still not been hypothesized. Separate literature/researchers used various forms of membership functions, such as trapezoidal, gaussian, sigmoidal, etc., depending on their application problems.

Rule base:

The fuzzy condition rule is metaphorically articulated as

if < fuzzy proposition > then < fuzzy proposition>

In which a fuzzy hypothesis is just one or more fuzzy assertions. The if-then rule expresses the relationship between the condition of the system and the output-controlling parameters.

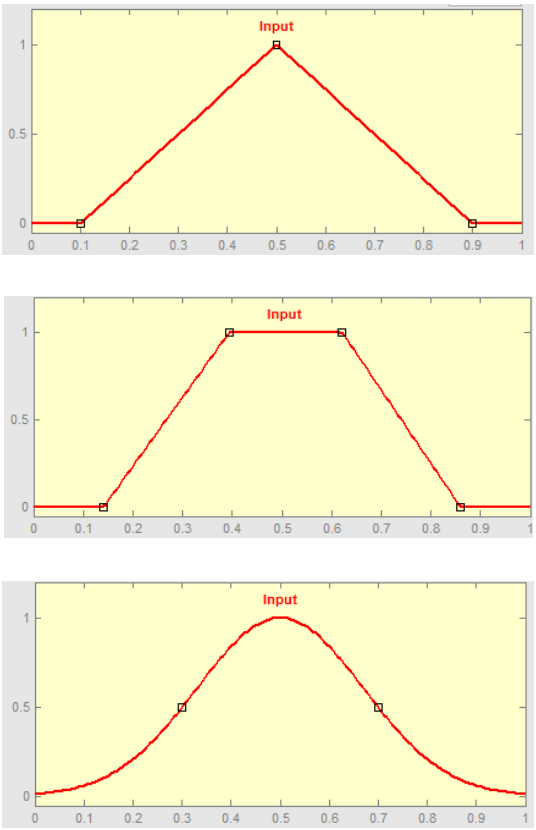


Figure 3: Membership Functions

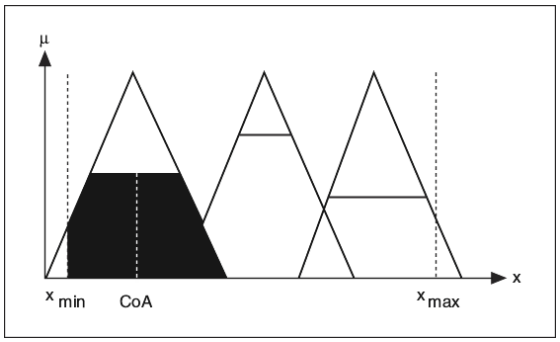
2.2 Defuzzification

The following fuzzy collection should also be substituted for a number that could be used as a control signal to the procedure. This is known as defuzzification. The various types of defuzzification methods are shown in Figure 4. The resulting fuzzy set is then defuzzied into a smooth control signal.

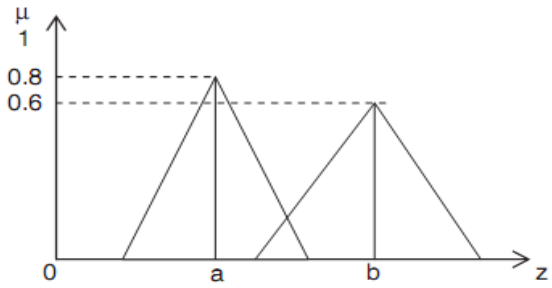
2.2.1 Types of Defuzzification Methods

A few techniques are used to defuzzify the output functions, and they are shown in Figure 4 and listed as:

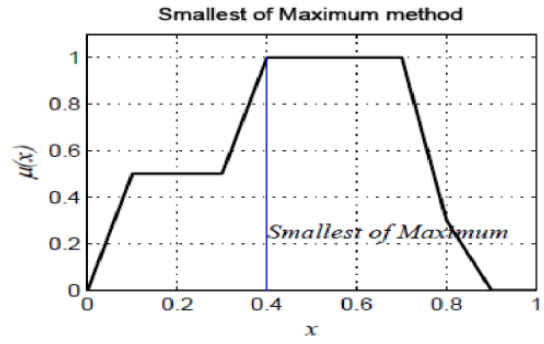
- Centre of Area (COA)
- Middle of Maximum (MOM)
- Bi-sector of Area (BOA)
- Centre of Gravity (COG)
- First of Maximum (FOM)
- Weighted Average Mean (WAM)
- Mean of Maxima (MeOM)
- Last of Maxima (LOM)

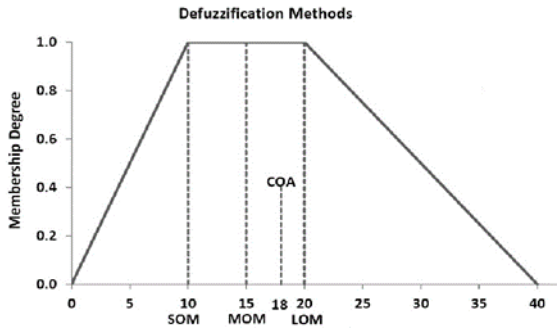


Centre of Area



Weighed average Mean





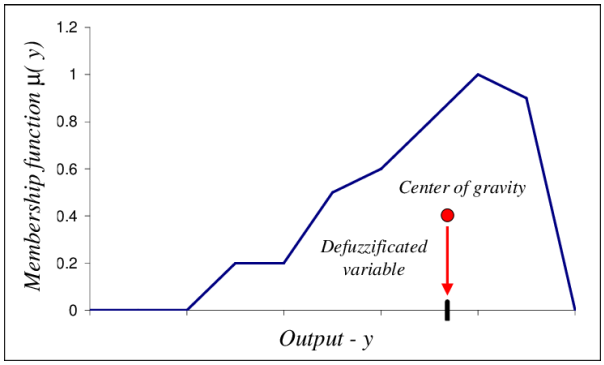


Figure 4: Defuzzification Methods

3. Problem Formulation

The task of scheduling and planning a control systems framework transcends governance work to ensure that varying demands are met using development resources. This involves the representation of consolidated expertise on specialized technological and economic limitations and can hardly be communicated as a solely analytical modelling endeavour. Making plans in process control will have two major components. Long-term planning entails expanding and redesigning the process control of any system. Short-term planning entails preparing activities to be completed quickly to guarantee proper mechanism and control framework functionality and benchmarking.

Analytical methods, including linear and dynamic programming, are typically used for planning and scheduling[8)-9)]. Be that as it may, the modelling assertions upon which the specific procedures are primarily focused do not frequently coordinate the actual arranging circumstance or result in restrictive calculation measures. Then again, heuristic and qualitative inclinations can't be effortlessly incorporated into investigative or analytical models. Hence KBS for scheduling and planning for process control can be correlative to the current scientific instruments.

4. Optimal Power Flow (OPF) Problem

The Optimum power flow is a profitable power system issue where certain control factors are modified in line with the expense limits of dynamic energy production while at the same time meeting physical and operational limitations on the various controls. The issue of the OPF is concerned with benchmarking the steady state execution of the energy system as an objective function and, at the same time, being exposed to different inequalities and constraints on equality. The overall cost of generated power is expressed by equation 1.

Minimize generating cost of thermal power

$$F = \sum_{j=1}^{NG} F_j = \sum_{j=1}^{NG} (a_j P_{g_j}^2 + b_j P_{g_j} + c_j) \frac{\$}{hour} \quad ----(1)$$

Where a, b and c are generator constants

Under different constraints mentioned in equations (2 to 8) :

Real power balance

$$P_j(\delta, V) + P_{d_j} - P_{g_i} = 0 \qquad (j = 1, 2, \dots, NB) \quad ---(2)$$

Reactive power (Q) balance equation

$$Q_j(\delta, V) + Q_{\mathrm{dj}} - Q_{g_j} = 0 \qquad --(3)$$

Security-related constraints

$$P_{g_j}^{min} \le P_{g_j} \le P_{g_j}^{max} \qquad (j = 1,2, \dots \dots, NG) \qquad --(4)$$

$$V_j^{min} \le V_j \le V_j^{max} \qquad (j = NV+1, NV+2, \dots \dots, NB) \quad -----(5)$$

$$\delta_j^{min} \le \delta_j \le \delta_j^{max} \quad (j = 2, \dots \dots, NB) \qquad ---(6)$$

$$P_j(V,\delta) = V_j \sum_{k=1}^{NB} V_k (G_{jk} \cos(\delta_j - \delta_k) + B_{jk} \sin(\delta_j - \delta_k)) \quad -----(7)$$

Where G = Line conductance and B Line susceptance

$$Q_j(V,\delta) = V_j \sum_{k=1}^{NB} V_k (G_{jk} \sin(\delta_j - \delta_k) - B_{jk} \cos(\delta_j - \delta_k)) \quad ----(8)$$

Where

F	Fuel Cost
NG	No. of generator bus
NB	No. of buses
NV	No. voltage-controlled buses
$\mathbf{P_j}, \mathbf{Q_j}$	Injected active and reactive power in j^{th} bus.
$\mathbf{V_j}$	Voltage magnitude of j^{th} bus.
$\boldsymbol{\delta_j}$	Phase angle of bus j.
$\mathbf{Q_{d_j}}, \mathbf{P_{d_j}}$	Reactive and active power load of bus j.
$\mathbf{Q_{g_j}}, \mathbf{P_{g_j}}$	Generated reactive and active power of j^{th} bus.

The improvement of OPF over the most recent two decades has followed the advance intently in numerical enhancement procedures and breakthroughs in soft computing techniques. Modern soft computing techniques can tackle substantial and complex optimization problems in a brief time. On the other hand, traditional power flow estimations of control factors are pre-indicated. In the OPF, estimates of a few or most control factors should be identified to upgrade the predetermined aim.

A portion of the alternative procedures that are effectively used for active power intercept, incorporate traditional strategic planning strategies that are dependent on active power dispatch, Lagrangian multiplier method[10)-11)], linear programming based strategies[12)-13)], quadratic programming method[14)], gradient approach utilizing steepest decent system[15)] and Newton's techniques[16)-17)]. An extensive survey of different optimization methods accessible in writing is accounted for in references[18)-20)]. A portion of such methods is that, as it may be, they have a decent confluence, yet most of them do not get a comprehensive solution. Because OPF is an integrative and non-linear issue, they are extremely dependent on the original assertion. Some advancement strategies have been used to address this issue, like genetic algorithms (GA)[21)-25)], evolutionary algorithms (EA)[26)], simulated annealing (SA), tabu search (TS) algorithms[26)].

GA is a heuristic check that emulates the procedure. This heuristic frequently produces valuable alternatives for optimizing and finding problem solutions. Genetic

algorithms have a place with a larger set of developmental heuristics that produce alternatives for optimization problems using systems that have been reused. A natural progression is the fundamental basis of the genetic algorithm. This is the most ground-breaking strategy for optimizing the issue of the electrical power system. A genetic algorithm is used to cope with the problem of active power flow, as mentioned in the literature[27)-30)].

5. Genetic algorithm and its synergism with fuzzy

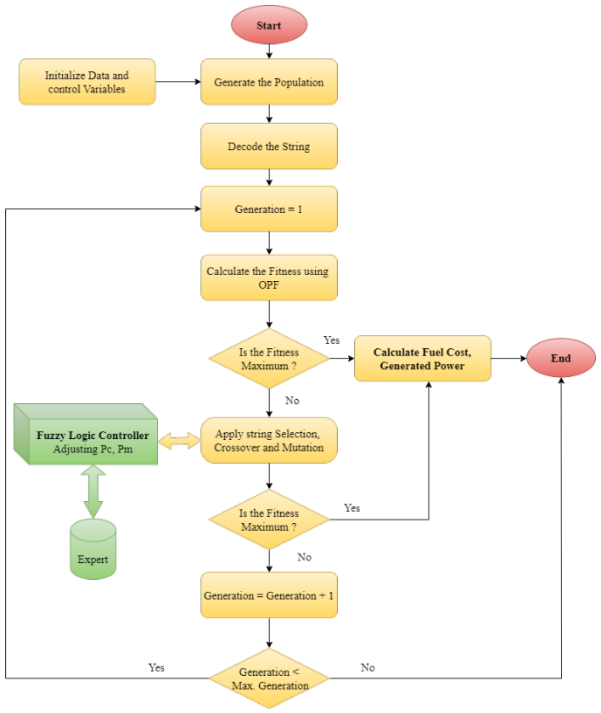


Figure 5: Flow chart of OPF using GA-Fuzzy

Genetic algorithms are useful optimization algorithms based on genetic drift mechanisms and inherited (genetic) attributes. They operate on sequence patterns, typically a connected list of binary digits reflecting a coding of code variables for a specific issue. Three primary contrasts exist between GAs and ordinary optimization calculations[28)-31)].

The theory behind changing crossover and mutation probabilities is that the optimization technique's responses largely rely on the optimization phase. As a result, an increased fitness value may need a minimal crossover and a moderate mutation probability for further refinement. On the other hand, the response with surprisingly high crossover and low mutation possibilities would be stronger at low fitness levels[32)-33)]. Figure 5 represents the optimum power flow solution's Genetic algorithm fuzzy (GAF) flow diagram.

5.1 Rule Base- GAF Approach

The factors in the GAF algorithm fluctuate based on the preceding fluctuating rule base for solving the problem. Based on the fitness function criteria, the GA variables (Probabilities of crossover and mutation) rely on the corresponding rationale:

1. The assessment of the best fitness value for every generation (BFT) is expected to alter over time. Yet, if it does not vary much between generations (UG), such data is known to cause both P_c and P_m shifts.

2. One of the elements is the sundry diverse range of a population, which affects the hunt for a genuine optimal level. Changing the population's objective function fitness estimate (EOF) is a proportion of its assorted variety. As a result, it is also viewed as a determinant that could change both P_c and P_m.

Controlling of P_c

If UG is H and FOE is L or M then PC is L.

Controlling of P_m

If BFT is H or M and UG is L then PM is L.

The surface rule viewer is shown in Figure 6.

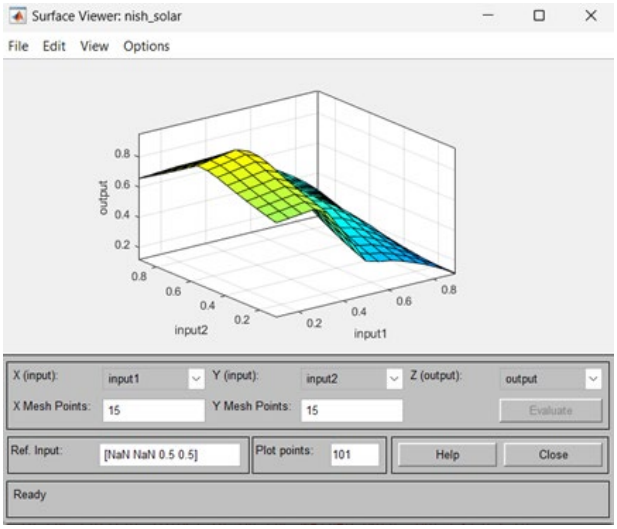


Figure 6: Surface Rule Viewer

6. Simulation and Results

The proposed approaches are now being tested with the modified and original IEEE 30-bus systems. The original IEEE 30 - bus includes six generator buses, fifteen load buses, and forty-one transmission lines. Modified IEEE 30 - bus system buses ten, twelve, fifteen, seventeen, twenty-twenty one, 23-24, and twenty-nine were chosen as compensatory buses.[34)-35)]. The proposed methods are developed in MATLAB 2016 software environment. The specification of the desktop is 8GB RAM, intel i3 processor.

Case A

This compares the GA - OPF and GAF - OPF and displays certain populations and criteria are given as

Pop size = 30, Max. Gen. = 100, Selection operator-SRRW, Initial value of $P_c = 0.9$ and $P_m = 0.001$

Transformer tap settings for GA - OPF and GAF - OPF are approved to be within 10%. The results of OPF employing proposed GA and GA-fuzzy for a modified IEEE 30-bus system are shown in Table 1. Table 2 compares the fuel cost and generator power generated for a modified IEEE 30-bus system using the proposed techniques.

Table 1: Comparison of proposed techniques for case A

	GA		**GA Fuzzy**	
	P_g	**V_g**	**P_g**	**V_g**
P_1	175.16	1.08	178.17	1.09
P_2	49.03	1.07	45.16	1.07
P_3	19.52	1.00	20.65	1.09
P_4	19.68	0.92	21.29	1.06
P_5	17.10	0.98	15.16	1.09
P_6	12.00	1.10	12.00	1.10
Total Power	292.48		292.43	
Fuel Cost	**801.96**		**801.21**	

Table 2: Correlations of various OPF strategies for an updated IEEE 30-bus system as mentioned in dissimilar literature

Techniques	**Cost**
GA-OPF [30]	802.38
GAF-OPF [30]	802.0003
Proposed Method	801.21

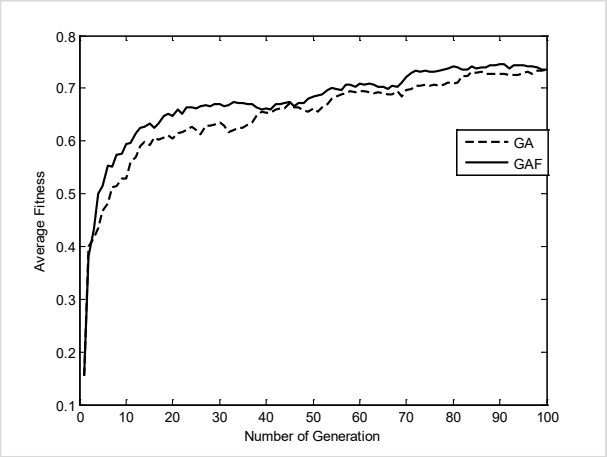


Figure 7: Mean fitness characteristics of proposed methods for case A

Figure 7 shows the enhancement of Mean fitness attributes for the adapted IEEE 30-bus system using suggested approaches. The mean fitness characteristics assess the average performance of proposed strategies for solving the optimum power flow problem in Case A. It reveals how efficiently proposed strategies identify near-optimal solutions on a consistent basis, allowing researchers to choose the most effective way for efficient power system functioning. Figure 8 depicts crossover and potential mutation progression before GA fuzzy. P_C and P_m are critical factors in the GAF for the optimum power flow problem. P_c regulates the possibility of crossover operations for exploration, whereas P_m controls the possibility of mutation for exploitation. These parameters must be balanced in order to efficiently travel the search space and locate optimum solutions while avoiding premature convergence or excessive unpredictability.The GA fuzzy methodology is better from this fitness curve than GA.

Case B

In this case, a sine portion is added to the cost curves of generator buses 1 and 2 to accentuate the impacts of valve point loadings.

The fuel cost with the valve point loadings is described as below in equation 9:

$$F(P_i) = \sum_{i=1}^{NG} \left(a_i P_i^2 + b_i P_i + c_i + \left|d_i \times sin\{e_i \times (P_i^{min} - P_i)\}\right|\right) - - - (9)$$

$$a_i, b_i, c_i, d_i, e_i = Generator\ cost\ coefficients$$

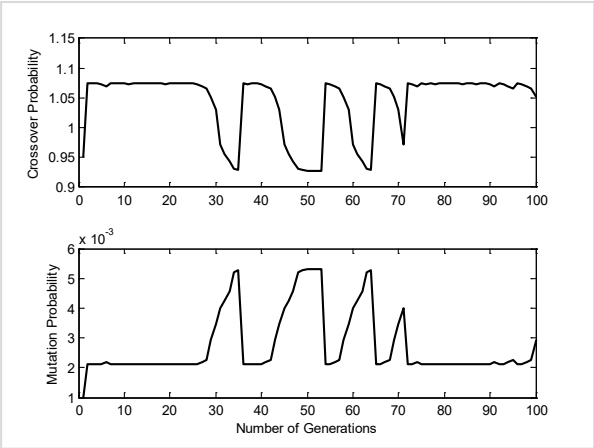


Figure 8: Characteristics of P_c and P_m for the GAF

The updated IEEE 30-bus system criteria with valve point loading impact of GA-OPF and GAF-OPF are presented below.

Size of Population= 50, Max. Generation = 150, P_c = 0.95, P_m = 0.001

Table 3 compares the cost utilisation method suggested for an updated IEEE 30-bus system with the effects of valve point loadings. The proposed methods promise minimum fuel cost and minimize power loss. Figure 9 depicts the typical fitness characteristics obtained by both methodologies. The mean fitness characteristics assess the average performance of proposed strategies for solving the optimum power flow problem in Case B. It has been discovered that combining fuzzy with GA

improves normal fitness while reducing fuel costs and loss.

Table 3: Comparison of proposed methods for case B

	GA	GA Fuzzy
P_L	10.31	9.97
Total P_G	293.710	293.370
Cost of Fuel ($/hour)	**925.5**	**921.880**

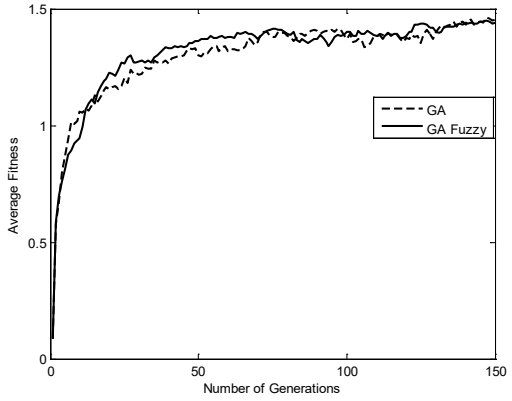


Figure 9: Mean fitness characteristics of the proposed method for case B

7. Conclusions

The synergism of a fuzzy system with a genetic algorithm gives a viable solution to the optimum power flow (OPF) problem. Combining the inherent strengths of both methodologies, this hybrid approach leverages the fuzzy system's ability to handle imprecise and uncertain information and the genetic algorithm's optimization capabilities.

In this research, the generating power is advanced to determine the base cost of fuel while fulfilling all of the system restrictions/constraints of the GA and its compatibility with the fuzzy. Such procedures deal with the issue of fuel cost of optimum power flow. Proposed approaches are implemented for the original and modified IEEE 30-bus systems. It has been observed that combining fuzzy with Genetic Algorithm techniques enhances the effectiveness of mean fitness determined using the optimal power flow technique when combined with fuzzy with Genetic Algorithm approaches. When the outcomes of combined GAF are measured against those of basic GA, synergetic approaches are shown to be superior.

The fuzzy system provides a flexible and robust framework for modelling and representing complex power system behaviour, considering real-world systems' inherent uncertainties and vagueness. It captures linguistic characteristics and expert knowledge using fuzzy sets and fuzzy rules, enabling more realistic and human-like decision-making.

On the other hand, the genetic algorithm excels in searching and optimizing large solution spaces, making it well-suited for solving complex optimization problems like OPF. It examines multiple solutions and evolves towards optimal or near-optimal solutions using genetic operators like selection, crossover, and mutation.

The fusion of the fuzzy system with the genetic algorithm results in a win-win situation. The fuzzy system assesses the quality of the solutions, prompting the genetic algorithm to produce better results. In turn, the evolutionary algorithm improves the performance of the fuzzy system by effectively searching the solution space, resulting in an effective and efficient optimisation strategy.

Combined, the fuzzy system and genetic algorithm create a strong symbiotic relationship. The fuzzy system provides a fitness function for evaluating the quality of solutions generated by the genetic algorithm, guiding the search towards more desirable solutions. At the same time, the genetic algorithm enhances the fuzzy system's performance by effectively exploring the solution space and improving the overall search efficiency.

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