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INSTITUTE OF GRADUATE STUDIES

Department of Electrical and Electronics Engineering

POWER SYSTEM OPTIMIZATION ALGORITHM FOR COMBINED ECONOMIC AND EMISSION DISPATH

Master Thesis

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Supervisor

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Turkish Anstract :

Ekonomik ve emisyon dağılımı sorunu, optimum çözümü bulmak için birçok çalışmada ve araştırmada ele alınmıştır. Bu çalışmada, insan davranışını simüle ederek çözümler bulma temeline dayanan yeni bir yaklaşım benimsenmiştir ayrıca ekonomik ve emisyon değerlerinin en düşük seviyelere ulaşılana kadar birden fazla adımda yaklaşımla sonuçlara ulaşılmıştır. Bu çalışmanın temeli bulanık mantıktır. Rastgele değerler seçilerek, insan bilgisine dayalı bulanık bir müdahale sistemi üzerinde yansıtılarak, jeneratörlere uygulanacak uygun değerleri belirlemek için kullanılır. Bu şekilde daha az yakıt maliyeti ve emisyon üreten değerleri elde etmek mümkün olur. Bulanık mantığın kullanımı arama alanını azaltıp arama sürecini güç talebi ve üretilen güçle ilgili belirli bir

bölgeye yönlendirir. Örneğin, güç talebi yüksekse, jeneratörler tarafından sağlanan gücün yüksek seviyelerde olması mantıklıdır, böylece üretilen güç, güç talebini eşitler ve iletken kayıplarını azaltır. Ayrıca, güç talebi orta seviyede olduğunda, üretilen gücün orta seviyede olması mantıklıdır, böylece güç talebi ve güç kaybı eşitliği sağlanır. Bu şekilde, güç yönlendirmesi belirli bir bölgeye yapılır ve çözümün bulunması için harcanan süre azaltılır. Sistemi herhangi bir durum veya güç talebi için uygulanabilir hale getirmek için bir dizi güç talebi tartışılmaktadır ve tüm bu değişiklikler ve sonuçlar, algoritmanın gerçek 30 IEEE şebekesi üzerinde uygulandığını kanıtlamak için kullanılmaktadır.

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

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SUMMARY

The economic and emission dispatch (EMD) problems have been investigated and considered as a research open topic and discussed in many studies and researches to find the optimum solution. In our study a new approach is made based on finding solutions by simulating the human's behavior for thinking and approaching the results by multiple steps until reaching the lowest values of economic and emission.

Fuzzy logic is the base of this study and it used by selecting random values and reflecting them on fuzzy interference system based on human knowledge for deciding the suitable values that should be applied for generators to obtain the value that produces less fuel cost and less emission. The use of fuzzy logic decreases the search domain and leads the search process to certain zone related to power demand and generated power. For example, if the power demand is high, then it is logical that power supplied by generators must be at high levels to make sure that generated power is equal to power losses and power demand in the grid. Also, if power demand is at middle level, then it is logical that generated power should be at middle levels to ensure the equality of power demand and power loss. In this way, a directing of generated power is made to certain zone to decrease the search process and time consumed to find the solution which represents the lowest value of total cost needed for power demand.

A various of power demands is discussed in order to modify the system so it could be applied for any case or power demand, all these modifications and results is applied on IEEE (30) grid to prove that algorithm is applied on real values of real grid.

Keywords: Combined Economic Emission Dispatch (CEED), Power Values with Fine Tuning (PVFT), Power Values with Normal search (PVNS), Power Demand (PD)

ÖZET

Ekonomik ve emisyon dağılımı sorunu, optimum çözümü bulmak için birçok çalışmada ve araştırmada ele alınmıştır. Bu çalışmada, insan davranışını simüle ederek çözümler bulma temeline dayanan yeni bir yaklaşım benimsenmiştir ayrıca ekonomik ve emisyon değerlerinin en düşük seviyelere ulaşılana kadar birden fazla adımda yaklaşımla sonuçlara ulaşılmıştır. Bu çalışmanın temeli bulanık mantıktır. Rastgele değerler seçilerek, insan bilgisine dayalı bulanık bir müdahale sistemi üzerinde yansıtılarak, jeneratörlere uygulanacak uygun değerleri belirlemek için kullanılır. Bu şekilde daha az yakıt maliyeti ve emisyon üreten değerleri elde etmek mümkün olur. Bulanık mantığın kullanımı arama alanını azaltıp arama sürecini güç talebi ve üretilen güçle ilgili belirli bir bölgeye yönlendirir. Örneğin, güç talebi yüksekse, jeneratörler tarafından sağlanan gücün yüksek seviyelerde olması mantıklıdır, böylece üretilen güç, güç talebini eşitler ve iletken kayıplarını azaltır. Ayrıca, güç talebi orta seviyede olduğunda, üretilen gücün orta seviyede olması mantıklıdır, böylece güç talebi ve güç kaybı eşitliği sağlanır. Bu şekilde, güç yönlendirmesi belirli bir bölgeye yapılır ve çözümün bulunması için harcanan süre azaltılır. Sistemi herhangi bir durum veya güç talebi için uygulanabilir hale getirmek için bir dizi güç talebi tartışılmaktadır ve tüm bu değişiklikler ve sonuçlar, algoritmanın gerçek 30 IEEE şebekesi üzerinde uygulandığını kanıtlamak için kullanılmaktadır.

Anahtar kelimeler: Kombine Ekonomik Emisyon Dağıtımı (CEED), İnce Ayarlı Güç Değerleri (PVFT), Normal Aramalı Güç Değerleri (PVNS), Güç Talebi (PD)

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ABBREDIVATIONS

ELD	**:**	Economic Load Dispatch
CEED	**:**	Combined Economic Emission Dispatch
PVFT	**:**	Power Values with Fine Tuning
PVNS	**:**	Power Values with Normal search
MFO	**:**	Moth-flame Optimization Algorithm
PD	**:**	Power Demand
DEED	**:**	Dynamic Economic Emission Dispatch
GA	**:**	Genetic algorithm
GSA	**:**	Gravitational Search Algorithm
PSO	**:**	Particle Swarm Optimization
NOx	**:**	Nitrogen oxide
SO2	**:**	Sulfur Dioxide
CO2	**:**	Carbon dioxide
ED	**:**	Economic Dispatch
ABC	**:**	Artificial Bee Colony
SA	**:**	Simulated Annealing
FL	**:**	Fuzzy Logic
BBO	**:**	Biogeography-based optimization
FPA	**:**	Flower pollination algorithm
BSA	**:**	Backtracking search algorithm
LFA	**:**	Lightning flash algorithm
RCCRO	**:**	Real coded chemical reaction algorithm
DE	**:**	Differential Evolution

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INTRODUCTION

The electrical power system must be secure, meet environmental constraints, economically and with high reliability. Economic Dispatch (ED) can be defined as “the procedure of determining the needed load between the obtainable generators to achieve lowest operation cost” (Abido 2003). Economic dispatch problem becomes an important responsibility in the planning and operation of the power generation systems (Halder and Chakrabarti 2010). It is a really complicated task to solve for a large number of constraints and a nonlinear objective function.

The US Air Act modification of 1990 mandates that the electric industry should lower its SO2 emissions by 10 million tons per year and the NOx emission by 2 million tons per year the 1980 level (Sudwrongha karan, M., Slochanal, M.R.S., et al 2004). In addition, the Kyoto protocol does not have enough to produce even the minimum value of energy production, and it is substantial for this to be undertaken at the same time, sending out the minimum level of gas emissions (Hazra, J. and Sinha, A.K. 2008). The target of CEED is to operate generators that produce energy in a power plant with both minimum emission levels and minimum fuel costs, at the same time, while satisfying operational constraints and the load demand. The aim of CEED problem is that the total load demand must be dispatched optimally to the generators (Z. Xin-gang, Z. Ze-qi.et al 2020), Researchers have been done a great effort to make a solution to the CEED problem using analytic or heuristic algorithms.

Power stations that operate using fossil fuel generate about two third of electricity worldwide (M. Beno and Rex 2017).

The electric power which is generated from fuel originate from fossil produces many harmful gases and wastes such as nitrogen oxide (NOx), sulfur dioxide (SO2), carbon dioxide (CO2), and particles which effect the atmosphere. The harmful gases can be minimized by suitably allocating the load to the available generating units (M.T. Hagh, S.M.S. Kalajahi et al 2020).

But this will increase the generation cost for power generators for that reason a solution for balancing the emission and fuel cost must be introduced. It may be solved by the combined economic emission dispatch problem (CEED). The primary goal to solve this problem is to minimize both emission and fuel cost in the same tame with satisfying load demand also inequality and equality constraints. Because of the two objectives that should be satisfied CEED problem is called two-objectives optimization research topic. Solution of this type of problems will produce a set of solutions and it's called Pareto solutions, instead of one solution (Guesmi et al. 2020).

According to mathematics point of view solving CEED problem can be accomplished using one of three technics. In the first, the fuel cost and emission are combined in a single objective function by normalizing emission and fuel cost using penalty factors of prices (Bhattacharya, Bhattacharjee, and H. Dey 2014; J. Ji, and Wang 2015; Pazheri et al. 2015). The second is performed by assuming that CEED problem is a one-objective topic but mixing the emission in system constraint (Jevtic et al. 2017; Chakraborty and Palit 2019). Finally, the third technic is done by solving the two functions at the same time where set of Pareto is found in one cycle of the algorithm of optimization (Morsali et al. 2014).

Researchers proposed many studies to find a solution for CEED problem using metaheuristic and classical algorithms. The classical optimization algorithms such as lambda (Aravindhababu and Nayar 2002), gradient (Dodu et al. 1972), multiplier of Lagrangian (El-Keib, Hart , and Ma 1994), linear programming (Parikh and Chattopadhyay 1996) and traditional technique based on equations of coordination (Nanda 1994) is used to solve CEED. However, most of these researchers have their problems to solve ED problems because of nonconvexity and nonlinearity emission and fuel cost characteristics. The traditional optimization algorithms are sensitive to the initial starting value and prematurely converge to the local optimal solution. Furthermore, these algorithms do not have the capability to find an optimum solution in a considerable computational time interval for CEED (Belmadani, Benasla and Rahli 2014).

Metaheuristic optimization methods has a critical role in relieving the problems of traditional classical methods, Simulated Annealing (SA) (Fung and Wong 1993), Genetic Algorithm (GA)(Hamid et al. 2005), particle swarm optimization (PSO) (H. Faris, M. Mahmood, and O. Al-Omari, 2021), biogeography-based optimization (BBO) (Bhattacharya and Chattopadhyay 2010), Artificial Bee Colony (ABC) (Bhongade and Agarwal 2016), flower pollination algorithm (FPA) (Abdelaziz, Ali, and Abd Elazim 2016), lightning flash algorithm (LFA) (Kheshti et al. 2018), backtracking search algorithm (BSA) (Bhattacharjee, Bhattacharya, and Halder nee Dey 2015) and real coded chemical reaction algorithm (RCCRO) (Bhattacharjee, Bhattacharya, and Halder nee Dey 2014). Many Metaheuristic methods are used to solve the CEED problem and it can be summarized as follows:

Hybrid methods that combining two single-objective algorithms such as the SA algorithm with ABC (Sundaram, Saranya, and Sangeetha 2013), or two different metaheuristic techniques as firefly and PSO (Arunachalam, A. Bhomila, and R. Babu 2014), bat and hybrid firefly (Gherbi, Bouzeboudja, and Gherbi 2016), and hybrid PSO-GSA (Radosavljević 2016).

Hybrid methods of two multi-objective algorithms such as hybrid NSGAII-MOPSO (Sundaram and Erdogmus 2017), multi-objective GA-PSO (Agarwal and Nanavati 2016) and the hybrid MOPSO Differential Evolution (DE) (Gong, Zhang, and Qi 2010). Although these heuristic algorithms give the best solution to the CEED problem, none of them insure the best optimal solution. In other algorithm a new method of optimization procedure without using penalty-based optimization was introduced by morphological filter algorithm (OMF using OWP-based) for solving CEED (Belmadani and Zaoui 2021).

CHAPTER ONE

STATE OF THE ART

1.1. Literature Survey

Optimization techniques are widely used in many fiels including energy optimization problems (S. Karim, C. Ozturk, M. Mahmood. 2021). Today. Metahuristics, swarm, and human based optimizations are among the hot research topics in energy and power production (H. Faris. Et al., 2022).

CEED problem still an open research topic because it has a great importance in both environmental and economic levels. The environmental effects of power generation units and the high cost of power distribution on power generation units gives the process of optimization of these two factors a great importance in operation of electrical grid and power plants. In practical point of view, the fuel cost and emission of generation stations must be both minimized simultaneously using multi-objective optimization formula (M. A. Abido,2003). Many methods have been introduced to solve the resulting multi-objective problem and many approaches concentrate on the use of evolutionary algorithms (EA) (J. G. Vlach Giannis and K. Y. Lee. et al.,2009). A new method called Dynamic economic emission dispatch is introduced to minimize the total cost of generated emissions and energy in a 24-h time interval. In the stochastic dynamic economic emission dispatch (SDEED), the problem is transferred to its corresponding deterministic dynamic economic emission dispatch. For that reason, solving the non-smooth, complex nonlinear and non-differentiable SDEED, a new approach called whale optimization algorithm (WOA) is introduced to minimize the overall cost and emission for wind operated thermal power system (S. Padhi, B.P. Panigrahi, et al, 2020).

Another paper proposes an environmental economic dispatch model for the coordinated operation of an integrated regional energy system, which consists of a a natural gas network and regional electricity supply network, along with district energy hubs. every energy hub contains a power unit and combined heat, a CO2-capture-based power to gas facility, a gas furnace and a heat pump, different energy storage facilities. To accomplish an optimized balance between emissions and operational cost during the environmental economic dispatch of this regional energy system, a price-based integrated demand response algorithm is introduced in the energy hub. Then the proposed model is converted into a mixed-integer linear programming problem to find solutions efficiently (L. He, Z. Lu et al,2020).

A new hybrid optimization method named gravitational PSO algorithm (GPSOA), is introduced based on gravitational search algorithm (GSA) and PSO to solve CEED problem. In GPSOA method the velocity of particles caused by the dependent random cooperation of GSA and PSO velocity is updated. CEED model consists of fuel cost objective emission level needed produced by classical thermal generators and operational cost produced by wind turbines. The success Of GPSOA methods have been tested on traditional thermal generators and modified wind thermal power plant. The main disadvantages of EA are the possible premature convergence and high computational burden which results in large time consumption.

Other study introduced all ELD, emission dispatch and CEED on renewable-integrated and an islanded micro grid separately using a developed novel called Whale optimization Algorithm (WOA). Four various behaviors of load sharing among the DERs are investigated. Then the results are compared with other developed bio algorithms to confirm the efficiency of the proposed technique. Further Wilcoxon signed rank test and statistical analysis such as ANOVA test are done to prove the efficiency of the proposed algorithm over the various other optimization algorithms used (B. Dey, S.K. Roy et al 2019). There are some applications of Semi-Defined Programing (SDP) to EMD problems were the constraints and objectives are liner or quadratic (R. Fuentes-Loyola and V. H. Quintana et al.,2003) .

A study implements a potent Multiobjective Multi-Verse Optimization algorithm to solve the high complicated combined economic emission dispatch and combined heat and power economic emission dispatch problems. Solving these problems operates the power system integrated with cogeneration plants economically and reduces the environmental impacts caused by the pollutants of fossil fuel-fired power plants. A chaotic opposition based strategy is proposed to explore the search space extensively and to generate the initial populations for the multiobjective optimization algorithm (A. Sundaram 2020).

Other paper proposes a convex model of Combined Economic Emission Dispatch (CEED) in a microgrid environment considering RES. A new algorithm depends on Teaching Learning Based Optimization (TLBO) approach is applied on an islanded 3 unit microgrid system consist of three conventional thermal generators, one solar photovoltaic system and one wind site to assess the economic impact of inclusion of renewable sources in microgrid for CEED study situations. The proposed approach examines the proficient operation of a microgrid with minimal pollutant emissions considering multiple renewable power sources, which makes it a suitable methodology to apply in real-time operating situations (E. B. Elanchezhian 2019).

A new paper deals with the multi-objective economic-emission dispatch problem of combined power (CHP) and heat power (CHP) generation in a large microgrid (MG). The MG comprises many types of fossil fuel wind power units, generating units, and solar power units. The objective functions involve unit, emission tax, operating costs, emission level, and cost of power purchase from the main external grid. Interdependencies of valve-point effects of thermal units and heat and power outputs of CHP units force nonlinearities, non-convexities and complications in the dispatch modeling and optimization (M.I. Alomoush, 2019).

Other study introduces an Exchange Market Algorithm (stocktickerEMA) algorithm for solving the Emission Economic Dispatch (EED) problem including wind farms in the power systems. The stocktickerEMA algorithm is a useful and powerful method for finding the optimal value of an optimization problem with high accuracy. In recent years, because of the emission of harmful gases from global warming and fossil fuels issues, the penetration level of cleaner energies such as the solar energy and wind has been increased in order to produce the electrical energy(M.T. Hagh, S.M.S. Kalajahi et al,2020).

In another paper a new method is proposed called a DE-CQPSO (Differential Evolution-Crossover Quantum Particle Swarm Optimization) algorithm based on the fast convergence of the particle diversity of crossover operators of genetic algorithms and differential evolution algorithms. In order to obtain better optimization results, a parameter adaptive control method is used to update the crossover probability. And the problem of multi-objective optimization is solved by introducing a penalty factor (Z. Xin-gang, L. Ji, et al 2020).

Other study aims to fill a gap in the literature by examining the impacts of an emissions trading scheme (ETS) in Vietnam, as the policy has been discussed for a decade in the country but the likely impacts on the economy and different sectors are still unidentified. The simulations are carried out in a global energy computable general equilibrium (CGE) model, an extension of the GTAP-E model, which treats Vietnam as a country region (D. Nong, T.H. Nguyen et al,2020).

A study introduced applied Multi-Verse Multi-Objective Optimization algorithm to solve the complicated case of emission economic dispatch and combined heat. The application of SDP to EED problem requires dealing with emission objective by using a polynomial function (at least second degree) and an exponential function when it is correctly modeled. It is recommended to express the exponential part of the objective in form of power series and use the algorithm to grantee nonexistence of the class of polynomial functions.

However, the exponential function is included in an infinite dimensional domain using the results in Devolder. The size of the matrix of the resulting SDP program increases prohibitively large with the degree of the polynomial (N.F. Aswan, M.N. Abdullah et al, 2019). This also increases the computational cost related to solve the resulting semi definite program. The problem difficulty can be moderated by using an alternative approximated function. This yields to a high accuracy and at the same time uses a rational function having lower degree of numerator and denominator. A key motivation for the approach adopted in that research the ability of optimal rational approximating function to achieve higher accuracy than the optimal polynomial approximation with same number of coefficients. Recent advances in rational function optimization.

1.2. Research Issues

The CEED problem can be defined as the process needed to find optimal solution for finding minimum fuel cost and minimum emission cost and meet the conditions of keeping generating power that can produce power demand and power loss in the limits of generating power units. Other factors should be taken in considerations which are valve point effect and losses in the network or grid, size of network, number of generating units and type of generated power. The time consumed by proposed algorithm also a very important factor due to changing power demand in real time application and this time interval should be reduced to minimum possible values.

In this research the main problem is how in order to find the best solution without time consuming also how to find the Fuzzy Rules (FRs) for fuzzy interference system and finally how to find the best Membership Function (MF) shape and boundaries.

1.3. Research Qustion

The main questions of this research are:

- Can Fuzzy Logic (FL) technique be a good alternative for other proposed algorithms?
- Is Fuzzy able to provide a solution for CEED without time consuming?

In results chapter and in comparing process with other algorithms these questions are answered definitely.

1.4. Research Objectives and Scope

Many research methods applied on economic and EMD problem based on artificial intelligent. In this research the method is based on fuzzy logic for finding the optimal solution in a short period of time.

The process of finding solution for the problem is based on generating random values that represents the initial value of power generated by generators in a certain grid,

applying these values to a fuzzy interference system is made to generate an output based on Mamdani defuzzification method to select a proper output value for each generator.

obtained values must satisfy the CEED problem conditions or constrains, many iterations are made to find optimal power values and lowest total cost value.

This study is based on IEEE- 30 grid to simulate the process of solving CEED problem.

1.5. Importance of Research

The importance of this research is to find a new algorithm that can provide a minimum total cost for generating units to reduce the power generated so as to reduce fuel cost and emission cost in same time using fuzzy logic to simulate the human intelligent for solving problems and to reduce the search domain.

1.6. Structure of the Thesis

This thesis includes five chapters:

- Chapter one includes general information about the thesis, including the problem statement, literature survey, and the objective of the thesis.
- Chapter Two introduces the theoretical background for the thesis including fuzzy logic fundamentals and CEED formulation and theory.
- Chapter Three outlines the methodology for the proposed method.
- Chapter Four presents the results of the proposed method using simulation by MATLAB and shows a comparison between the proposed method with other methods.
- Chapter Five contains a conclusion and proposed future works.

CHAPTER TWO

THEORETICAL BACKGROUND

2.1 Minimizations of fuel cost

One of the objectives for CEED problem is to reduce the fuel cost consumed by power generators, the ED problem defined as the sum of a quadratic function, fuel cost function is taken the sum of power produced by any generator multiplied by coefficients of cost as shown in the formula (Wilbert Ruta, 2018):

$$F(P_{Gi}) = \sum_{i=1}^{N_G} \left[a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left\{ e_i \left(P_{Gi}^{\min} - P_{Gi} \right) \right\} \right| \right] \tag{2.1}$$

where $i = 1, 2, 3 \ldots\ldots N_G$

P_{Gi} : power of i^{th}. Generator

N_G : number of generators

a_i, b_i, and c_i are cost coefficients of the i^{th} unit, (e_i) and (d_i) are only used if the valve point effect is taken into consideration.

2.2 Minimizations of Emission

The complete quantity of emissions, like NOx or SO2, released by fossil fuels burning in thermal power stations, can be introduced by the total summation of a quadratic function and an exponential function. In this research, just NOx emission is taken into consideration for calculations simplification. This function is explained as (U. Guvenc, Y. Sonmez, 2012):

$$E(P_{Gi}) = \sum_{i=1}^{N_G} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \eta_i \exp(\delta_i P_{Gi}) \tag{2.2}$$

α_i, β_i and γ_i are cost coefficients of the i^{th}. unit, (η_i) and (δ_i) are calculated if the valve point effect is considerable.

2.3 Limitations

Through the procedure of minimization, some inequality and equality conditions must be taken in consideration. In this procedure, an equality condition is called a balance of power. Therefore, the complete power introduced by generators must supply the complete power losses and complete power demand in the network.

Also, an inequality constraint is the capacity of generation. According to this, the generator's output powers are limited by a minimum and a maximum power limitation (Bharathi, R., Kumar, M.J. et al.,2012). These two constraints can be shown as:

(I) Total power constraint

$$\sum_{i=1}^{NG} P_{Gi} - P_{id} - P_{loss} = 0, \tag{2.3}$$

where (P_{loss})is called network losses

where (P_{id}) is power demand, which can be estimated by B matrix and formulated as:

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{Gi} B_{ij} P_{Gj} \tag{2.4}$$

where $i = 1 ,2, ,3 , \ldots \ldots , N_G$

where $j = 1 ,2, 3 , \ldots \ldots , N_G$

B_{ij} : represents the transmission loss coefficients

P_{Gj} : power of j^{th} . Generator

(II) Generation capacity constraint:

$$P_{Gi}^{\min} \langle P_{Gi} \langle P_{Gi}^{\max} \tag{2.5}$$

$P_{Gi}^{\min}$: minimum acceptable generation power of i^{th} . Generator

$P_{Gi}^{\max}$: minimum acceptable generation power of i^{th} . Generator`

2.4 CEED formulation

To achieve the two goals in one dispatch a combination between EMD and economic methods is used where the main issue is how to find so-called price penalty factor. It is a complicated process to find these penalty values and how to select them in a suitable way. With important penalty values, a local minimum appears when a minimization algorithm is used. Furthermore, low penalty values cannot find the optimum solution in an easy way. The penalty values are adjusted according to the equality/ inequality conditions. The penalty factors (h), can be determined from the heuristic method given in (Palanichamy & Srikrishna, 1991). The two objectives of CEED problem are introduced in form of one objective problem. To solve the CEED problem a minimization of fuel cost and emission should be done while satisfying the constraints mentioned earlier, the one objective CEED problem can be expressed as:

Minimize $F_{CEED} = \mathrm{F} + \mathrm{hE}$

$$Min(F_{CEED}) = \sum_{i=1}^{N_G}((a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left|d_i \sin\{e_i(P_{Gi}^{\min} - P_{Gi})\}\right|) + h_i(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \eta_i \exp(\delta_i P_{Gi}))) \quad (2.6)$$

Where $i = 1, 2, 3, \ldots\ldots, N_G$

h_i is the price penalty factor units ($/h) which represents ratio between maximum fuel cost and maximum emission, and is illustrated as (Bharathi, R., Kumar, M.J. et al., 2012)

$$h_i = \frac{F(P_{Gi}^{\max})}{E(P_{Gi}^{\max})} = \frac{a_i + b_i P_{Gi}^{\max} + c_i P_{Gi}^{\max 2} + \left|d_i \sin\{e_i(P_{Gi}^{\min} - P_{Gi}^{\max})\}\right|}{\alpha_i + \beta_i P_{Gi}^{\max} + \gamma_i P_{Gi}^{\max 2} + \eta_i \exp(\delta_i P_{Gi}^{\max})} \quad (2.7)$$

The objective of an EED problem has non discriminable points regarding the change of fuels and valve-point effects; for that reason, the objective formula could be consisting of a set of non-liner cost functions. Therefore, non-liner cost functions are accounted due to two main cases. One case is with valve-point loading problem where the objective formula is generally introduced as the combination of sinusoidal functions and quadratic functions. The other case is a multiple-fuel problem where the objective formula is introduced as the multi-defined quadratic cost functions. In the two cases, the solution presents multiple minimums, for that reason, the task of finding the global solution remains unsolved (C. E. Lin and G. L. Viviani, 1984).

The generator with multivalve steam turbines has very diverse input-output curve compared to the smooth cost function. The valve point occurs when every steam valve begins to open which causes curves and ripples as shown Figure 1. To take the valve point effects in consideration, sinusoidal functions are added to the quadratic function (Ismail Marouani, Tawfik Guesmi et al 2022). Figure 1 displays the valve-point effects on the nonlinearity of the cost function. besides the effects of valve's position, any other costs such as maintenance costs or contaminants can be added to the cost function. A representing first valve, B represents second valve, C represents third valve, D represents forth valve and E represents fifth valve.

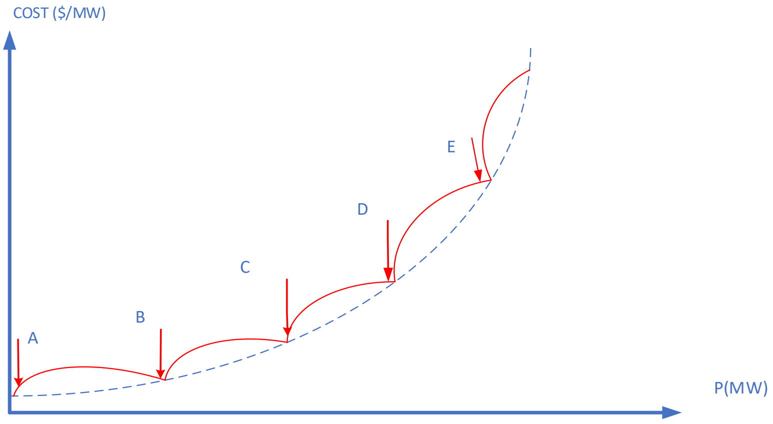


Figure 1.Valve point effect curve

Some generators are supplied with various fuel sources (oil and gas), and determination of the most economical fuel to burn problem is faced. As fossil fuel costs augment, it becomes even more important to have a good model for the production cost of each generator so, a more accurate formulation is acquired for the ED problem by using the hybrid cost function and hybrid incremental cost function as shown in Figure 2 (Ismail Marouani, Tawfik Guesmi et al 2022).

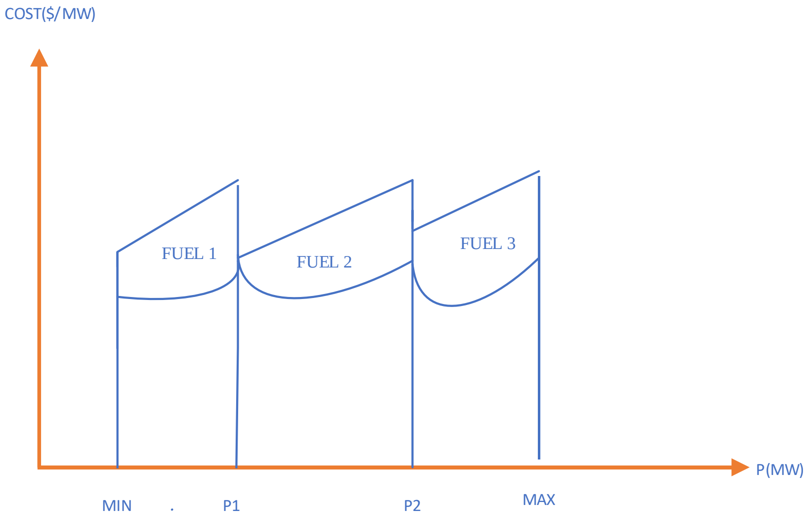


Figure 2. Incremental cost function

The x-axis represents upper and lower power limits of generated power, while y-axis represents total cost in dollar per megawatt. The main aims of "Economic dispatch with multiple fuel options" is to know which kind of fuel is most economical to use. The multi-defined quadratic function is used to represent many fuel options and the incremental behavior of cost functions as illustrated in Figure 2.

ED may be classified as a static optimization and dynamic problem. The static where the cost of generators outputs change is ignored. While, a dynamic dispatch is a method that the change in costs is taken in consideration (B. H. Chowdhury, Sulfur Rahman,2012). The dynamic ED takes the ramp rate limits and prohibited operating zone of the generating units into consideration.

2.5 Fuzzy logic

Fuzzy logic is a part of traditional Boolean logic that has been expanded to handle the concept of partial truth to truth values between "completely true" and "completely false". The FL method can be defined as: "The information was always vague or fuzzy or inexact. Science treated the gray or fuzzy information as if they were the white-black facts of math. Yet no one had put forth a single fact about the world that was 100% false or 100% true" (Kosko B.,1988).-Usually, engineering likes using an accurate mathematical representation. This statement matches with exact information, such as "$3 \leq u \leq 7$", "x = 5.0," or "y = 4t + 20." The value of "x = 5" has a relation membership can be compared with 100% equals (1); for other values (2.9, 3.1, 2.8, 3.2), the relationship of membership in the result is zero. However, the percentage of membership is wrong due of the influence of the observer, nonspecific of tools as example. (Zadeh LA.,1965) proposed a theory to make a rapprochement between the inexact information from the real life and the precision of real mathematics. This theory is known as fuzzy Sets (FSs) and deals with the relationship of membership of x included in A, that is, $\mu A(x)$, is taken from F set (Birkhoff G.D.,1948). Generally, F is the interval [0, 1]. (Goguen JA. 1967) proposed a wider generalization of the theory using values of the membership taken from the set $L \in [-1, 1]$ for a normalized set) or [-∞, ∞]. FL emulates the human brain by imitating that in smart machines, so an approximate human being thinking method is introduced. FL analysis systems with control perhaps electro-mechanical in nature, or related just to data, instance economic data, in all cases navigable by "If-Then rules" declared in human being's language.

2.6 Fuzzy Set

FSs have a so-called membership, which is defined as a value in [0, 1] interval. For example, if we take a color like 'green' we can define the color of any certain apple as a relation included in this fuzzy set. We can assume that it is 40% green so it has a Truth Value of fuzzy (FTV) relation value of 0.4. The relationship between FTV and real values depends on the desired random reflection coming from actual-life facts to the membership range varies from 0 to 1. FSs depend on an elastic sense of membership of portion to a set. While in the crisp set, a part either included or not in a set, where any degree of membership (between 0 and 1) is applicable in fuzzy set. For that, a MF μÃ (x) is related to a set of fuzzy Ã such that the function reflects members of the universe of discourse X to an interval between 0 and 1.

FSs includes: i. Union ii. Complement iii. Intersection iv. Associativity v. the law of De Morgan vi. Commutatively vii. Distributive union: X OR Y = Maximum of the truth values of fuzzy (FTVs) i.e., (0.6), Intersection: X AND Y = Minimum value of the FTVs i.e., (0.4), Negation NOT X = 1 – FTV X i.e., (0.6).

2.7 Membership Function

The MF can be represented graphically by a continuous function instead of discrete values function. It relates a weighting with each of the inputs that are processed, describe the functional overlap amongst inputs, and finally determines an output response (Wilbert Ruta,2018). The Fuzzy Membership Function (FMF) for “cool” term pertaining to temperature can be explained in Figure 3, where the cool MF represents a numerical value between 0 and 1 to indicate the deviation from the full membership to no membership (S.Rajasekaran , G. A. Vuayalkashmi ,2003).

In figure 3 cool boundaries starts from 20 and ends in 45 with membership varies from 0 to 1 to indicate the relationship of actual values to temperature. Many different shapes of MFs exist. The widely adopted shape to represent MF is triangular, also trapezoidal and normal can also be used as in Figure 4 (with difference). A Gaussian function was used for the MF is given mathematically as $\mu A(x) = 1/(1+x)^2 \times (3.14)$ (Vijayalakshmi. G.A., Raj Sekaran. S,1998).

Humans generally make decisions according to rules if-them (as computer programing). For example, we go out if the weather is expected to be good, otherwise we stay at home. Rules relate ideas and inter-relate events together (Li, L.-L.; Liu, Z.-F. et al 2021). Fuzzy machines act in the same way where the decisions and rules are replaced by sets and rules of fuzzy. FRs are operating using iterative if-then loops. For example, if F is negative then B, and if E is positive then A where A and B are all sets of E and F. Fuzzy patches is represented by FRs, which is the idea in fuzzy theory.

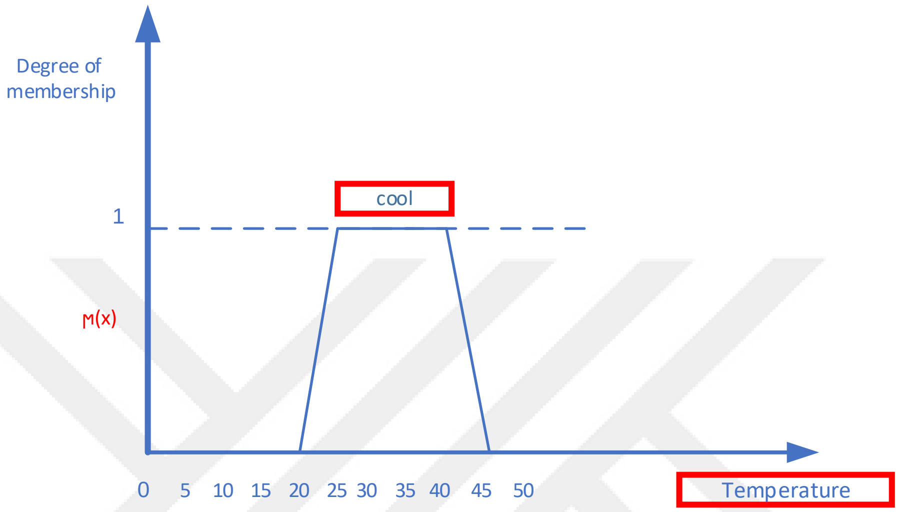


Figure 3.MF for 'cool'

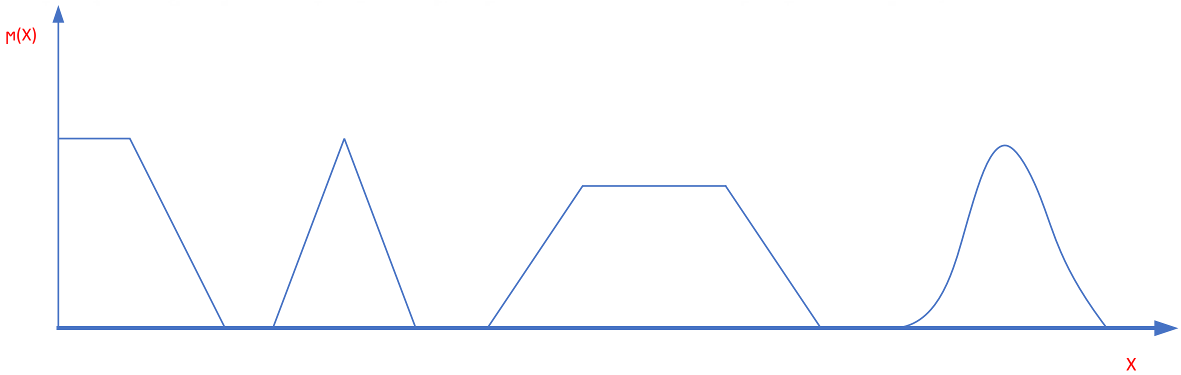


Figure 4.Different shapes of MF

2.8 Fuzzy Set Versus Crisp

Crisp sets need a good realization of the exact equation, system, and precise numeric value. FL presents another way of thinking, which allows modeling complicated system using a higher level of abstraction originating from human experience and understanding. FL gives a term to this knowledge with individual notions like very cold, bright green and a high time delay that are reflected into numeric ranged values. For example, the sentence “Is water colorless?” The answer to this is question is definite no/false or yes/true as related to the situation. If "no/false" is a value of 0 and "yes/true" is a value of 1, this statement produces a 0/1 type situation. A treatment based on binary (0 or 1) is called crisp in the domain of fuzzy set algorithm.

For that reason, a statement like "the running time of program is 4 seconds", "temperature is 320 C" are examples of crisp situations. The differences between crisp and fuzzy may be easily understood as shown in Figure 5 which represents the FMF in comparison with crisp MF, in fuzzy membership value could be 0.5 or 0.3 but in crisp logic only two values are available 0 or 1.

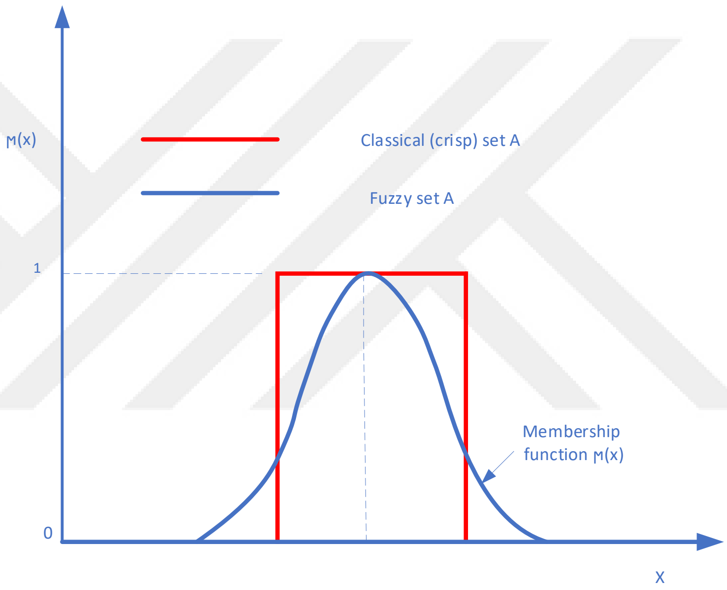


Figure 5.the differences between crisp and fuzzy logic

2.9 Feature of Fuzzy Logic

FL gives many important characteristics, making it a good choice for control systems:

1. Noise-free, and exact inputs are not required, so, system can be programmed to fail safely if a sensor destroyed or fails. The output results are soft control functions in spite of a wide range of input variations.

2. The FL control processing is user-defined rules governing the target control system, it can be adjusted easily to improve system performance. New sensors can be incorporated into the system simply by generating suitable governing rules.

3. FL is having no limitations to feedback inputs or to control outputs. Thus, it is not urgent to compute rate-of-change or measure parameters to be executed. Any amount of sensor data giving description of a system's reactions/actions may be enough. This allows designer to use inexpensive and inexact sensors which keeps the overall system complexity and cost.

4. Any input number can be treated (1-8) or more and many outputs (1-4) or more can be initiated. The rule-based operation, while defining the linguistic rule base quickly becomes complex if too many outputs and inputs are selected for one application, since rule's objective is to define their inter, relation must also be defined. It is better to break the control system into small segments and use several smaller FL controllers on the system.

5. The main advantage of FL is its capability to control nonlinear systems for which it is difficult or impossible to find a convenient mathematical model.

2.10 Fuzzy Expert System

A fuzzy expert system is a skilled system that employs a collection of fuzzy and rules MFs, without using Boolean logic, to reason data. The rules are generally of a form similar to the following conditions: if a is low and b is high then c is medium where a and b are input variables, c is an output variable, low term is a MF represents a, high term is a MF represents b, and medium term is a MF represents on c. The previous gives the degree the rule applies, when the conclusion specifies a MF to each of one or more output variables.

Generally, the knowledge base or rule base is the name used for the set of rules in fuzzy expert system, where most of the tools permit more than one conclusion for each rule. The general inference procedure is done in four steps:

1. *The Fuzzification step*: The MFs introduced on the input variables are applied to their actual values, to define the degree of truth for each rule hypothesis.

2. *The Inference step:* The real value for the is calculated, and applied to the conclusion for each rule. This is done on one fuzzy subset to be selected to every output variable for each rule. Generally, only PRODUCT or MIN are applied as inference rules. In MIN, the output MF is cut off at a height related to the rule premise's

calculated for degree of truth. In PRODUCT inference, the output MF is mapped by the rule premise's degree of truth.

3. *The Composition step*: Fuzzy subsets for each output are collected together to form one fuzzy subset, where usually MAX or SUM are used. In MAX, the collected output fuzzy subset is gathered by taking the point wise maximum over all of the fuzzy subsets allocated to variable by the inference rule. In SUM composition, the combined output fuzzy subset is gathered by taking the point wise sum over all of the fuzzy subsets allocated to the output variable by the inference rule.

4. *The Defuzzification:* It is used when needed to assign the fuzzy output set to a crisp number. There are more defuzzification ways in which two of the more common techniques are the MAXIMUM and CENTROID methods. In the CENTROID method, the crisp value of the output variable is completed by finding the variable value of the center of gravity of the MF for the fuzzy value. In the MAXIMUM method, one of the variable values at which the fuzzy subset has its maximum truth value is chosen as the crisp value for the output variable.

2.11 Fuzzy Control

Control based on Fuzzy, that uses the FRs, is an important implementation in fuzzy method. Using a method proposed by Ebrahim Mamdani, there are three steps that should be done to establish a fuzzy controlled system:

(1) Fuzzification (Using MFs to visually describe a condition),

(2) Rule assessment (use of FRs),

(3) Defuzzification (getting the actual results or crisp) Advantages (i.) permits the use of fuzzy linguistic terms in the rules. (ii.) FL solutions can be easily confirmed and modified.

main disadvantages (i.) optimize MF is very difficult to be achieved. (ii.) There are many ways to design the rules of fuzzy, a set of combination of output of many FRs and de fuzzifying the outputs.

CHAPTER THREE

METHODOLOGY

3.1. Implementation

present section, we will describe the techniques that are applied for attaining the goals of the thesis. The used technique includes the application of Fine-tuned FL method in economic dispatch considering emissions.

The main Idea of using FL in this study is to make approximate decision about the amount of generated power to achieve minimum of both economic and emissions in power plants. The procedure of finding best solution of CEED problem can be summarized as below:

Step 1: Assuming initial numbers for power generated in power plant.

Step 2: Taking these random initial numbers as an input for fuzzy system.

Step 3: Fuzzy system will generate values according to the inputs and FRs with the De-Fuzzification process using Mamdani method (decision is made by using center of gravity for intersection area in output MF to give a crisp value for output power).

Step 4: The generated power values will be calculated to match the constrains of CEED inclusive power generators limits and the power equality to demanded power and loss power.

Step 5: A number of inner iterations is made to approximate the output values to the needed power to compensate the demand and losses for the system.

Step6: A number of outer iterations is made to discover lower values for total cost of the system.

Step7: A fine tuning method is applied for the final results to obtain better approximate values and achieve best results. Noticed that used membership functions are Gaussian and triangular MF.

3.2. Fuzzy system

In this research FMF consist of Gaussian as shown in fig. 6 (for generator 2). The input represents random numbers as an initial value for the power of generators (the simulation is made depending on IEEE (30) which contains 6 generators and 30 bus).

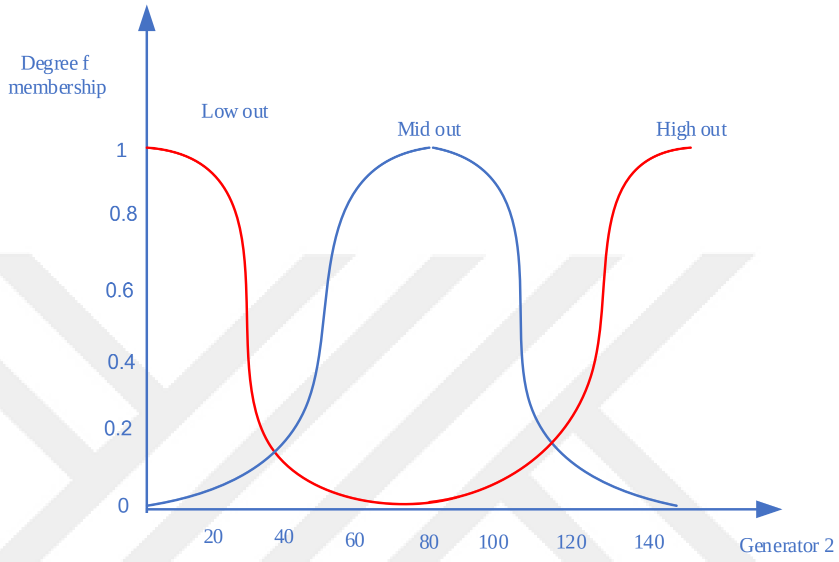


Figure 6.Input MF for generator (2)

The boundaries of MFs were selected to satisfy the minimum and maximum power for each generator given for IEEE (30) system which is given by a matrix obtained from a simulation program applied for load flow and it has a parameter as follows:

coffmat= [10 125 0.15240 38.53973 756.79886 0.00419 0.32767 3.85932

10 150 0.10587 46.15916 451.32513 0.00419 0.32767 3.85932

35 225 0.02803 40.39655 1049.9977 0.00683 -0.545 40.26690

35 210 0.03546 38.30553 1243.5311 0.00683 -0.545 40.26690

130 325 0.02111 36.32782 1658.5596 0.00461 -0.511 42.89553

125 315 0.01799 38.27041 1356.6592 0.00461 -0.511 42.89553]

The first two columns represent minimum and maximum power provided by each generator so the first constrain is to limit the output power by the given values.

The third, fourth and fifth columns represents $\mathbf{a_i}$, $\mathbf{b_i}$,$\mathbf{c_i}$ which are the cost function parameters or coefficients as shown in (Wilbert Ruta,20 18):

$$Cost = \sum a_i P_i^2 + b_i P_i + c_i \tag{3.1}$$

The sixth, sevens and eighth columns represents α_i , β_i ,γ_i which are the emission function parameters or coefficients as shown in (Wilbert Ruta,20 18):

$$EC = \sum \alpha_i P_i^2 + \beta_i P_i + \gamma_i \tag{3.2}$$

The main process in this research for fuzzy system is to take random values, applying it on FMF using FRs as follows:

Rule 1: "generator1==midout & generator2==lowout & generator3==midout & generator4==lowout & generator5==midout & generator6==midout & demand==middemand => p1=verylow, p2=very low, p3=very low, p4=very low, p5=verylow, p6=verylow (1)"

Rule 2: "generator1==lowout & generator2==midout & generator3==lowout & generator4==midout & generator5==lowout & generator6==midout & demand==middemand => p1=verylow, p2=low, p3=verylow, p4=low, p5=verylow, p6=low (1)"

Rule 3: "generator1==midout & generator2==lowout & generator3==midout & generator4==lowout & generator5==midout & generator6==lowout & demand==middemand => p1=low, p2=verylow, p3=low, p4=verylow, p5=low, p6=verylow (1)"

Rule 4: "generator1==highout & generator2==lowout & generator3==highout & generator4==lowout & generator5==highout & generator6==lowout & demand==highdemand => p1=high, p2=low, p3=low, p4=mid, p5=verylow, p6=high (1)"

Rule 5: "generator1==highout & generator2==midout & generator3==highout & generator4==midout & generator5==lowout & generator6==midout & demand==highdemand => p1=high, p2=low, p3=verylow, p4=low, p5=high, p6=low (1)"

Rule 6: "generator1==midout & generator2==lowout & generator3==midout & generator4==lowout & generator5==midout & generator6==lowout & demand==highdemand => p1=verylow, p2=low, p3=verylow, p4=low, p5=verylow, p6=low (1)"

Rule 7: "generator1==midout & generator2==midout & generator3==midout & generator4==midout & generator5==midout & generator6==midout & demand==highdemand => p1=low, p2=low, p3=low, p4=high, p5=low, p6=high (1)"

Rule 8: "generator1==midout & generator2==highout & generator3==midout & generator4==highout & generator5==midout & generator6==highout & demand==highdemand => p1=low, p2=mid, p3=low, p4=mid, p5=low, p6=mid (1)"

Rule 9: "generator1==highout & generator2==highout & generator3==midout & generator4==highout & generator5==highout & generator6==midout & demand==highdemand => p1=mid, p2=mid, p3=high, p4=mid, p5=mid, p6=high (1)"

Rule 10: "generator1==highout & generator2==highout & generator3==highout & generator4==highout & generator5==highout & generator6==highout & demand==highdemand => p1=high, p2=high, p3=high, p4=very high, p5=very high, p6=very high (1)"

The output MFs consist of triangular functions the following in fig. 7

Rule one states that if random value is given to Generator1 in the middle region and Generator2 the in low region and Generator3 in middle region and … Etc., then the output will be $\mathbf{p_1}$=low region, $\mathbf{p_2}$=very low region, $\mathbf{p_3}$=low region, $\mathbf{p_4}$=very low region, $\mathbf{p_5}$=low region, $\mathbf{p_6}$=very low region according to Mamdani and center of gravity calculation.

Noticed that these rules are estimated depending on human being experience and way of decision-making style.

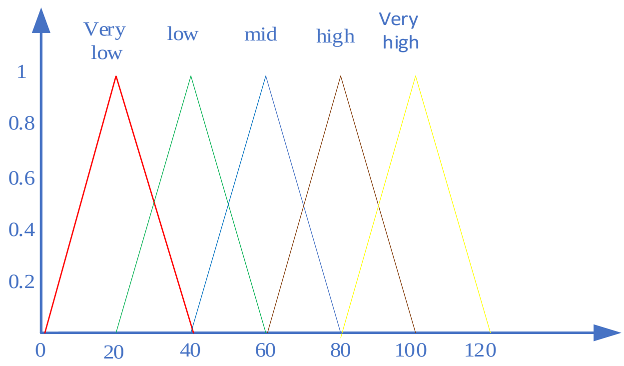


Figure 7.output MF for generator (1)

After finding power output values which are limited to every generator minimum and maximum values because the boundaries of MF s are made according to these limits. After that a process will be repeated number of times to find the suitable values and to satisfy the second condition which is given by EQ. 3.3.

$$P_i = \sum_{i=1}^{NG} P_D + P_L \tag{3.3}$$

wherever P_D represents power demand and P_L represents power loss for transmission line so the produced power values should equal to power demand and power loss values to achieve the minimum cost values.

A second iteration loop is made to locate the lowest cost function values generated from Fuzzy system. After finding the most accurate value and for get the best value a fine-tuning procedure is applied to modify the accuracy of the system to get best generated power values from our system.

The main the base goal in solving CEED problem is to minimize the function:

$$Minimize(F_T) = \sum_{i=1}^{N} (A + hB) \tag{3.4}$$

A representing the function of fuel-cost, B representing the emission function, and h represents the factor of penalty. Also, the EQ 3.4 Above can be expressed by EQ. 3.5

$$Minimize(F_T) = \sum_{i=1}^{N} ((a_i P_I^2 + b_i P_i + c_i) + h(\alpha_i P_i^2 + \beta_i P_i + \gamma_i)) \tag{3.5}$$

So, the price penalty factor can be expressed by the following formula:

$$h_i = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i}{\alpha_i P_{i(\max)}^2 + \beta_i P_{i(\max)} + \gamma_i} \tag{3.6}$$

Where generator limit in (MW) is represented by $\mathbf{p_i}$(max).

3.3. Economic Emissions Dispatch with Valve-Point Effect

The valve-point impact is the effect of switching between valves in generating units, valve point happens when each steam valve starts to open which cause ripples as in Fig.1. The formula of economic emission dispatch problem with valve-point effect taken into consideration is illustrated in EQ. (3.7) (Wilbert Ruta, 2018)

$$Minimize(F_T) = \sum_{i=1}^{N} (A + hB)N \tag{3.7}$$

A is fuel cost function, B is emissions function and h is price penalty factor and they are given by equations (3.8 – 3.10) and N is the total number of generating units.

$$A = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin(f_i (P_i^{\min} - P_i)) \right| \qquad (\$lhr) \qquad (3.8)$$

$$B = \alpha_i P_i^2 + \beta_i P_i + \gamma_i + \eta_i \exp(d_i \times P_i) \qquad (Kg/hr) \qquad (3.9)$$

$$h_i = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i + \left| e_i \sin(f_i (P_{i(\min)} - P_{i(\max)})) \right.}{\alpha_i P_{i(\max)}^2 + \beta_i P_{i(\max)} + \gamma_i + \eta_i \exp(d_i \times P_{i(\max)})} \qquad (\$/Kg) \qquad (3.10)$$

Where e_i and (f_i)are parameters of fuel cost while (d_i) and (η_i) are the emission parameters with valve point effect.

3.4. Economic Emission Dispatch with NOX, SOX and COX

The primary goal of the object function is to make the fuel cost as minimum as possible, considering the three main emitted gases generated by a plant that include NOX , SOX and COX . There are three emissions and one fuel cost “objective” functions. Optimization is performed in parallele by considering the multi objective as single objective optimization using the price penalty factor into consideration for every single emission as following in EQ. (3.11) (Wilbert Ruta, 2018)

$$\text{Minimize (Total cost)} = \sum F_f + h_N E_N + h_s E_s + h_c E_c \qquad (\$/hr) \qquad (3.11)$$

Whereby $\boldsymbol{F_f}$, $\boldsymbol{E_N}$, $\boldsymbol{E_S}$ and $\boldsymbol{E_C}$ are fuel cost, $\boldsymbol{NOX}$ emission, $\boldsymbol{SOX}$ emission and $\boldsymbol{COX}$ emission objective functions respectively are given by equation (3.12 – 3.15), while $\boldsymbol{h_C}$, $\boldsymbol{h_N}$ and $\boldsymbol{h_S}$ are price penalty factor of $\boldsymbol{COX}$ emissions, $\boldsymbol{NOX}$ emissions and $\boldsymbol{SOX}$emissions respectively given by equation (3.12 – 3.15)

$$F_f = a_i P_i^2 + b_i P_i + c_i \qquad (\$/hr) \qquad (3.12)$$

$$E_N = \alpha_{i(N)} P_i^2 + \beta_{i(N)} P_i + \gamma_{i(N)} \qquad (Kg/hr) \qquad (3.13)$$

(3.14)

$$E_S = \alpha_{i(S)} P_i^2 + \beta_{i(S)} P_i + \gamma_{i(S)} \qquad (Kg/hr)$$

$$E_C = \alpha_{i(C)} P_i^2 + \beta_{i(C)} P_i + \gamma_{i(C)} \qquad (Kg/hr) \tag{3.15}$$

here $\boldsymbol{\alpha}_{\mathbf{i(N)}}$, $\beta_{i(N)}$ **i** and $\gamma_{i(N)}$ are coefficients of NOX emission of the I^{th} generating unit $\alpha_{i(S)}$, $\beta_{i(S)}$ and $\gamma_{i(S)}$ are coefficients of SOX emission of the I^{th} generating unit $\alpha_{i(C)}$, $\beta_{i(C)}$ and $\gamma_{i(C)}$ are coefficients of COX emission of the I^{th} generating unit.

$$h_{i(N)} = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i}{\alpha_{i(N)} P_{i(\max)}^2 + \beta_{i(N)} P_{i(\max)} + \gamma_{i(N)}} \qquad (\$/Kg) \tag{3.16}$$

$$h_{i(S)} = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i}{\alpha_{i(S)} P_{i(\max)}^2 + \beta_{i(S)} P_{i(\max)} + \gamma_{i(S)}} \qquad (\$/Kg) \tag{3.17}$$

$$h_{i(C)} = \frac{a_i P_{i(\max)}^2 + b_i P_{i(\max)} + c_i}{\alpha_{i(C)} P_{i(\max)}^2 + \beta_{i(C)} P_{i(\max)} + \gamma_{i(C)}} \qquad (\$/Kg) \tag{3.18}$$

3.5. System Constraints

The boundaries of every optimization research topic are generally named as the system boundaries or constraints. The procedure of optimization in this research is related to both inequality and equality constraints which limits the factors of optimization by the both of them which is represented by power. The power stabilization of the electrical grid consecrates on the equality constraint where the produced power generated in power plant was equal to power demand (P_D) and system losses as it given in EQ. (3.3). Test systems Depending on the presence of data, application of this thesis was made according to IEEE (30) bus test system without taking the valve-point into consideration.

3.6. IEEE-30 Bus Test System

The IEEE-30 bus test case represents a plain approximation of the American Electric Power system as it was in December 1961, it consists of 6 generators and 30-bus. The test system is applied in the problem under study implementation. The required data for the study which consist of emission and cost coefficients of each generating unit, generators upper and lower limits and B-loss coefficient matrix are also introduced.

3.7. Data Table of Test System for IEEE-30 Bus

Table -1 shows the values of the matrix coefficients or parameters of the cost function and the power values of each generator the (max and min). While, Table-2 shows the nitrogen emission coefficients for each of the six generators, which we other than other gases to simplify it in calculations.

Table 1. Fuel cost Coefficients and generator boundaries of IEEE (30) bus system

unit	**ai ($/MW hr.)**	**bi ($/MWhr)**	**ci ($/hr.)**	**Pmax (MW)**	**Pmin (MW)**
1	0.1524700	38.5397300	756.7988600	125	**10**
2	0.1058700	46.1591600	451.3251300	150	**10**
3	0.0280300	40.3965500	1049.3251300	250	**40**
4	0.0354600	38.3055300	1243.531100	210	**35**
5	0.0211100	36.3278200	1658.569600	325	**130**
6	0.0179900	38.2704100	1356.2704100	315	**125**

Table 2. Coefficients of NOX emissions in IEEE (30) bus system

Unit	**αi (Kg/MWhr)**	**βi (Kg/MWhr)**	**γ i (Kg/ hr)**
1	0.0041900.	0.3276700.	13.8593200.
2	0.0041900.	0.3276700.	13.8593200.
3	0.0068300.	-0.5455100.	40.266900.
4	0.0068300.	-0.5455100.	40.266900.
5	0.0046100.	-0.5111600.	42.8955300.
6	0.0046100.	-0.5111600.	42.8955300.

3.8. Calculation of Penalty Factor Load Price (h) of IEEE-30 Bus Form

The penalty is evaluated for IEEE-30 bus as in Table 3. By which multi-objective optimization is converted into a single objective optimization (Wilbert Ruta, 2018).

Table 3. Calculated price penalty Coefficients of IEEE (30) bus system

h1	h2	h3	h4	h5	h6
66.147000	62.035700	39.001600	47.822200	43.153300	44.786300

applying $\sum_{i=1}^{N} P_{i(\max)} \geq P_D$ (3.19)

In Table- 4, the price penalty factors are written in the ascending by using formula 3.6 for each generator in the system order to identify the power penalty parameters of load price. The maximum demand of the individual price penalty factor was added one after another whereby the price penalty factor which consort to the cumulative maximum demand which is equal or greater to the system load qualified as a system load price penalty factor.

Table 4. Price penalty Coefficients at multiple load demand of IEEE-30 bus system

Load demand	Price penalty factor. (h)
500MW	**43.1533**
700MW	**44.7863**
900MW	**47.8222**

3.9. Proposed method

The proposed method consists of generating initial values for power generators randomly then making it as input for fuzzy interference system as shown in fig 8. This is in order to give crisp values based on given input to reduce the search space by applying human sense for deciding the appropriate generating values. The main idea is to estimate generating power values depending on power demand, if power demand is high then normally generating units should be in a region from mid. To high and if power demand is low then normally generating units should be in a region from low to mid, all these estimated values are included in FRs. After considering the output values a calculation is made to find the nearest values to achieve the goal for providing generated power equals power demand plus power loss in the system, many iterations are made to find the optimum values. At the beginning of the flowchart, we define the matrix coefficients for IEEE -30 bus system for the values of the generators and the losses the obtained from a simulation program applied for load flow. The initial values of the generators will generate power values according to the inputs of the fuzzy interference system (FIS) by using Mamdani method to detecting the best power values that do not exceed the limits of each generator in the matrix (highest and lowest). Then you enter the process of internal iterations to approximate the output values to the required power, if the result satisfies the condition (YES) will detecting the total cost values, and if the values are otherwise (NO), it will return to the of step generating the initial values. Then you enter the process of external iterations to discover the lowest value of the total cost of the system, if it is a satisfactory result (YES) will arrange or sort the best total cost values, and if it is (NO) will return again by generating initial values for the values of the generators, and in the end the show results of the best cost values.

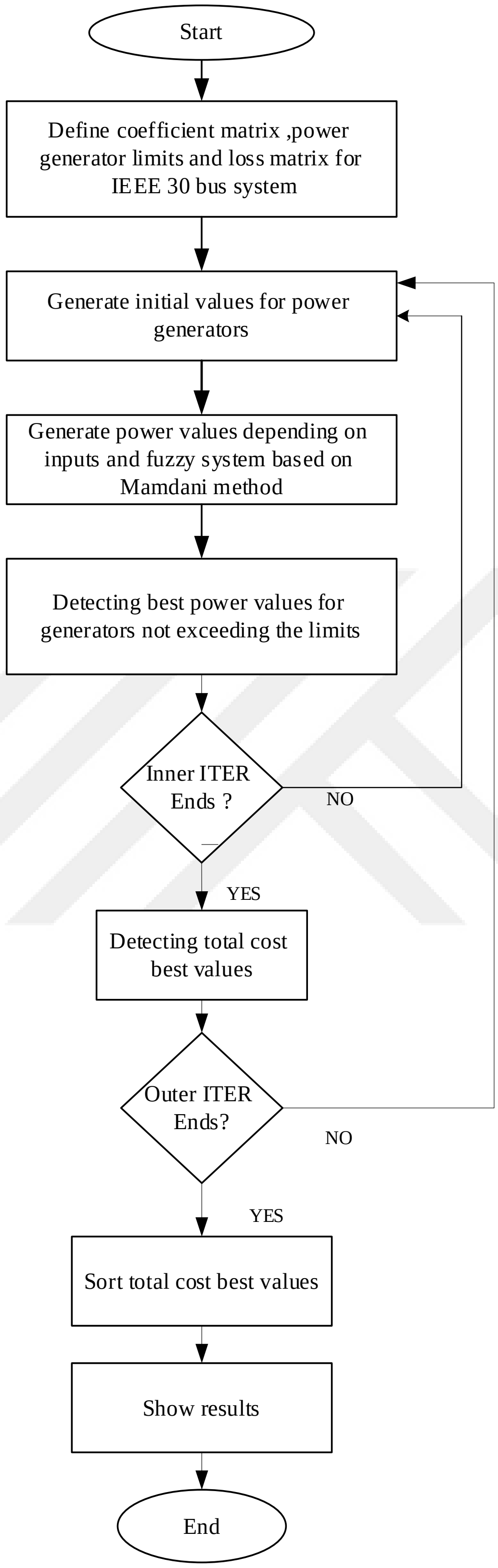


Figure 8.proposed method flowchart

CHAPTER FOUR

SIMULATION AND RESULTS DISCUSSION

4.1. General

In order to develop a power generation value that satisfies the constraints to introduce the best power with the best economic and emission values, a fuzzy interference system with a Gaussian membership function is utilized for the CEED problem Discover the better solution. In the IEEE (30) system, initial power values are generated randomly, and the fuzzy interference system subsequently uses rules created specifically for this purpose to provide the best power

values. To discover the optimal value of generated power, the Mamdani method is used. It is a defuzzification method that produces output values for a number of inner and outer iterations. The power demand must be provided with minimum fuel consumption and lower emission values. Thus, requires minimum power losses accomplished through a search procedure to investigates the optimal solution. For this study, the necessary values are located using two different methods. The first is the Power Values with Fine Tuning (PVFT), while the second is the Power Values with Normal search (PVNS).

PVFT depends on determining the difference between generated power values, power demand, and power loss. Dividing this difference by the number of generators (in this case, six), adding the delta power values to each power, and then recalculating power loss.

The goal of PVFT is to reduce the difference between generated power and (demand plus power loss). PVNS method depends on finding the minimum difference between generated power values and power demand plus power loss until reach the minimum total cost and best power values needed.

4.2. IEEE (30) grid

The IEEE (30) grid is shown in Figure 9 which contains 6 generators and 30 bus bars, where all the Results in this research are based on this grid. The IEEE (30) -bus test case represents a simple approximation of the American Electric Power system as it was in December 1961. The (11 kV) and (1.0 kV) base voltages are estimate, and may not reflect the actual data. The model In fact, has these buses at either 132 or 33 kV; what is worth mentioning is that the 30-bus test case does not have line limits.

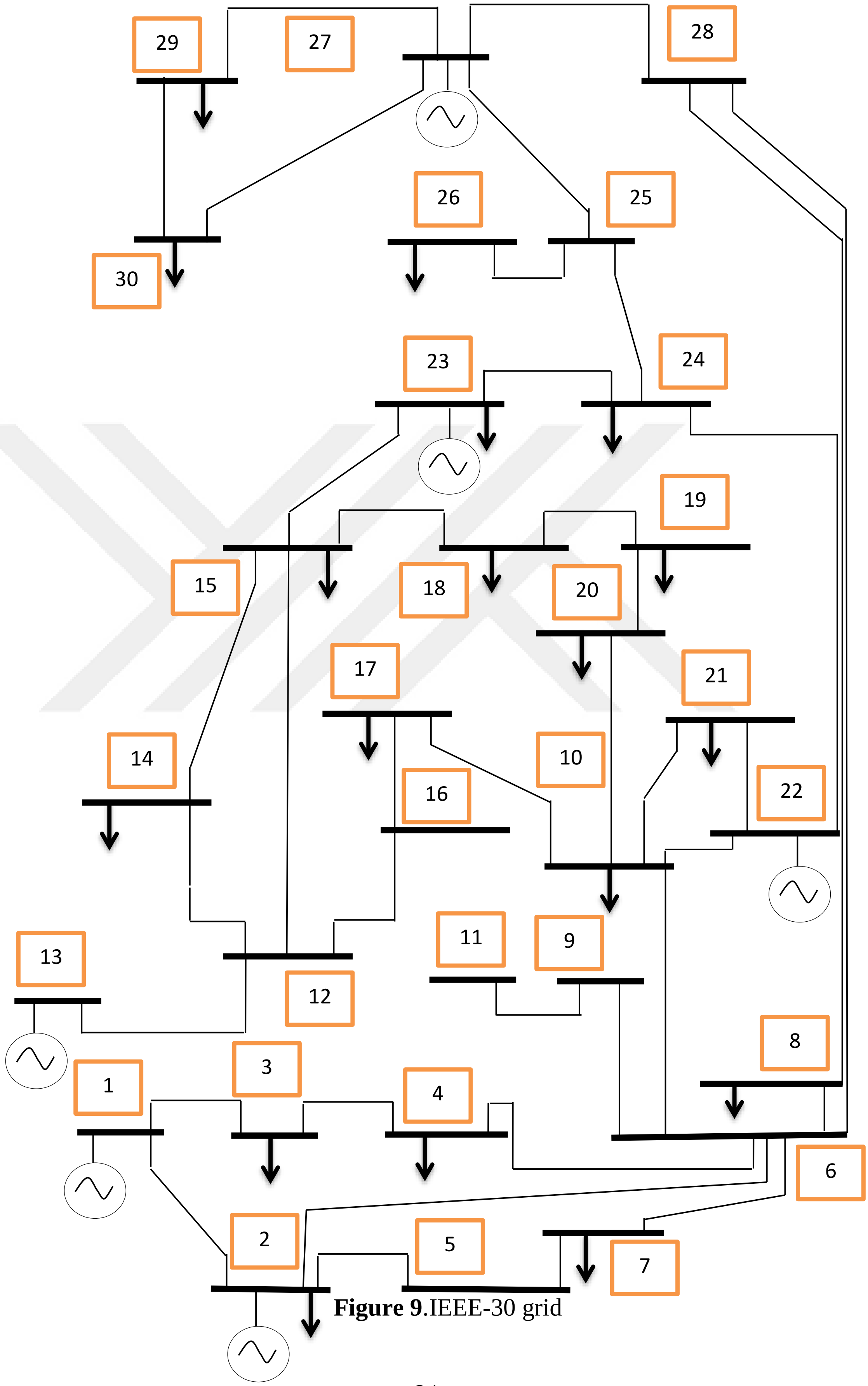


Figure 9.IEEE-30 grid

4.3. simulation

In the simulation section, we use a fuzzy interference system using the Gaussian function for the input and a triangular function for the output to find the best solution to the CEED problem. The main process in this research for fuzzy system is to take random values applying it on FMF using FRs depending on human being experience.

Three values of power demand (500, 700, and 900 MW), three widths of the Gaussian function (10 ,20 30), and with internal iterations equal to (10 ,100) are taken. Different values of the outer iterations are used to calculate the power loss and sum of generated power, and to find the maximum accuracy and minimum total cost. The detailed simulations that have been tested and summarized in Table 5.

Table 5.simulation cases for multiple power demand, iterations and methods

Case No.	Proposed method	Power demand	Inner iteration	Gaussian width (2 sigma)
Case1	PVFT	500MW	10	10
Case2	PVFT	500MW	10	20
Case3	PVFT	500MW	10	30
Case4	PVFT	500MW	100	10
Case5	PVFT	500MW	100	20
Case6	PVFT	500MW	100	30
Case7	PVNS	500MW	10	10
Case8	PVNS	500MW	10	20
Case9	PVNS	500MW	10	30
Case10	PVNS	500MW	100	10
Case11	PVNS	500MW	100	20
Case12	PVNS	700MW	10	10
Case13	PVNS	700MW	10	20
Case14	PVNS	700MW	10	30
Case15	PVNS	700MW	100	20
Case16	PVNS	700MW	100	30
Case17	PVNS	900MW	100	20

4.3.1. Case 1

The input and output MFs are used to calculate the target values. The input is a Gaussian function while the output is a triangular function as shown in Figure 10. For the input, the x-axis is the initial random values for generator1, and y-axis presents the degree of membership. In the other hand, for the output x-axis is the power value for generator 1 given by the fuzzy system, while y-axis is the degree of MF.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

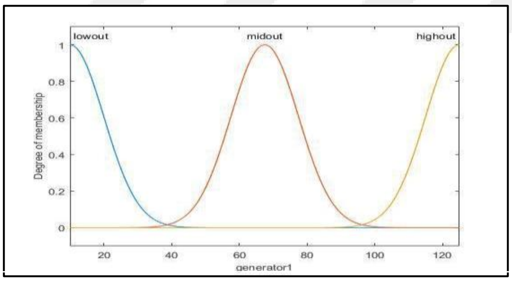
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

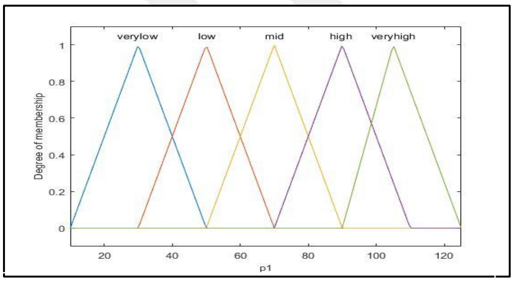
2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a)



(b)

Figure 10. Input and output MF

Different outer iteration values, calculated power loss, generated power sum, accuracy, and the total cost are presented in Table 6. The best iteration outer value for accuracy is found to be 500, while for the total cost is 90. It is clear from the table that small numbers of iterations (≥10) give good values with minimum computing time.

Table 6. Case 1 data

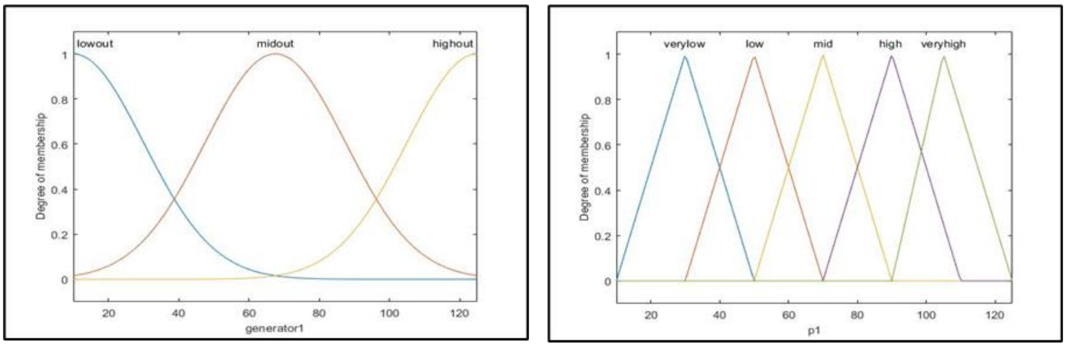
N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	42.1386	651.6159	78.1045	5.2237
2.	10	26.2085	527.0274	99.8362	4.1568
3.	30	26.2085	527.0274	99.8362	4.1568
4.	50	26.2085	527.0274	99.8362	4.1568
5.	70	26.1788	526.9765	99.8405	4.1560
6.	90	26.0546	526.7619	99.8585	4.1549
7.	100	26.2085	527.0274	99.8362	4.1568
8.	200	26.0724	526.8304	99.8484	4.1551
9.	500	26.0591	526.7628	99.8593	4.1551

4.3.2. Case 2

The input is the Gaussian while the output is the triangular functions that are shown in Figure 11. The power loss represents the power dissipation in the IEEE (30) grid transmission line.

The rule used to estimate power values is as follows:

```
rule = [ 2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;
            1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;
            2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;
            3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;
            3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;
            2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;
            2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;
            2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;
            3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;
            3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];
```



(a) (b)

Figure 11. Input and output MF

Table 7 presents the different outer iteration values, power loss, generated power, accuracy, and the total cost. The best outer iteration value for accuracy is found to be 500, while the total cost is 70 and 200. It is clear from the table that for a number of iterations (≥30), acceptable values with minimum computing time are found.

Table 7 . Case 2 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	36.2733	647.6628	77.722100	5.155600
2.	10	29.0921	552.9827	95.221900	4.360100
3.	30	26.4318	527.5140	99.783600	4.159700
4.	50	26.1813	527.0114	99.834000	4.156600
5.	70	26.0780	526.8035	99.854900	4.155300
6.	90	26.0666	526.8137	99.850600	4.155500
7.	100	26.3958	527.4030	99.798500	4.159200
8.	200	26.0762	526.7983	99.855600	4.155300
9.	500	26.0569	526.7637	99.858600	4.155400

4.3.3. Case 3:

The input and output MFs are used to calculate the target values as presented in Figure 12.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

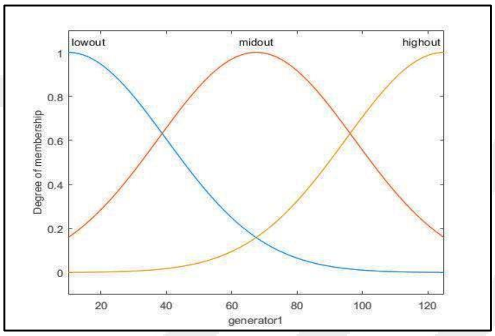
3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

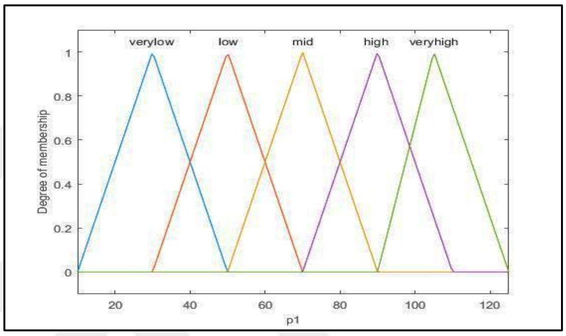
2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1];



(a)



(b)

Figure 12.Input and output MF

Different outer iteration values, calculated power loss, generated power sum, accuracy, and the total cost are presented in Table 8. The best outer iteration value for accuracy is found to be 500, while for the total cost is 90 and 500. It is clear from the table that small numbers of iterations (≥70) give good values with minimum computing time.

Table 8 .Case 3 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	32.8250	591.6201	88.2410	4.6668
2.	10	26.8398	528.3551	99.6969	4.1676
3.	30	26.4532	527.5592	99.7788	4.1610
4.	50	26.2513	527.3053	99.7892	4.1595
5.	70	26.2629	527.1722	99.8181	4.1579
6.	90	26.2475	527.1549	99.8185	4.1578
7.	100	26.2657	527.1779	99.8176	4.1580
8.	200	26.2578	527.1637	99.8188	4.1579
9.	500	26.2527	527.1547	99.8196	4.1578

4.3.4. Case 4:

The input Gaussian and the output triangular functions are shown in Figure 13. The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

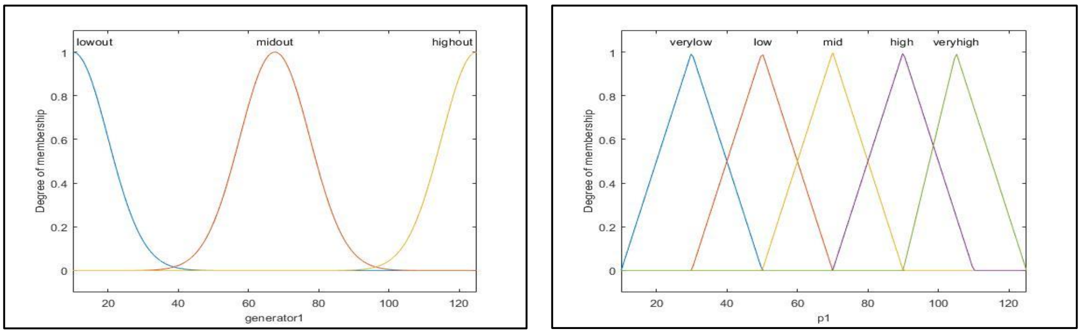
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 13.Input and output MF

Simulation outputs are depicted in Table 9. The best outer iteration value for both accuracy and the total cost is 500. The Table shows that for iterations ≥10, good values with minimum computing time are found.

Table 9. Case 4 data

N	**outer iteration**	**Power loss**	**Generated power**	**accuracy**	**Total cost (10^4)**
1.	1	27.8385	530.2782	99.5121	4.1790
2.	10	26.2089	527.0281	99.8362	4.1568
3.	30	26.2085	527.0274	99.8362	4.1568
4.	50	26.2087	527.0277	99.8362	4.1568
5.	70	26.2085	527.0274	99.8362	4.1568
6.	90	26.1989	527.0109	99.8376	4.1566
7.	100	26.2085	527.0274	99.8362	4.1568
8.	200	26.2085	527.0274	99.8362	4.1568
9.	500	26.0533	526.7613	99.8584	4.1551

4.3.5. Case 5

The input is a Gaussian function while the output is a triangular function as shown in Figure 14.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

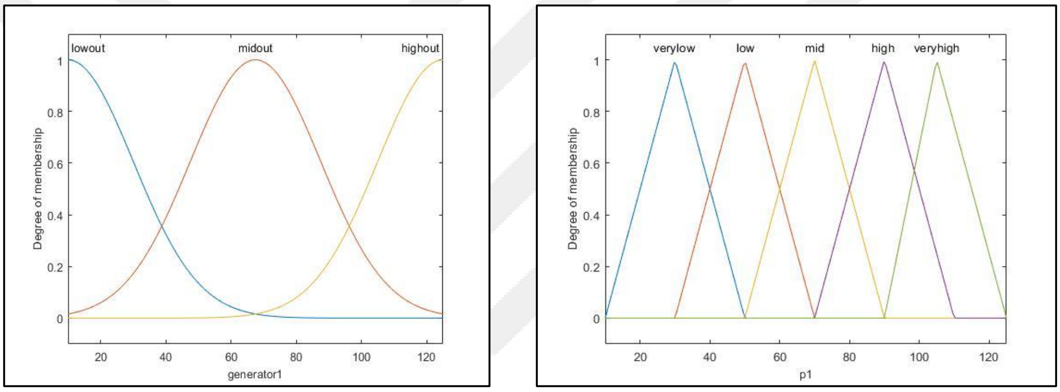
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 14. Input and output MF

From table 10, the best iteration outer value for accuracy is found to be 500, while for the total cost is 100.

Table 10. Case 5 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	28.1006	530.8051	99.4591	4.1827
2.	10	26.9519	528.5865	99.6731	4.1667
3.	30	26.0804	526.8035	99.8554	4.1556
4.	50	26.0540	526.7951	99.8518	4.1557
5.	70	26.0986	526.8662	99.8465	4.1561
6.	90	26.3501	527.3116	99.8077	4.1586
7.	100	26.0710	526.7937	99.8555	4.1552

8.	200	26.1162	526.8879	99.8457	4.1558
9.	500	26.0605	526.7804	99.8560	4.1555

4.3.6. Case 6

The input and output MFs are presented in Figure 15. Rule values are:

[2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

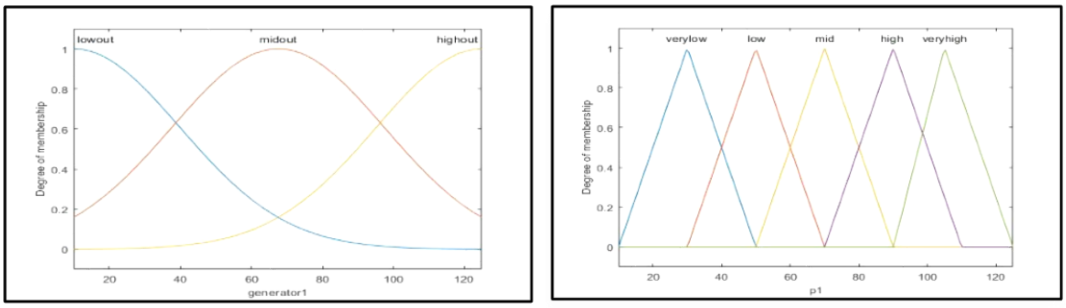
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 15.Input and output MF

Table 11 outlines data collected from case 6. The best outer iteration is 90 for both accuracy and total cost.

Table 11 . Case 6 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	26.5691	529.2161	99.470600	4.1802
2.	10	26.5441	528.6896	99.570900	4.1731
3.	30	26.3434	528.0795	99.652800	4.1685
4.	50	27.4485	529.5170	99.586300	4.1717
5.	70	27.2438	529.2175	99.605300	4.1739
6.	90	27.1330	528.8654	99.653500	4.1690
7.	100	26.8035	528.8722	99.586300	4.1709
8.	200	26.9045	528.7517	99.6306	4.1691
9.	500	27.1473	528.9787	99.6337	4.1694

As a conclusion for PVFT method, the accuracy, and total costs are presented through Figures 16 to 19. Given the high convergence of the accuracy, it is found that 4 iterations are enough to represent various cases.

Figure 16 shows that better accuracy starts from width 30 for Gaussian Membership Function (GMF) at the second iteration then at third iteration all values for accuracy will be approximately the same.

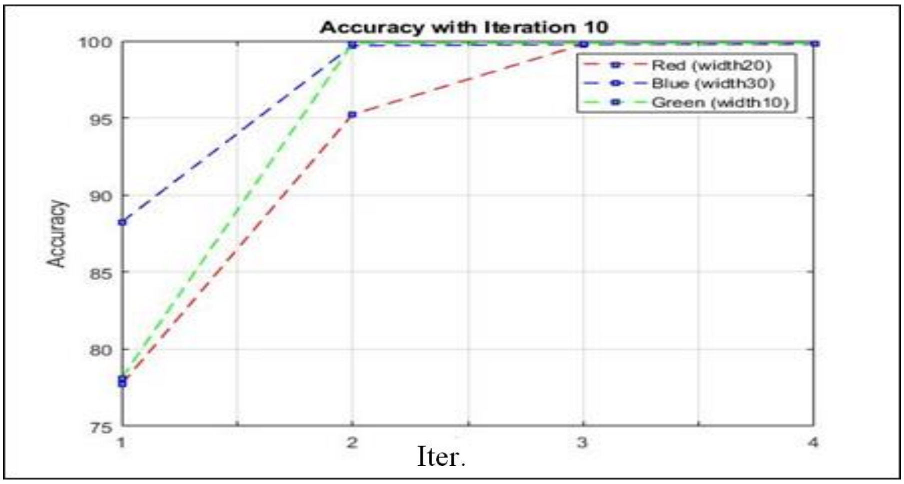


Figure 16. Accuracy in multiple width of GMF iter. 10 PVFT method

It is noticed that the maximum accuracy starts from widths 30 and 10 for GMF at the first iteration as shown in Figure 17. After the third iteration, all values for accuracy will be approximately the same but with a slight difference as in Tables.

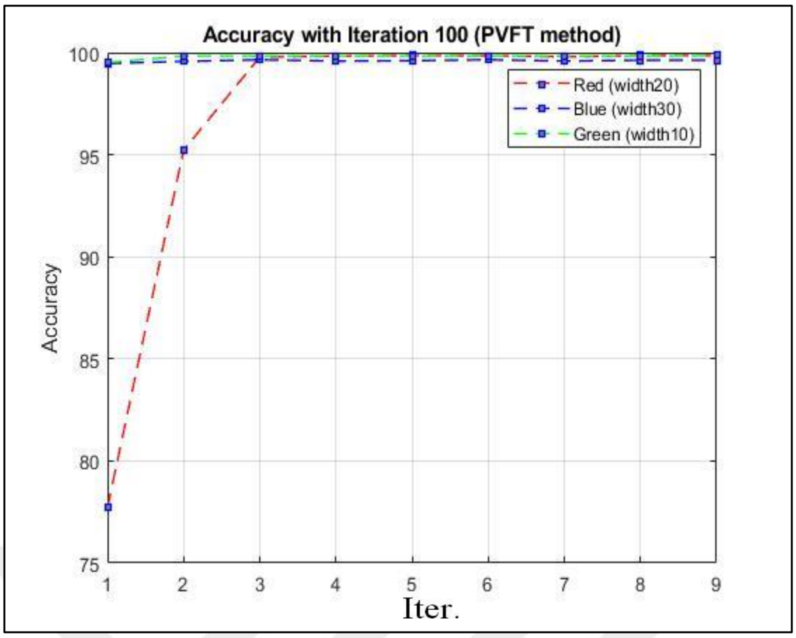


Figure 17. Accuracy in multiple width of GMF iter. 100 PVFT method

The total cost from width 30 is decreasing at the first iteration as shown in figure 18. At the

second iteration, both width 30 and width 10 will be at approximately their minimum, while, for width 20 this minimum is accomplished at iteration 3.

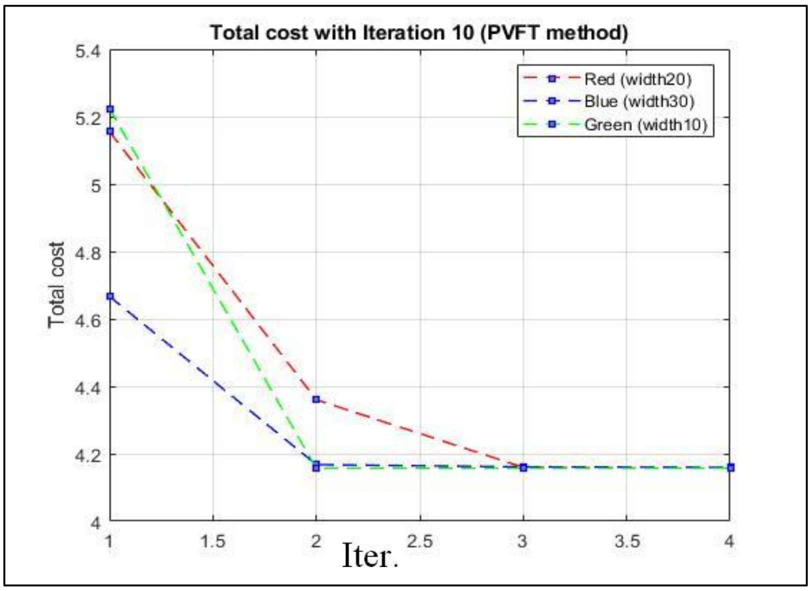


Figure 18. Total cost in multiple width of GMF iter. 10 PVFT method

Figure 19 presents the total cost for the inner iteration equal to 100. It is noticed that for width 20, the cost starts at a high value in comparison with other widths. The cost for width 30 is still higher than the others. The convergence is slower compared with the case of 10 inner iterations.

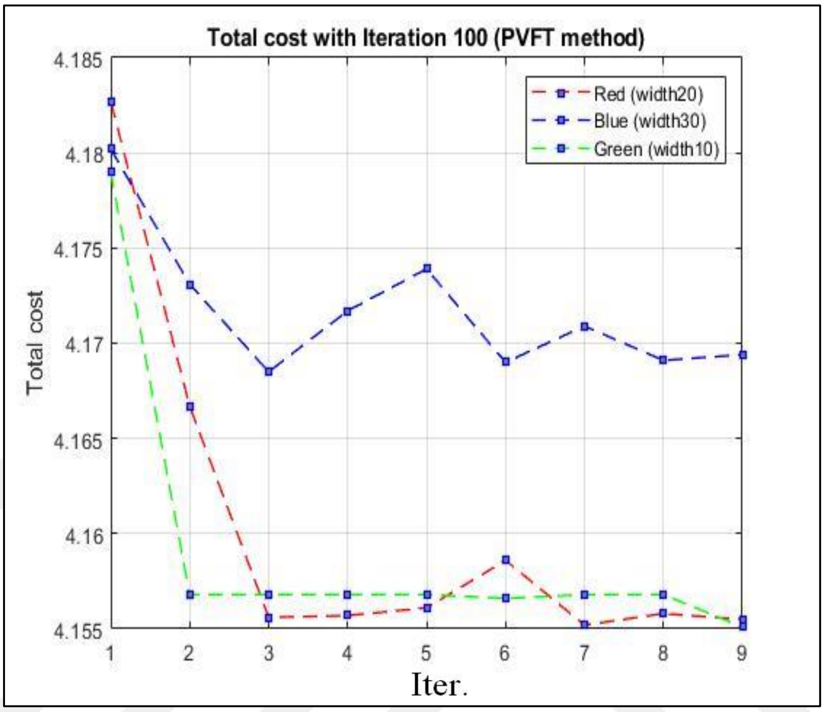


Figure 19. Total cost in multiple width of GMF iter. 100 PVFT method

4.4. PVNS method

4.4.1. Case 7:

The input Gaussian and the output triangular functions are shown in Figure 20.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

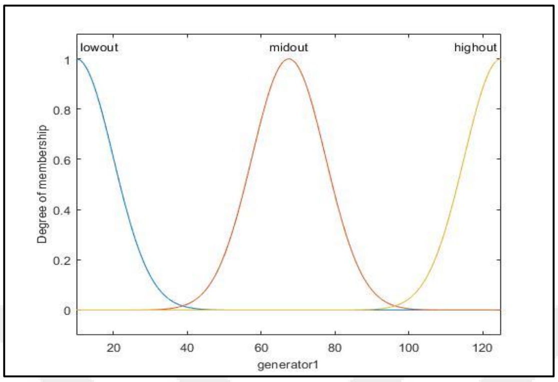
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

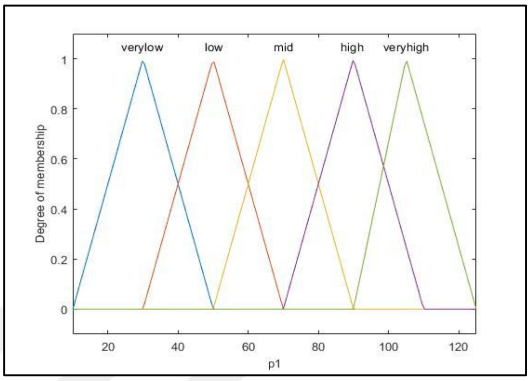
3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a)



(b)

Figure 20. Input and output MF

Table 12 shows that the best iteration outer value for accuracy is found to be 70, while the total cost is 200.

Table 12. Case 7 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	37.3666	596.7728	88.1188	4.7021
2.	10	29.6176	542.2438	97.4748	3.9117
3.	30	27.0482	522.8309	99.1565	3.9779
4.	50	29.3903	540.4278	97.7925	3.9108
5.	70	27.5577	525.5305	99.5946	3.9108
6.	90	28.2879	531.5329	99.3510	3.9108
7.	100	28.6962	534.8512	98.7690	3.9108
8.	200	27.3330	523.6645	99.2663	3.9020
9.	500	-	-	-	-

4.4.2. Case 8

The input is a Gaussian function while the output is a triangular function as shown in Figure 21

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

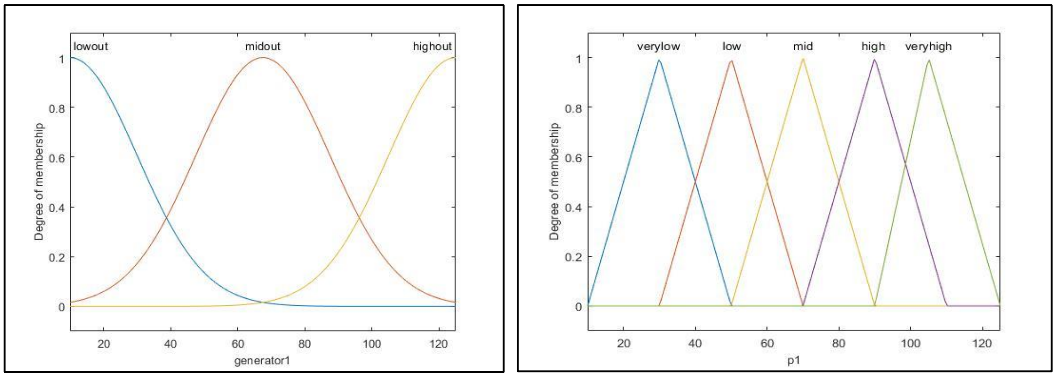
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1]



(a) (b)

Figure 21. Input and output MF

various outer iteration values, calculated power loss, generated power sum, accuracy, and the total cost are presented in Table 13. The best iteration outer value for accuracy is found to be 30, while for the total cost is 100.

Table 13. Case 8 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	25.6247	509.3680	96.7487	3.9776
2.	10	26.8965	520.0139	98.6235	3.9283
3.	30	27.2803	527.3062	99.9948	3.8995
4.	50	28.0056	529.2806	99.7450	3.9134
5.	70	27.7988	527.1372	99.8677	3.9020
6.	90	27.4678	528.9889	99.6958	3.9263
7.	100	28.0046	529.2745	99.7460	3.8991
8.	200	27.8646	528.0765	99.9576	3.9009
9.	500	-	-	-	-

.

4.4.3. Case 9:

The input is a Gaussian function while the output is a triangular function as follows in Figure 22.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

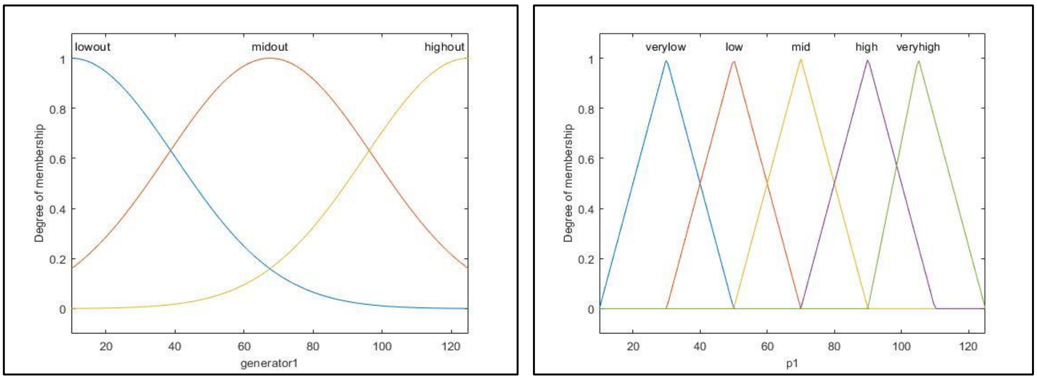
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 22. Input and output MF

From the following table14 , the best outer iteration value for accuracy is found to be 200, while for the total cost is 100.

Table 14. Case 9 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	37.7081	602.9455	86.9525	4.7428
2.	10	26.5600	529.0652	99.4990	3.9447
3.	30	26.5124	526.5846	99.9856	3.9313
4.	50	28.2114	530.7326	99.4957	3.9533
5.	70	26.7165	526.3847	99.9336	3.9418
6.	90	26.3717	526.6250	99.9493	3.9315
7.	100	26.9728	526.8675	99.9789	3.9207
8.	200	27.8681	527.8084	99.9880	3.9262
9.	500	-	-	-	-

4.4.4. Case 10:

The input is the Gaussian while the output is the triangular functions that are shown in Figure 23

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

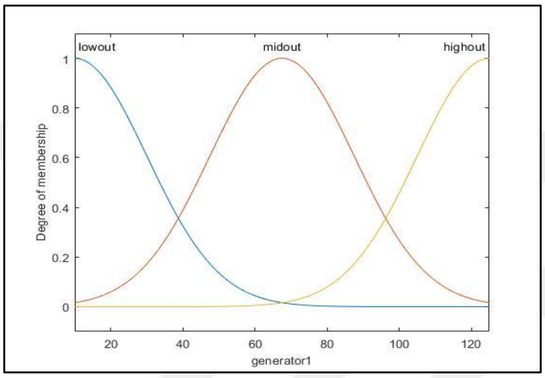
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

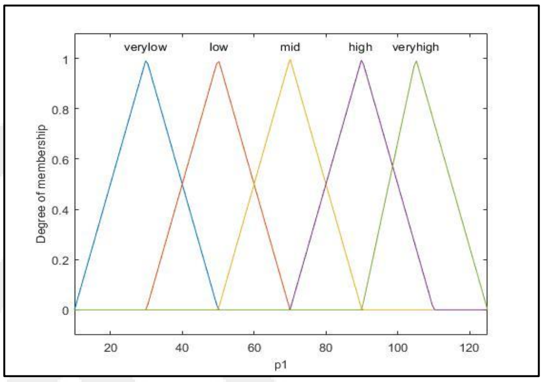
2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a)



(b)

Figure 23.Input and output MF

Table 15 presents the different outer iteration values, power loss, generated power, accuracy, and total cost. The best outer iteration value for both accuracy and the total cost is 200.

Table 15.Case 10 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	26.1827	514.3912	97.6417	4.0137
2.	10	27.7761	527.4053	99.9258	3.8992
3.	30	27.9243	527.8036	99.9759	3.9283
4.	50	27.8139	528.1490	99.9330	3.9210
5.	70	27.7066	527.6598	99.9906	3.9389
6.	90	27.8456	527.9079	99.9875	3.9250
7.	100	27.7066	527.6598	99.9906	3.9086
8.	200	27.8496	527.8889	99.9921	3.8974
9.	500	-	-	-	-

4.4.5. Case 11:

The input and output MFs are used to calculate the target values as presented in Figure 24.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

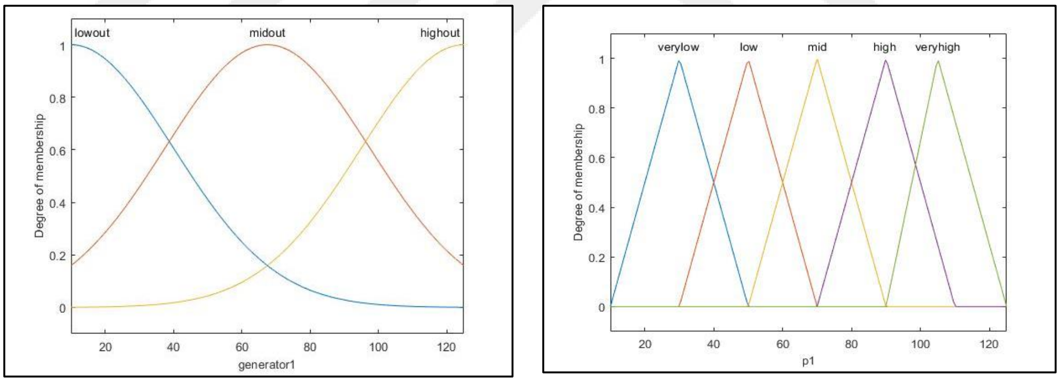
3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1];



(a) (b)

Figure 24 Input and output MF

As shown in Table 16, the best iteration outer value for accuracy is found to be 30 and 70 while for the total cost is 200.

Table 16 . Case 11 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	27.8080	527.6379	99.9660	4.1093
2.	10	26.3231	526.0130	99.9380	4.0576
3.	30	26.8401	526.8476	99.9985	4.0431
4.	50	26.9352	527.0812	99.9708	4.0568
5.	70	27.8658	527.8735	99.9985	4.0650
6.	90	26.5299	526.5017	99.9944	4.0192
7.	100	26.5299	526.5017	99.9944	4.0192
8.	200	26.9811	526.5017	99.9723	4.0163
9.	500	-	-	-	-

As a conclusion for PVNS method all with power demands equal to 500 MW, the accuracy and total costs are presented in Figures 25 to 28. Given the high convergence of the accuracy, it is found that 8 iterations are enough to represent various cases.

The best values are given when the width of (GMF) is 20 dues to the suitable intersection area in input membership which gives good reliability and more accurate output results as shown in Figure 25.

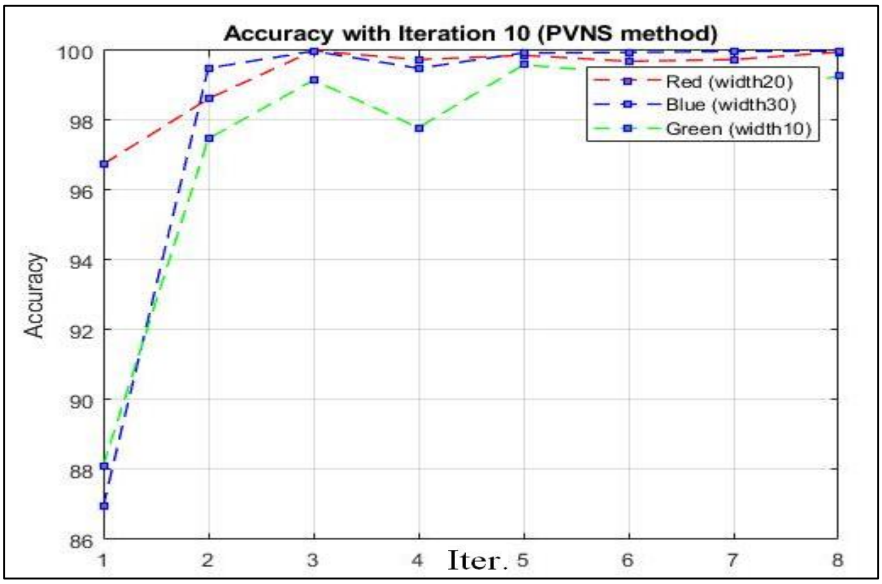


Figure 25.Accuracy in multiple widths of GMF iter. 10 PVNS method

It is noticed from the Figure 26 with outer Iteration of 100, the width of 20 gives a low accuracy in the starting and gives better results as much as inner iteration increases.

The total cost for the cases of 10 and 100 inner iterations are presented in Figures 26 and 27. The width of 20 gives a good result in low inner iteration values and high iteration values. In Figure 27, it is presented that width of 20 gives a good result in low inner iteration values and high iteration values. The convergence is lower than the case of ten inner iterations.

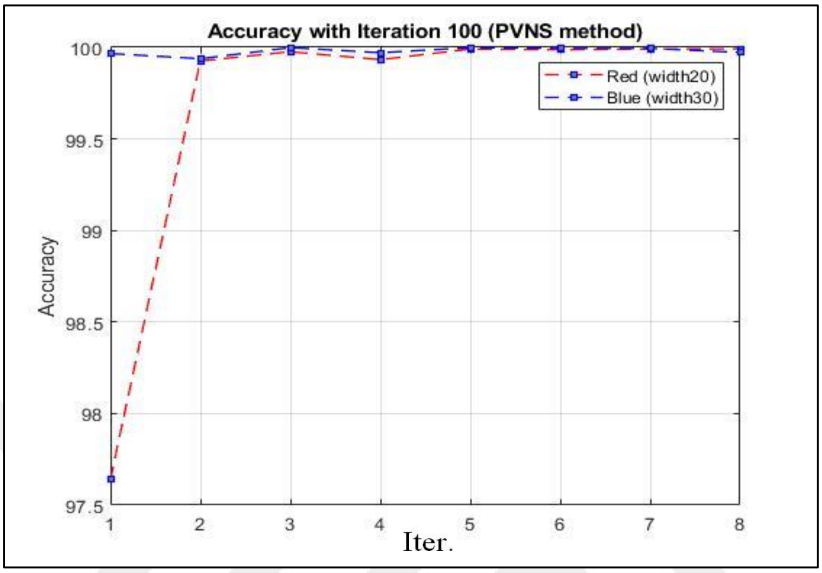


Figure 26 Accuracy in multiple widths of GMF iter. 100 PVNS method

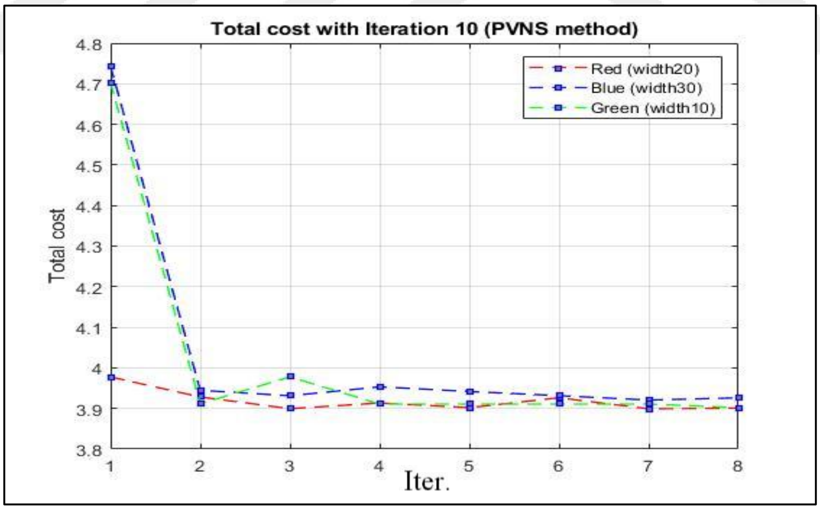


Figure 27.Total cost in multiple widths of GMF iter. 10 PVNS method

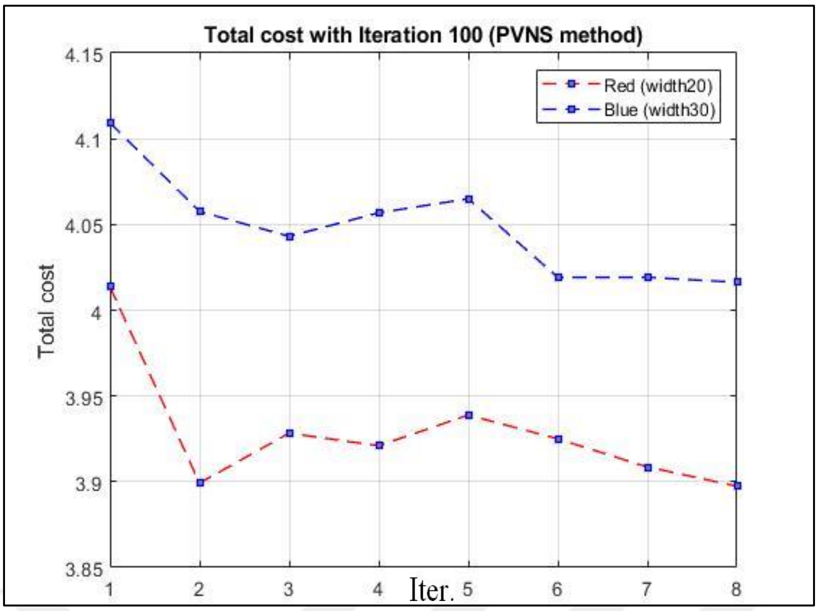


Figure 28.Total cost in multiple widths of GMF iter. 100 PVNS method

As shown in above obtained results (graphs and tables) that the (PVNS) method is more accurate than (PVFT) method so and application is done on IEEE (30) grid for (700MW and 900MW) in order to compare the results to other algorithms to prove that the proposed method is better than other algorithms so below the rest of results will be included.

4.4.6. Case 12

For this case the input Gaussian and the output triangular functions are shown in Figure 29. Here the power demand is increased to be 700 MW.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

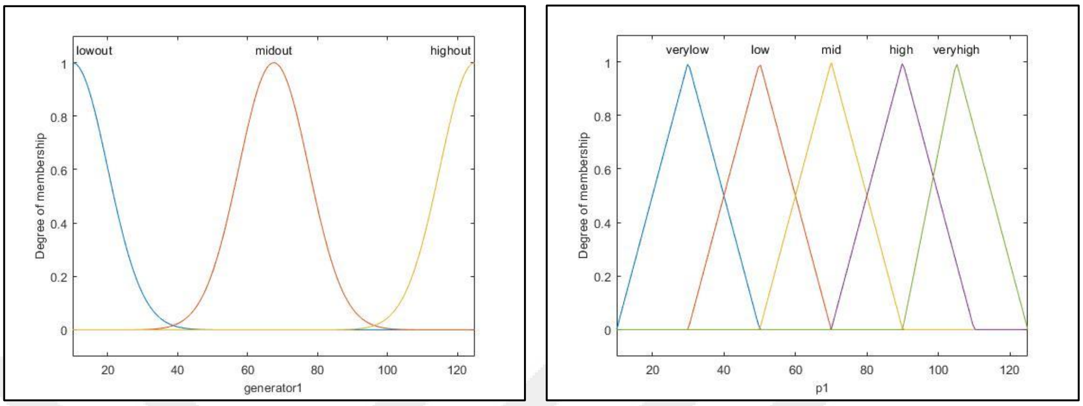
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 29.Input and output MF

Table 17 presents the different outer iteration values the best value of outer iteration is 70 for accuracy and 100 for total cost.

Table 17. Case 12 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	70.1386	808.6136	94.5036	6.7855
2.	10	35.4200	757.0440	96.9108	5.8350
3.	30	65.0357	765.6593	99.9109	5.8350
4.	50	52.5399	752.4764	99.9909	5.8350
5.	70	38.2541	738.2376	99.9976	5.7316
6.	90	65.2839	766.3439	99.8486	5.7507
7.	100	65.3058	766.9789	99.7610	5.6616
8.	200	64.9795	764.8170	99.9768	5.7369
9.	500	-	-	-	-

4.4.7. Case 13

The input and output MFs are used to calculate the target values as presented in Figure 30.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

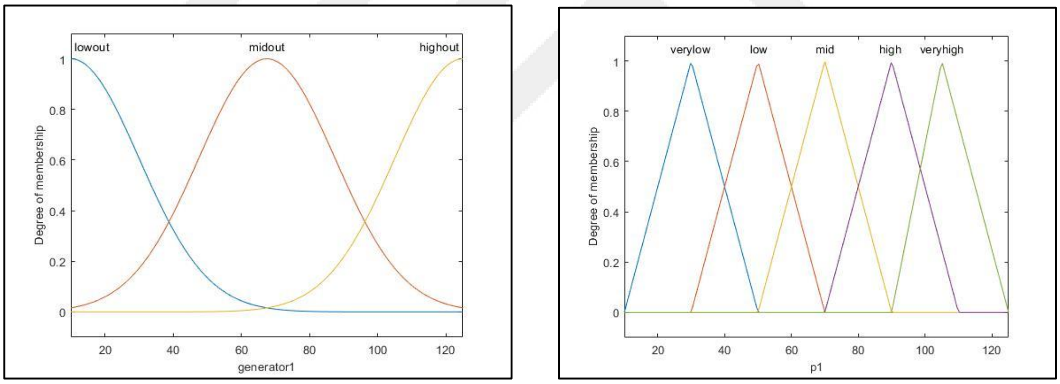
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a) (b)

Figure 30.Input and output MF

Different outer iteration values, calculated power loss, generated power sum, accuracy, and the total cost are presented in Table 18. The best outer iteration value for accuracy is found to be 90, while for the total cost is 70.

Table 18. Case 13 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	64.4331	762.4900	99.7224	6.3376
2.	10	64.3953	764.1023	99.9581	5.9965
3.	30	53.3707	753.5900	99.9687	5.8350
4.	50	65.1885	766.4081	99.8258	5.8581
5.	70	63.9158	763.0297	99.8734	5.5978
6.	90	63.5858	763.5414	99.9937	5.6576
7.	100	64.8213	763.8469	99.8608	5.8357
8.	200	64.3618	764.1268	99.9664	5.6527
9.	500	-	-	-	-

4.4.8. Case 14:

The input is the Gaussian while the output is the triangular functions that are shown in Figure 31.

The rule used to estimate power values is as follows:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

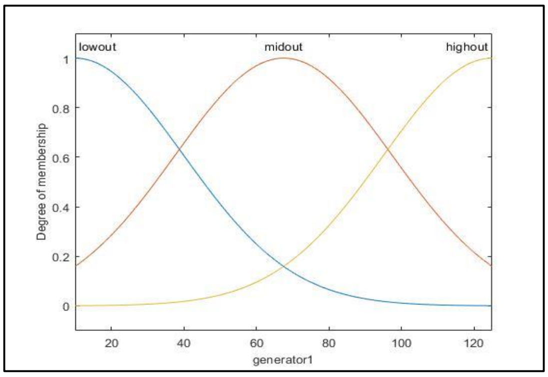
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

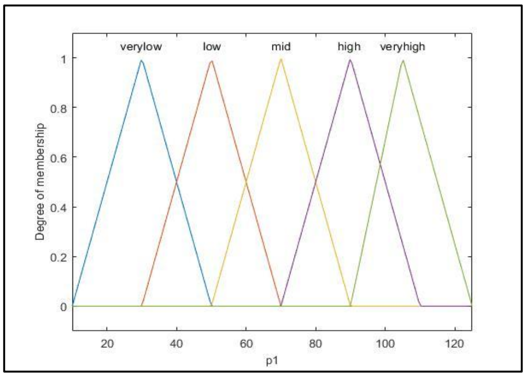
2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a)



(b)

Figure 31. Input and output MF

Table 19 presents the different outer iteration values, that the best value of outer iteration is 90 for accuracy and 50 for total cost.

Table 19. Case 14 data

N	outer iteratio n	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	50.3440	738.6129	98.3241	6.0536
2.	10	58.1287	759.3665	99.8232	6.0163
3.	30	64.1847	764.0647	99.9828	5.9921
4.	50	64.9642	764.8398	99.9822	5.8089
5.	70	59.8803	759.9006	99.9971	6.0155
6.	90	51.0898	751.0858	99.9994	5.8341
7.	100	65.0376	764.9315	99.9848	5.9733
8.	200	60.1490	760.1186	99.9957	5.9199
9.	500	-	-	-	-

4.4.9. Case 15:

The input and output MFs are presented in Figure 32. Rule values are:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

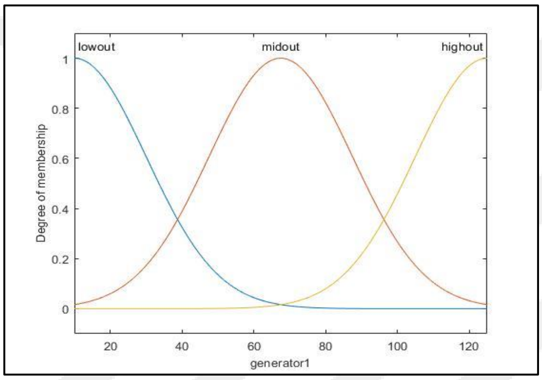
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

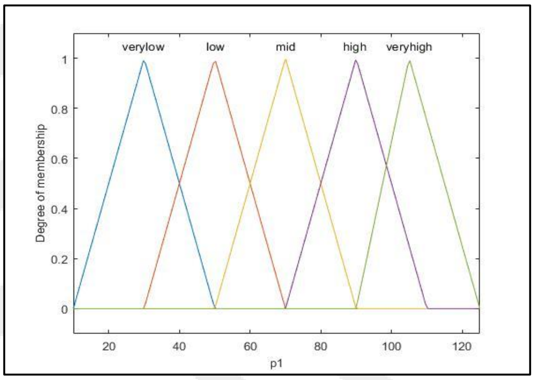
2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 4 4 4 5 5 5 1 1];



(a)



(b)

Figure 32.Input and output MF

Simulation outputs are depicted in Table 20. The best outer iteration value for is 10 and 100 for accuracy and 90for total cost.

Table 20 . Case 15 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	52.5465	752.602	99.9920	6.2118
2.	10	63.1346	763.1483	99.9980	6.2890
3.	20	65.1313	765.6646	99.9238	6.1280
4.	50	38.2953	738.0168	99.9602	6.0697
5.	70	38.2475	738.2732	99.9963	6.0469
6.	90	63.5858	763.5414	99.9937	5.9907
7.	100	63.1346	763.1483	99.9980	6.0352
8.	200	38.2475	738.2732	99.9963	6.0289
9.	500	-	-	-	-

4.4.10. Case 16:

Next table contains an outer iteration of different values, The input and output MFs are presented in Figure 33. Rule values are:

rule = [2 1 2 1 2 2 2 1 1 1 1 1 1 1 1;

1 2 1 2 1 2 2 1 2 1 2 1 2 1 1;

2 1 2 1 2 1 2 2 1 2 1 2 1 1 1;

3 1 3 1 3 1 3 4 2 2 3 1 4 1 1;

3 2 3 2 1 2 3 4 2 1 2 4 2 1 1;

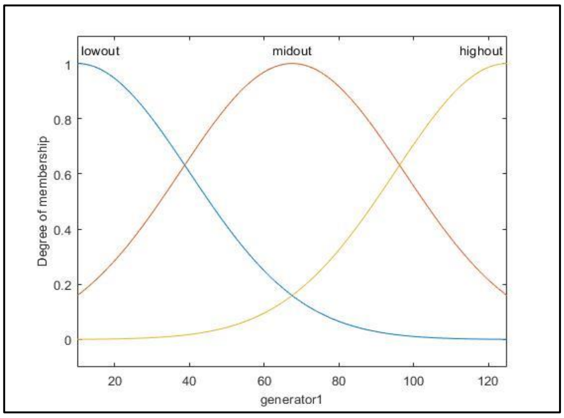
2 1 2 1 2 1 3 1 2 1 2 1 2 1 1;

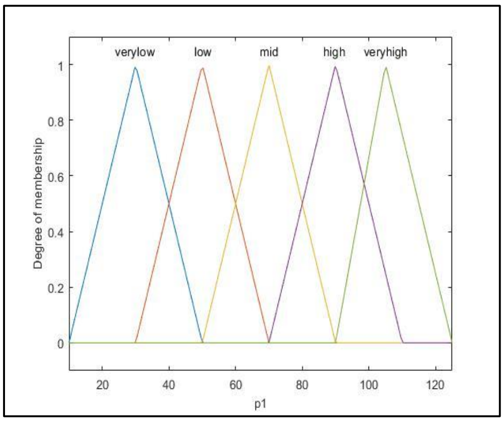
2 2 2 2 2 2 3 2 2 2 4 2 4 1 1;

2 3 2 3 2 3 3 2 3 2 3 2 3 1 1;

3 3 2 3 3 2 3 3 3 4 3 3 4 1 1;

3 3 3 3 3 3 3 4 4 4 5 5 5 1 1];





(a) (b)

Figure 33.Input and output MF

Simulation outputs are depicted in Table 21 The best outer iteration value for both accuracy and the total cost is 50.

Table 21.Case 16 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	65.2353	766.3133	99.8460	6.3770
2.	10	64.2282	764.1997	99.9959	6.1830
3.	30	64.7008	764.6505	99.9928	6.1118
4.	50	52.6545	752.6553	99.9999	6.0456
5.	70	51.0898	751.0858	99.9994	6.1267
6.	90	45.9419	745.9354	99.9991	6.1102
7.	100	63.6472	763.6352	99.9983	6.1080
8.	200	65.0721	765.0743	99.9997	6.1032
9.	500	-	-	-	-

the accuracy presented through figures 34 and 35 as for power demand 700 MW it is noticed that in PVNS method and outer Iteration Of 100, width 30 give a low accuracy in lower iterations and gives better results as much as inner iteration increases

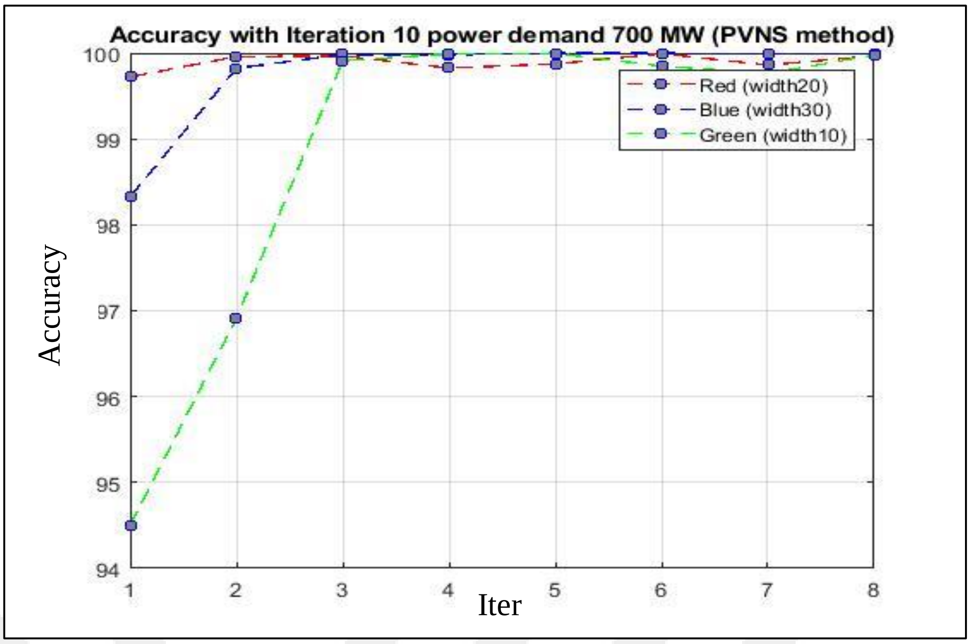


Figure 34.Accuracy in multiple width of Gaussian GMF iter. 10 PVNS method

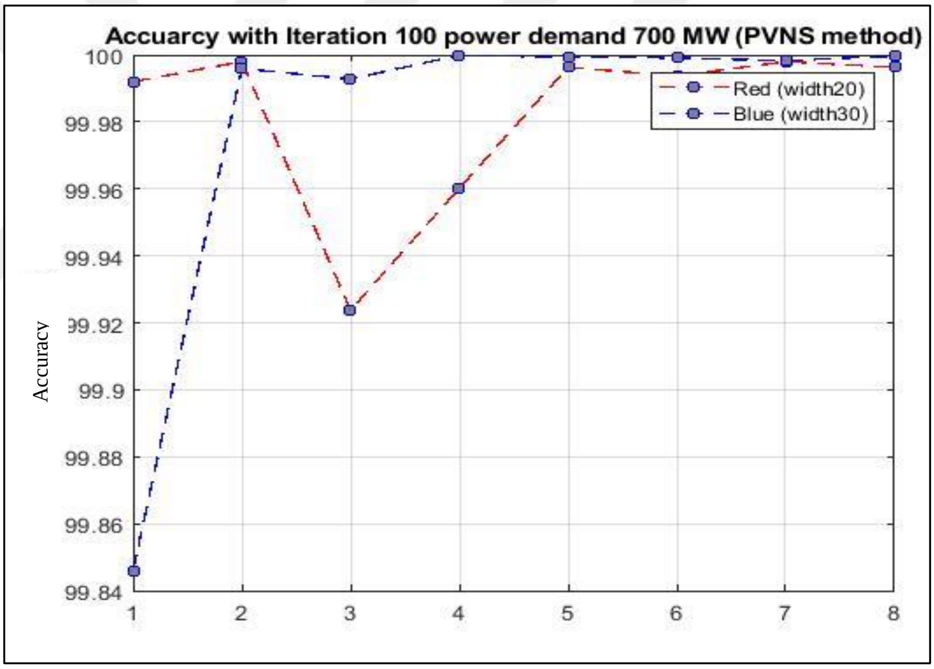


Figure 35.Accuracy in multiple width of Gaussian GMF iter. 100 PVNS method

They provide both figures 36 and 37 for the total cost in power demand 700 MW, width of 20 gives better values in low and high inner iteration values and could be considered as with 20 is the optimum value for finding better results.

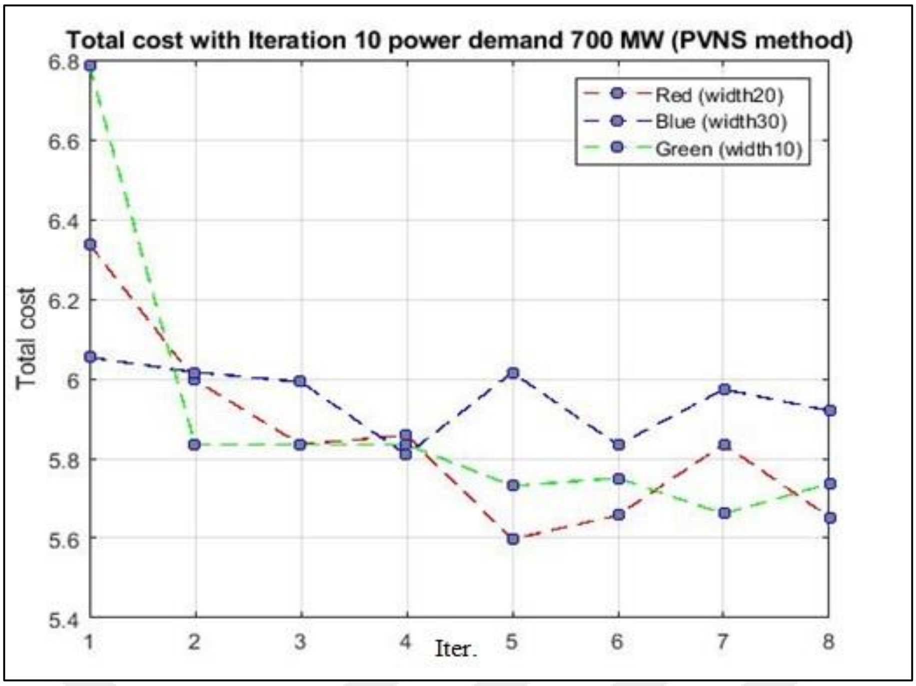


Figure 36.Total cost in multiple width of Gaussian GMF iter. 10 PVNS method

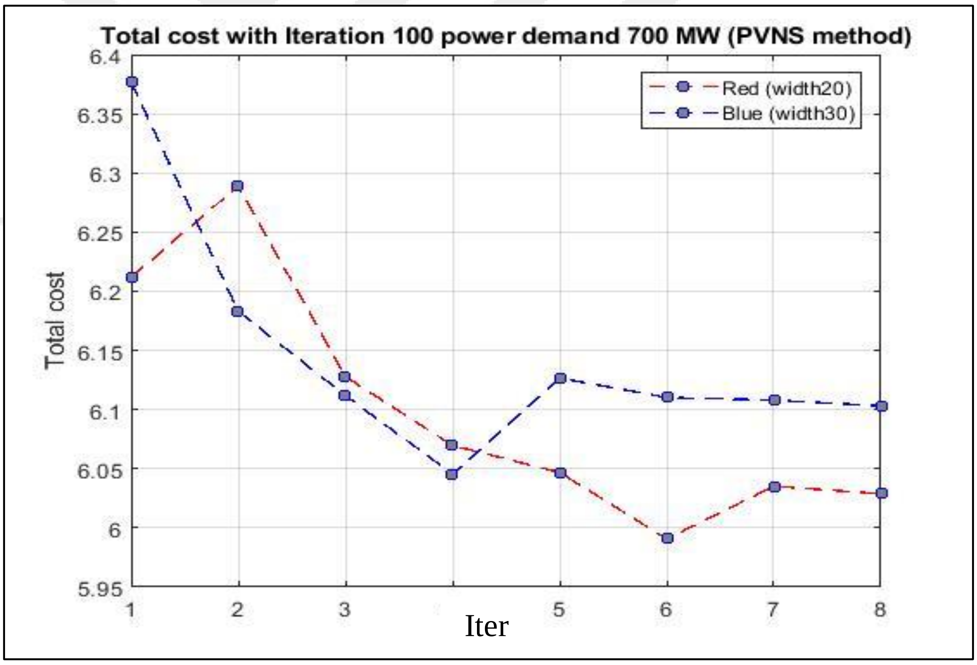


Figure 37.Total cost in multiple width of Gaussian GMF iter. 100 PVNS method

4.4.11. Case 17:

This case results are presented in Table 22 for power demand equal to 900 MW. It contains an outer iteration of different values, calculated power loss, sum of generated power, accuracy and total cost.

Table 22. Case 17 data

N	outer iteration	Power loss	Generated power	accuracy	Total cost (10^4)
1.	1	114.2229	1.0585	95.0810	9.9039
2.	10	103.9711	993.4783	98.8341	8.1283
3.	30	108.9484	1.0102	99.8655	7.9161
4.	50	108.8568	1.0098	99.8923	7.8872
5.	70	108.2652	1.0078	99.9506	8.2005
6.	90	108.2340	1.0079	99.9587	8.0054
7.	100	102.4978	1.0023	99.9748	7.7788
8.	200	108.4756	1.0080	99.9523	7.5894
9.	500	-	-	-	-

From **figure 38** it is noticed that in PVNS method and outer Iteration Of 100, width 20 give a low accuracy in lower iterations and gives better results as much as inner iteration increases.

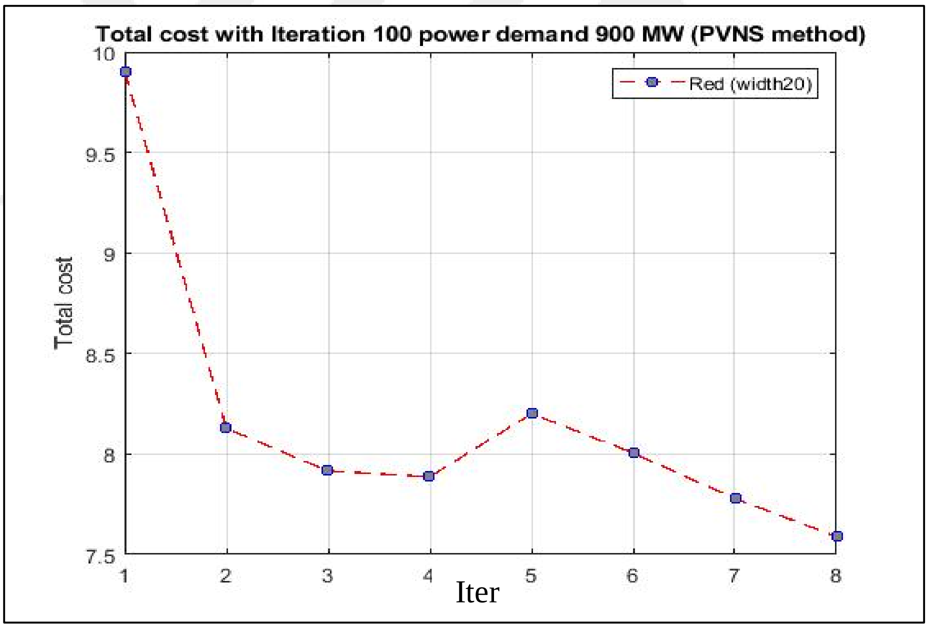


Figure 38. Accuracy with Iteration 100 power demand 900 MW PVNS method

as shown figure 39 it is noticed that in PVNS method in 900 MW demand, width of 20 gives better values in low and high inner iteration values and could be considered as width 20 is the optimum value for finding better results.

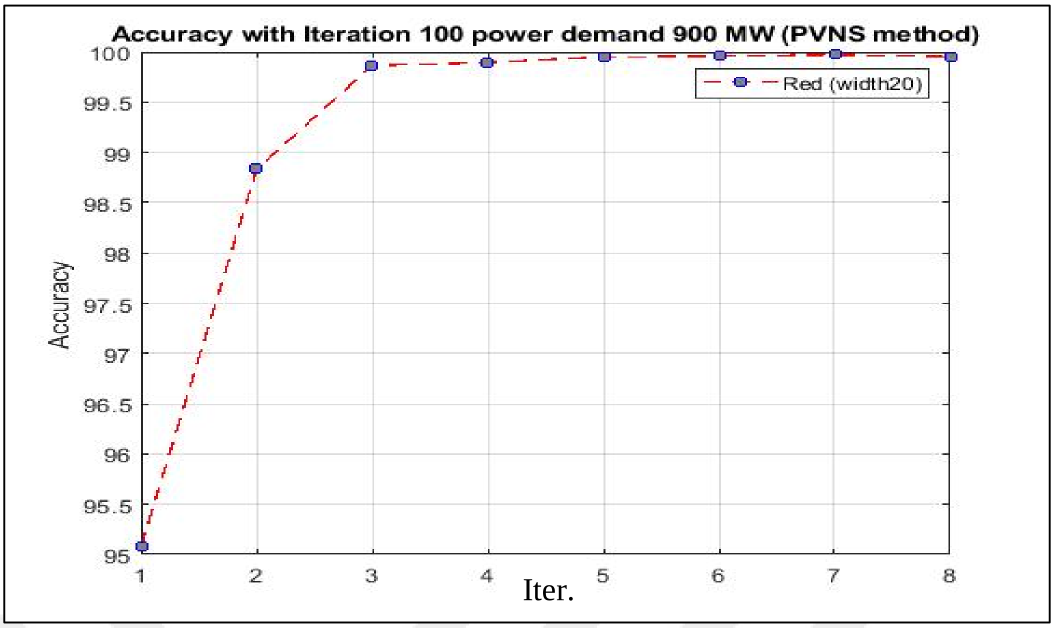


Figure 39.Total cost with Iteration 100 power demand 900 MW PVNS method

4.5. Algorithm comparison

Results of this study which are based on the procedure of analyzing economic emission dispatch using FL are introduced. To explain the strength of the proposed methods, results are compared with different methods as shown in **tables 23, 24, and 25** (Wilbert Ruta 2018).

Table 23. Pure economic EMD at a load of (500MW)

Economic dispatch				
Generating unit (MW)	MFO	BAT	MFO_BAT	PVNS
P1	10.00	10.00	10.00010	31.66990
P2	10.00	10.00	10.19670	31.73770
P3	40.00	118.75350	75.69580	63.42800
P4	35.00	35.45520	80.14960	70.38330
P5	281.36160	204.14810	179.54890	163.56630
P6	125.00	125.00350	148.66360	167.10380
Total generation	501.36160	503.36030	504.25460	527.88890
Losses	1.36160	3.36030	4.25460	27.84960
Fuel cost	27390.79360	27344.96130	27204.73870	2.71560e+04
Emission	409.07950	318.13220	282.24350	276.31740
Pure EMD				

Generating unit (MW)	MFO	BAT	MFO_BAT	PVNS
P1	10.00	34.55080	19.32430	33.84020
P2	31.33140	12.56440	28.59470	31.06060
P3	92.93260	94.51000	93.44650	62.13250
P4	97.50050	92.14740	95.37280	66.94700
P5	141.23070	131.91950	139.48830	167.94510
P6	137.51820	150.48770	136.23470	164.42930
Total generation	510.51340	516.17980	512.46130	526.35470
Losses	10.51340	16.17980	12.46130	26.44680
Fuel cost	27690	27852	27745	2.7326e+04
Emission	268.79810	272.59460	267.8190	278.66620
Economic dispatch considering emissions				
Generating unit (MW)	MFO	BAT	MFO_BAT	PVNS
P1	10.00	10.77450	13.83520	33.47090
P2	10.00	10.00	10.00	30.87960
P3	102.85990	120.70700	95.87990	66.26290
P4	104.22750	85.56810	96.62160	66.15870
P5	130.00	151.94780	152.26720	167.31580
P6	149.26260	126.31820	137.26850	163.21840
Total generation	506.35000	505.31560	505.87260	527.30620
Losses	6.350	5.31560	5.87260	27.28030
Fuel cost	27411	27371	27327	2.7103e+04
Emission	272.79480	276.51020	270.36380	275.50830
Total cost	40456.26630	40594.81130	40256	3.89920e+04

Table 24. Pure economic EMD at a load of 700MW

Economic emissions dispatch				
Generating unit (MW)	MFO	BAT	MFO_BAT	PVNS
P1	90.78870	72.12890	94.05340	44.75210
P2	63.80340	76.37610	65.69110	56.63380
P3	83.68570	87.53120	82.27470	84.78970

P4	108.28280	87.62650	109.44330	141.2297 0
P5	207.09460	206.34050	203.00480	188.8615 0
P6	181.34050	211.58950	179.80690	246.8815 0
Total generation	734.99560	741.59270	734.27420	763.1483 0
Losses	34.99560	41.59270	34.27420	63.13460
Fuel cost	38748	38909	38816	3.8246
Emission	470.24570	487.20560	468.33890	516.4458 0
Total cost	59808.94410	60729.34340	59791.60830	6.06970

Table 25. Pure economic EMD at a load of 900MW

Economic emissions dispatch				
Generating unit (MW)	MFO	BAT	MFO_BAT	PVNS
P1	109.06610	101.20870	121.60720	77.98680
P2	118.96090	131.09990	124.02190	78.40910
P3	115.90070	116.68360	122.07510	157.1992 0
P4	210.00	161.30760	177.48860	155.7958 0
P5	211.69640	221.97540	214.27920	260.5154 0
P6	194.55660	240.57760	205.13790	277.9279 0
Total generation	960.18080	972.85290	964.60980	1.00780
Losses	60.18080	72.85290	54.62410	108.2262 0
Fuel cost	50952	51398	5.1437	4.5608
Emission	766.50410	761.68480	745.74550	695.5594 0
Total cost	87607.8942	87823.8286	87099.9792	7.8872

4.6. Discussion

In this work, two algorithms named PVFT and PVNS were tested and both of them are based on FL to reduce search domain to find the optimum values for generated power.

PVNS is proved to be better in all simulation results and values although PVFT is faster and reliable for online applications. Furthermore, in this research we approved that FL used decision making can considered as a good alternative for other algorithms used in CEED problem but more options and more cases for MFs boundaries and shapes should be investigated.

The results show that whenever the search process increases then the probability to find best values increases.

If results in Table 7, and 8 are compared, it can be concluded that the accuracy and total cost is better in case of using GMF with width of 20 than of 30.

This is due to the mixed boundaries of width 30 that don't give the fuzzy system the chance to differentiate between two of MFs of the input in a good way in comparison with width 20. Furthermore, FRs could be changed to obtain better results, it is very important to say that FRs depend on the fuzzy system designer and his experience towards the problem behavior.

Note that the calculation process in de fuzzification in this research uses center of gravity other methods can be tested to find more results for CEED problem

Also, the method used is Mamdani and it could be changed to Sugeno method to adopt better solutions and results. but the ease of calculation of de-fuzzification process in mamdani makes it more repairable in real world applications.

Using fuzzy logic in search process reflects the human knowledge on artificial intelligent application in a way that uses the human experience for solving problems to solve the single or multi objective problems, fuzzy logic can be summarized as a multistep output logic and this makes it overcome the main problem of the crisp logic that makes it not applicable in many real life applications and problems.

The main challenge in applying PVNS is to find the optimum values in short period of time to give the system the ability to modify output values according to the changing demand, to overcome this problem it is necessary to find the optimum iterations needed for locating best power values to apply it on generators in the system.

CHAPTER FIVE

CONCLUTION AND FUTURE WORK

5.1. Conclusion

In the process of finding optimum solution for CEED problem a GMF is used for fuzzy interference system, to produce a power generation value needed for electrical grid. power values should satisfy the constrains to introduce best economic and emission values.

As noticed from results PVNS method has better results than PVFT method from both accuracy and total cost point of view in all values of sigma for Gaussian membership functions.

Using FL to find an optimal solution for CEED problem may be considered as a good alternative - based on this research - in comparison to other algorithms but the main disadvantage is the time consumed to find this solution but in some cases like Gaussian membership function with (2sigma =10) it is noticed that a solution found in small iterations and consumed a little period of time.

Two types of iterations were used in Matlab code (inner) and (outer) iterations, inner iteration is responsible of finding the best power values and best accuracy, outer iteration is responsible of finding best total cost values.

5.2. future works

In order to modify the PVNS algorithm a modification could be made as follows:

1. FRs may be investigated to find the solution based on human experience and knowledge.
2. Other types of MFs need to be tested to find the optimum FMF solution like impulsive, triangular where a, b > 0, right sided trapezoidal where a > 0, left sided trapezoidal where a > 0.
3. Other de-fuzzification calculation methods may be examined - in Mamdani method - like Center of Sums Method (COS), Centroid of Area (COA) Method, Center of Area / Bisector of Area Method (BOA), Weighted Average Method, Maxima Methods (First of Maxima Method (FOM), Last of Maxima Method

(LOM), Mean of Maxima Method (MOM)) in order to decide which method, produce best optimum value.

4. Many variations in inner iteration, outer iteration, sigma values, membership functions boundaries and shapes could be investigated.
5. Comparison with other modified algorithms should be investigated also taking all gas types such as NOX, SOX and COX will give a realistic simulation for real life cases.
6. Taking valve point affection into consideration will be better for learning real life situation also taking more grids into simulation will prove the capability of FL to handle more electrical grids and variations.

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