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Development of hybridized evolutionary algorithm for solving economic environmental dispatch problem in Nigerian power system

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Abstract
Economic Pollution Dispatch (EED) has been the subject of several approaches in recent years. EED-based algorithms may be used in place of traditional optimization approaches. Many different types of modern power generation units include non-linear properties such as valve charging effects, ramp rate constraints, and polynomial estimates of fuel cost and pollution that these approaches haven't been proven to explain. All of this may lead to poor results and lengthy calculations. Because of the global optimum of functional EED problems, conventional techniques have found it difficult to produce a range of metaheuristic solutions in the last two decades. EP, PSO, DSO, self-adapting modified firefly algorithm, chaotic quantum genetic algorithm. Various methods for addressing the EED issue have been described in the literature. As a result, traditional approaches that rely on derivate are unable to provide large ranges of Pareto fronts since the real EED problem is significantly non-linear. Load scheduling becomes more difficult because of these constraints. Meta-heuristic optimization is becoming more popular among academics as a way to get around the limits of traditional approaches. Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and the Classification Based Surrogate Aided Algorithm (CSEA) were used in this work to solve the issue of convergence to a diverse assortment of Pareto front solutions for the EED problem. This method will handle convex and non-convex dispatch economic issues, as well as microgrid dispatch problems. With demand for the power system and operational limit limitations, the convex ED problem yields the quadratic cost structure. The non-convex ED problem explains the engine's nonlinearities, such as valve point loads, restricted working zones, and various power alternatives. This problem aims to find a strategy for distributing a generation of dedicated generators in order to meet demand while minimizing fuel costs and pollutant emissions while adhering to different fairness and inequality restrictions. Nonlinear and linear constraints are used in a multi-objective optimization problem with the purpose of reducing costs and pollution. This research will provide the groundwork for more efficient power generator dispatch, allowing power system managers to make more informed choices.

Keywords: Economic pollution dispatch (EED), classification based surrogate aided algorithm (CSEA), non-dominated sorting genetic algorithm II (NSGA-II)

1. Introduction

Economists utilize economic dispatch to ensure that power is distributed in a fair and equitable manner while also meeting demand for energy at low operational costs. As of 2019, (El-Keib, Ma and Hart, 2019) [9]. All three of these pollutants (COx, SOx, and NOx) are emitted by these power plants (NOx). These greenhouse gases have the effect of hastening global warming and ecological instability. A solution to the economic dispatch problem aims to obtain a power plant's schedule of generating units that minimizes total generation costs while satisfying all equality and inequality constraints on units and systems. There are several health and environmental issues associated with the release of gaseous pollutants including sulfur dioxide (SO2), nitrogen oxides (NOx), and carbon dioxide (CO2) into the atmosphere from thermal power plants. Greater environmental consciousness has made reduction of these emissions a requirement for power plants and the traditional economic dispatch problem no longer satisfies the environmental need (El-Keib, *et al.*, 1994). This expands the definition into the economic environmental dispatch (EED) problem. Non-convex optimization is a high-dimensional, conflicting problem for both economic and environmental goals. Nations have put pressure on utilities to adjust their working methods to meet environmental standards as a consequence of a shift in public perception of emissions and the adoption of clean air legislation (Helsin & Hobbs, 2018).

Economic shipping is a power usage issue for any participating producing plant, with the goal of minimizing total operating costs while meeting the requirements. Without regard for emission restrictions, economic transportation reduces the total cost of fuel. Pollution shipping reduces emissions without taking into account economic factors. Modern power networks have a number of problems, one of which is economic dispatch (ED). ED enables all dedicated generating units to be scheduled to meet the requirements for charge at the lowest possible operating cost while addressing various physical and organizational constraints (Granelli, Montagna, Pasini, & Moranino, 2017) [11]. Many studies have been conducted using traditional methods such as lambda repetition, grade process (Farag, Al-Baiyat, & Cheng, 2015) [10], branch and bound method (Huang & Huang, 2017) [13], and quadrant programming to solve ED problems (Muslu, 2015) [17]. (Sinha, Chakraborty, & Chattopadhyay, 2017) [22], both Economic and Environmental objective are diametrically opposed, and both must be considered in order to achieve overall optimal transportation, since businesses need suitable and safe energy at the lowest feasible cost and with the least amount of pollution.

The incremental cost curves for generating units are monotonously rising and partially linear in these typical conventional methods, with nonlinear features in functional systems such as restricted operating regions, different fuel choices, and ramp-rate limitations, etc (Jiang, Yan, & Hu, 2018) [16].

For this reason, standard approaches are ineffective in dealing with ED concerns since the ED problem is not a convex optimization problem. A dimensional curve has been encountered in DP (Gaing, 2015) [12], which has relieved this limitation. Due to the difficulty of perfecting these procedures, they should be enhanced locally. The ED issue has recently been solved by a number of evolutionary and swarm-based meta-heuristic approaches that resolve these inadequacies. Replication, selection, recombination and mutation are all part of the natural selection and biological development of evolutionary algorithms. (Balamurugan & Subramanian, 2018) [7], real-coding GA (RCGA) (Niknam, Azizipanah-Abarghooee, & Roosta, 2019) [18], modified differential evolution (MDE) (Liao, 2018), PSO algae (DEPSO) (Arul, Ravi, & Velusami, 2013) [2], and improved quick-evolutions programming (IFEP) This method will handle convex and non-convex dispatch economic issues, as well as microgrid dispatch problems. With demand for the power system and operational limit limitations, the convex ED problem yields the quadratic cost structure. (Chen, 2002) [8]. The non-convex ED problem explains the engine's nonlinearities, such as valve point loads, restricted working zones, and various power alternatives.

Economic Pollution Dispatch (EED) has been the subject of several approaches in recent years. EED-based algorithms may be used in place of traditional optimization approaches (Alsumait, Qasem, Syskulski, & Al-Othman, 2010) [3]. Many different types of modern power generation units include non-linear properties such as valve charging effects, ramp rate constraints, and polynomial estimates of fuel cost and pollution that these approaches haven't been proven to explain. All of this may lead to poor results and lengthy calculations. Because of the global optimum of functional EED problems, conventional techniques have found it difficult to produce a range of metaheuristic solutions in the last two decades. EP (Basu, 2006) [6], PSO (Pandi & Panigrahi, 2018), DSO (Aghaei, Niknam, Azizipanah-Abarghooee, & Arroyo, 2013) [1], self-adapting modified firefly algorithm (Pandit, Tripathi, Tapaswi, & Pandi, 2019) [19], chaotic quantum genetic algorithm (Basu, 2019) [5].

The economic dispatching (ED) issue addresses the challenge of allocating the output of one power system's producing units in order to minimize fuel costs and satisfy power balance and performance constraints. Because environmental safety is becoming more sensitive, reducing pollutant emissions is a priority in the ED crisis, and the resultant issue is known as the environmental/economic shipment or economic pollution dispatch (EED).

Various methods for addressing the EED issue have been described in the literature. As a result, traditional approaches that rely on derivate are unable to provide large ranges of Pareto fronts since the real EED problem is significantly non-linear. Load scheduling becomes more difficult because of these constraints. Meta-heuristic optimization is becoming more popular among academics as a way to get around the limits of traditional approaches. Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and the Classification Based Surrogate Aided Algorithm (CSEA) were used in this work to solve the issue of convergence to a diverse assortment of Pareto front solutions for the EED problem.

2. Literature review

For a variety of real-world issues, multiple objective functions must be optimized at the same time. These responsibilities are often seen as incompatible because they pursue often diametrically opposed ends. Conflicting objective functions in multi-objective optimization allow for multiple optimal solutions rather than a single optimal one. There is no one solution that is better than any other when it comes to the objective functions, which is why many solutions are considered optimal. It is termed Pareto-optimal solutions when the best solution is found.

The Multiobjective optimization issue can be stated as follows mathematically:

$$\text{Min } f(x) \tag{1}$$

$$\text{Subject to: } \begin{cases} g(x) = 0 \\ h(x) \leq 0 \end{cases} \tag{2}$$

Fuel cost generators, line losses, etc. are good examples of objective functions that may be used in this way. etc., and g(x) is a compare constraint, h(x) is an injustice restriction, and x is a controlled variable, such as the actual power output generator, generator voltage, switchable reactive power, and transformer tap setting. The goal function is f(x) (Roy, 2013) [21].

a. Total fuel cost: The overall fuel cost (in $/h) can be represented by a quadratic function expressed as

$$F(P_G) = \sum_{i=1}^{N} a_i P_{G_i}{}^2 + b_i P_{G_i} + c_i \tag{3}$$

where a_i, b_i and c_i are the fuel cost coefficients of the

i^{th} generator.

b. Emission totals: The ton/hour ton total emission of pollutants into the atmosphere is stated mathematically as

$$E(P_G) = \sum_{i=1}^{N} 10^{-2}(d_i P_{G_i}{}^2 + e_i P_{G_i} + f_i) + g_i \exp(h_i P_i) \quad (4)$$

The problem of MULTI objective optimization (MOPs) is extensively utilized in real life, for example, in electrical engineering, industrial planning, and robotics. More than two mathematically specified goals are being worked on at the same time in these situations, and they are often at odds (Hemamalini & Simon, 2018) [14].

$$\begin{aligned} \text{minimize} \quad & F(x) = (f_1(x), f_2(x), \ldots, f_m(x)) \\ \text{subject to} \quad & x \in X, \end{aligned} \quad (5)$$

Here, the judgment variable x is a function of both m, the number of targets, and The region-dependent selection algorithm, the improved Pareto evolutionary algorithm (SPEA 2), the elitist non-dominated genetic sorting algorithm, and the multi-objective evolutionary algorithm based have all been suggested in recent decades. MOPs with two or three goals may be solved using these strategies (Huang & Huang, 2017) [13]. Multi-objective optimization problems, or MOEAs with more than three goals, significantly reduce the efficiency of MOEAs concentrating on dominance relations (MaOP).

Non-dominated solutions in a small community expand exponentially, making it impossible to discern between typical MOEAs and Pareto solutions as the number of targets rises. Many evolutionary multi-objective optimizer algorithms (NSGA-3), such as HyperE and KNIEA, have been created, although these are only a few examples (NSGA-III). There are tens of thousands of fitness assessments required for current MOEAs for MaOPs, according to (Jagat, Mousumi, & Deba, 2017) [15].

The introduction of computationally cheap surrogates for approximating the costly fitness assessments is one technique to tackling optimization issues, particularly if function evaluations are computationally expensive. Polynomial response surface approach, radial basis function, Gaussian process model, artificial neural networks, and support vector machines are all examples of frequent surrogates (Pan, Cheng, Tian, & Wang, 2018) [20]. To speed up the evolution of multi-objective surrogate aided evolutionary algorithms (SAEAs), the surrogate may be utilized to approximate functions other than the objective function. In a general sense, existing SAEAs can be divided into two categories based on the surrogate's intended use. The fitness function is approximated using one or more surrogates in the first category. SMS-EGO. As a classifier in the second category, the surrogate determines if the potential solutions are excellent or poor, such as solutions that are dominated or not.

- Use of computationally efficient surrogates for approximating the costly fitness assessments reduces computationally expensive function evaluations.
- Other frequent surrogates include radial basis functions and Gaussian process models as well as the artificial neural networks and support vector machines. (Pan and colleagues, 2018) [20].
- To speed up the evolution of multi-objective surrogate aided evolutionary algorithms (SAEAs), the surrogate may be utilized to approximate functions other than the objective function.
- For example, Knowles' ParEGO (Knowles, 2006), SMS-EGO (Ponweiser *et al*., 2008), k-RVEA (Zhang, *et al*., 2010) and CSEA (Knowles, 2006) are examples (Linqiang *et al*., 2018) [20].

It is for costly multi-objective optimization that CSEA, a classification-based surrogate-assisted evolutionary method, is used. Candidate solutions and a set of chosen reference solutions were taught to the CSEA surrogate. In order to anticipate the dominance connection between candidate solutions and reference solutions, CSEA (a neural network) is used. Optimization problems that are computationally intensive may be solved more quickly using this surrogate-assisted approach, which also increases convergence rates.

In the surrogate-aided optimization model, a candidate solution's target function or fitness function is typically approximated by x. (Li & Pan, 2019):

$$\hat{f}(x) = f^*(x) + \varepsilon(x) \quad (6)$$

This is the real value of the goal or the solution's fitness value. f* may be used to estimate an approximation of a surrogate model's estimated value, as well as its error function. Surgery optimization aims to reduce the time needed to solve time-consuming optimization issues by replacing cost-effective fitness assessments with computationally less costly alternatives. There has been an increase in the use of multi-objective SAEAs to resolve MOPs during the last several decades, according to studies. A few SAEAs were particularly created to handle the MaOPs, though. Liao, (2018) has suggested an evolutionary technique for costly many-objective optimization based on the Kriging replacement-assisted reference vectors.

The model management method in K-RVEA focuses on achieving a balance of diversity and convergence by incorporating insecurity knowledge into estimated goal values focused on the angel-based, penalized gap proposed by the first evolutionary algorithm (RVEA) based on reference vector. For costly multi-objective optimization, K-RVEA has been proven to be competitive with a number of advanced SAEAs (Liao, 2019). Apart from the objective function, the replacement may be used to estimate a variety of activities to aid development in multifunctional or multi-target SAEAs. Based on the surgeon's objective function, contemporary SAEAs may be classified into two categories. In the first division, a single or many replacements are used to approximate the fitness function. It's worth noting that the health characteristic in this category may be either an empirical or aggregating function or a success prediction. Instead of randomly selecting a weight vector from a pool of standardized weight vectors as is done in ParEGO, an aggregate function is generated by simulating one adding feature per generation using a single Kriging model. The hyper-volume function is approximated using a Kriging model in SMS-EGO, where an individual's fitness is defined as their contribution to the community's hyper-volume score

(Lin & Chen, 2002) [8]. MOEA/D-EGO builds a single Kriging model for each objective feature of each sub-issue, whereas K-RVEA uses a separate replacement model to approximate m objective functions. It corresponds to the second category of SAEAs, which ranks candidates' solutions as good or bad, such as a dominant or non-dominant answer The MOEA (CPS-MOEA) and MOEA based on decomposition/pre-selection (MOEA/DP) classifications, as well as Pareto dominance, have been used to classify objects in fewer studies to date. According to the non-dominated grouping, the CPS-MOEA community is split into two equal groups: a positive group and a negative group. An evolutionary approach for costly multi-objective optimization using a classification-based surrogate (Linquiang *et al*. 2018) [20] In the multi-objective evolutionary method, the newly constructed descendant category is used as a classification and regression tree (or KNN) to forecast FE reduction, which has been found to be more efficient than regularity modeling (RM-MEdA).

There is a differential evolution (DE) approach known as the CRADE that is suggested for pricey single-objective optimization. Offspring solutions are rejected in accordance with the proxy designation, which is worse than their relative, during the gathering of environmental products in CRADE. A memetic algorithm was used to choose people to be refined in order to tackle optimization issues with a single degree of equality in this grouping (Lu, Zhou, Qin, Wang, & Zhang, 2018) [20]. Help vector machines were used to identify whether a solution was outside of the feasible zone and whether local refinement should be used in this technique. Help vector machines. The computation time was significantly reduced.

Hybridizing Evolutionary Algorithms is a typical method for addressing complex Optimization problems. Stochastic search was one of the early MultiObjective EAs for handling Economic Environmental Dispatch issues. For this, a hybrid of real-coded genetic algorithms and simulated annealing was used in the design. Local search methods were used to make sure the results returned were accurate. Premature convergence was a problem with this approach. Using the principles of Differential Evolution and Particle Swarm Optimization, a new hybrid Multiobjective Evolutionary algorithm was developed. Particle swarm optimization (global) and Differential Evolution (local) were used in this experiment (local). Using a combination of the two techniques, the approach may be better used and explored for use in Economic Environmental Dispatch problems. The Nondominated Sorting Genetic Algorithm II was enhanced with a convergence accelerator operator to handle the Economic Environmental Dispatch challenges. In their 2011 paper, Bhattacharya and Chattopadhyay A neural network-based approach is used in conjunction with a deterministic local improvement process to create this new convergence accelerator operator. In terms of effectiveness, the modified NSGA-II was superior than the original NSGA-II.

The problem of fossil-fuel greenhouse gas emissions from the combustion of fossil-fuel fuels during the generation of electricity is referred to as Environmental Dispatch (ED). The effect of fossil fuel combustion on electricity generation is the worst in large cities. Many people are concerned about the harmful effects of toxic gas leakage into the environment, which causes ecological imbalance and global warming. As a result, an effective solution to the issues is required. In essence, EED aids in the evaluation of committed generating units in order to react to demand with the lowest possible operating costs and harmful gas emissions. Device limitations, such as power balance and lower and higher active power, apply to all of the aforementioned topics. EED is considered as a restricted multi-objective subject. Furthermore, the dilemma's goals are incompatible, making it tough and complex to solve the issue. Researchers have used a variety of techniques to tackle the issue, including target programming methods, multi-target differential evolution, and many more, in an effort to overcome the challenge. In contrast, the majority of approaches regard the problem as a single, objective issue and rely on presuppositions. In the meanwhile, assessing EED is a multi-target problem, yet computationally costly and time-consuming methods have been found. This is due to EED's difficulties as a multi-purpose optimization subject.

Power generating costs and emissions from thermal power plants are two objectives in this multi-objective optimization issue. The EED is a multi-target, limited problem of optimizing fuel and greenhouse gas emissions to satisfy numerous comparable and inequitable limits while reducing two conflicting goals for fuel consumption and thermal unit emissions. This problem of environmental/economic dispatch entails balancing the two opposing goals: fuel and emissions, as well as adhering to a number of constraints on fairness and inequity. The issue is mathematically stated as follows in general.

It is the goal of the economic environmental dispatch problem (EED) to reduce both fuel costs and emissions while fulfilling different power system equity and inequality restrictions. Mathematically, the issue may be represented as

$$\begin{aligned} &min.\ \ [F(P_G), E(P_G)] \\ &s.t.\ \ g_j(P_G) = 0,\ \ j = 1,2,\dots,J; \\ &h_k(P_G) \le 0,\ \ k = 1,2,\dots,K; \\ &P_{G_i}{}^{min} \le P_{G_i} \le P_{G_i}{}^{max}, i = 1,2,\dots,N. \end{aligned} \tag{7}$$

where $F(P_G)$ and $E(P_G)$ represent the fuel cost and emission cost functions, g_j are the equality constraints and h_k are the inequality constraints. P_{G_i} is the real power output of the ith generator while P_G represents the vector of real power output of the generators and is defined as $P_G = [P_{G_1}, P_{G_2}, \dots P_{G_N}]^T$. N is the number of generating units while J and K are the number of equality and inequality constraints respectively.

3. Methodology

Non-dominated fronts are formed as a consequence of this strategy, which identifies non-dominant solutions in the community at each generation. A fitness assignment system and a sharing strategy would be used for non-dominated solutions in order to preserve the diversity of solutions obtained from each non-dominated front. GA activities such

as collection, replication, crossover, mutation, and elitism would then be applied to the population.

One of the most common elitist multi-objective optimization techniques is the Non-dominated Sorting Genetic Algorithm (NSGA-II). Fast non-dominated sorting is used to rank non-dominated solutions into distinct fronts and crowded distance estimation is used to keep the solution set diverse. Using a packed comparison operator, the next generation of solutions may be selected. For both Pareto front convergence and solutions diversification, the NSGA-II is an effective method. Due of its effectiveness in addressing actual optimization problems, the crowded comparison operator frequently results in non-uniform convergence to the Pareto front.

The major processes involved in the implementation are:

a) Initialization
b) Execution of NSGA-II

This NSGA-II is implemented using MATLAB 2019a language for the Economic Environmental problem on an AMD processor running at 2.33GHz with 1GB RAM. PLATEMO v3.2 was used for algorithms which is called in function to perform the optimization.

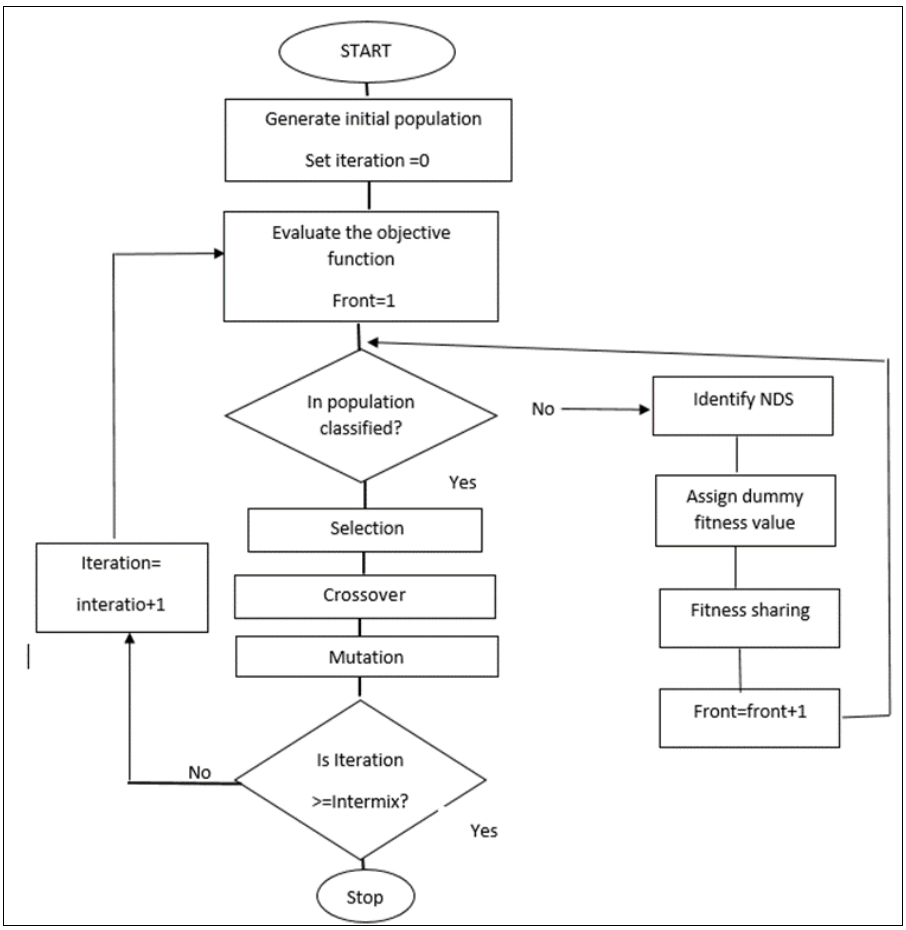

Fig 1: NSGA-II

A dummy fitness value would be assigned to those in the community who aren't very important. The first non-dominant front would be here. A sharing method may be utilized to guarantee variety if everyone is given the same attention when it comes to fitness. To build the second non-dominated front, the majority of the country would be handled in the same manner as the non-dominated front. It is necessary to create a new front and assign it a lower dummy fitness value, and this process must be done until the whole population is divided into non-dominated fronts.

CSEA is a multi-objective optimization algorithm that is computationally intensive. A feed forward neural network classifier is trained using this method. Using this classifier, it is possible to discover solutions that are heavily influenced by their predecessors. Using this CSEA, solutions to multi-objective problems may be brought closer together faster while yet preserving their variety (Pan, 2018). Selecting reference solutions, building a surrogate model, and then evaluating actual function solutions are all part of this process. The neural network component of CSEA is transformed from a feed forward neural network to a radial basis function neural network, which is quicker, to produce a good and efficient solution to the issue. Radial basis function neural network is trained utilizing choice variables and objective function values as inputs. In order to increase convergence and retain variety, a neural network is incorporated.

Because of its accessibility, structure, and practical experience in real-world applications, NSGA-II is an appealing Multiobjective optimization technique. Non-uniform convergence is an issue since comparisons are so dense. Multi-objective optimization using the CSEA-Classification based surrogate-assisted evolutionary method is also possible. The CSEA's surrogate learned the dominance connection between candidate solutions and a collection of chosen reference solutions. Uses an artificial neural network to forecast the dominance relationship between candidate solutions and those chosen. Reduced

computation time and improved convergence are the goals of this surrogate-assisted optimization approach.

CSEA Algorithm

The key structure for the CSEA is described in the diagram below and is given in Figure 2. The Figure indicates that CSEA includes a key loop that reflects the evolutionary mechanism with actual goals and a second loop in which alternatives with a classification replacement are chosen.

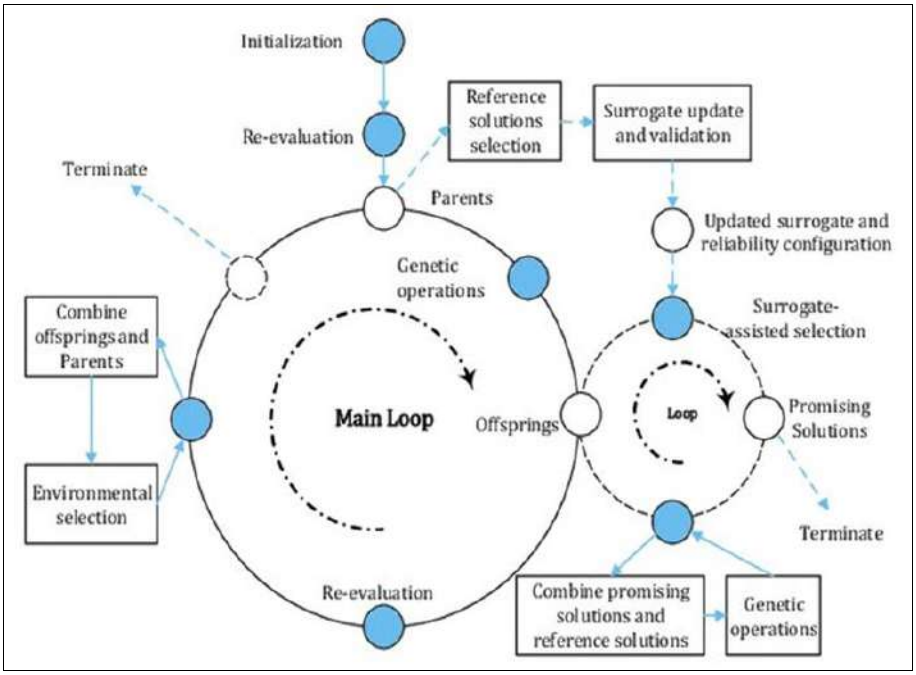

Fig 2: CSEA Framework (Linqiang *et al*., 2018) [20].

Hybridization of CSEA and NSGA-II

The primary purpose of surrogate aided optimization is to substitute costly exercise evaluations with computationally cheap surrogates, thus reducing computing time for solving expensive optimization problems. The CSEA has the ability to efficiently speed the integration of solutions on costly many goals optimization. Convergence is also strengthened by NSGA-II.

The below are the reasons for hybridization

1. Increasing the speed of the evolutionary algorithm. i.e convergence pace
2. To increase the accuracy of the evolutionary algorithm's solutions
3. Including the evolutionary algorithm as a component of a broader scheme

An algorithm describes how the NSGA-II/CSEA hybrid algorithm works and what stages are involved in each phase. To create a set of nondominated solutions, gen/2, NSGA-II runs during the first generation, and the gen is the maximum number of generations on which the halting criteria relies. Other than that, NSGA-II solutions are improved using a modified version of CSEA. While combining these two methods improves convergence, there isn't much of a difference in terms of diversity.

As part of this study, an RBF/NSGA-II neural network surrogate (CSEA) is hybridized with the NSGA-II method. N p children and an elite subpopulation from it are generated using the NSGA-II first utilizing the crossover operator (mutation), followed by the crowded comparison operator (convexity). As inputs and outputs for an artificial neural network (ANN), choice variables are used, and objective function values are used as a goal for assessment. To construct a new population, an inverse RBF neural network is formed and trained using the function values of the elite sub-population (in the decision variable space). It is therefore possible to integrate the results of NSGA-II and RBF and pick the best solutions of size N p, based on crowding distance. Algorithm 1 shows the RBF/NSGA-II algorithm's pseudo code.

4. Results and Discussion

IEEE Test system

Line diagram of IEEE 30-bus test system used to assess the efficiency of the hybrid NSGA-II/CSEA in tackling the EED issue is shown in Fig.1. A total of 283.4 MW is served by six thermal generators linked by 41 transmission lines. Data on the lines, the buses, the fuel cost coefficients, and the pollution coefficients were all sourced from the same database (Abido, 2006). To begin the NSGA-II algorithm, the population of N p=50 was established, and the generation number was 500. To account for genetic drift, we set the crossover probability to 0.90 and the mutation probability to 1/N, where N equals 6. The spread of the radial basis function was set at 1/N where N=6 for the hybrid NSGA-II/CSEA algorithm.

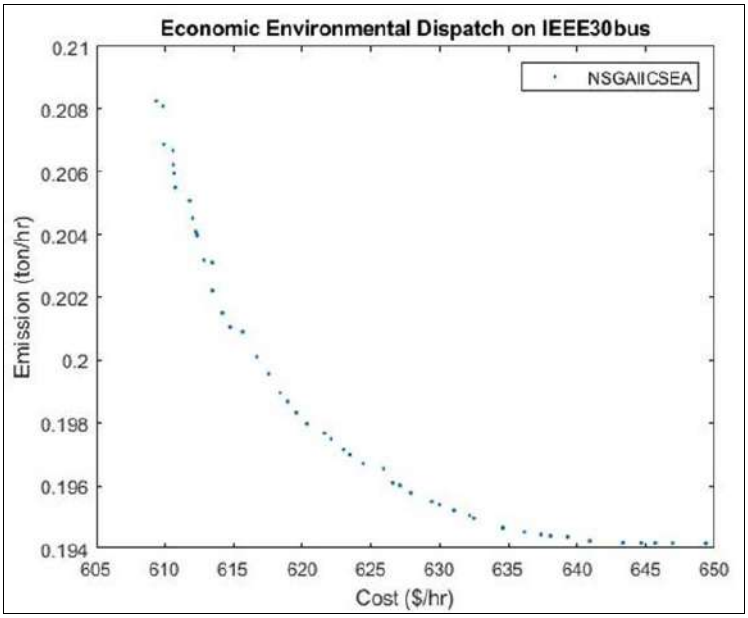

Fig 3: Pareto fronts of the hybrid

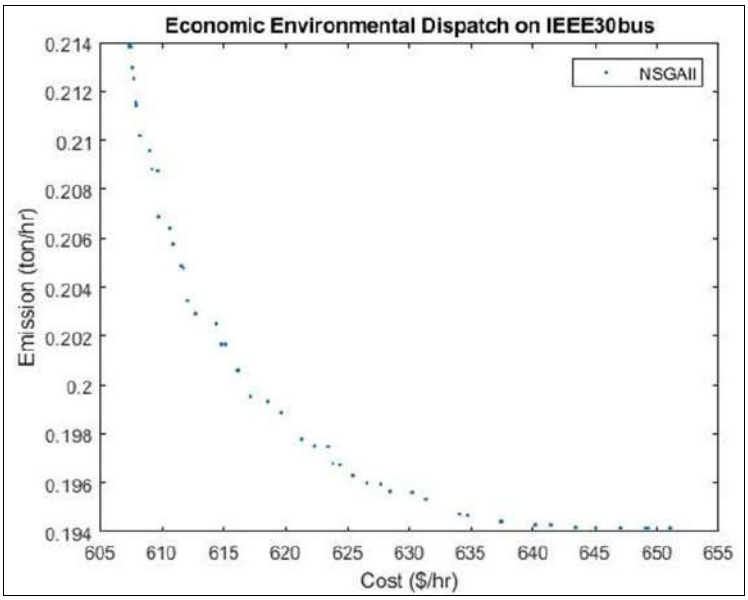

Fig 4: Pareto fronts of the standalone (NSGA-II)

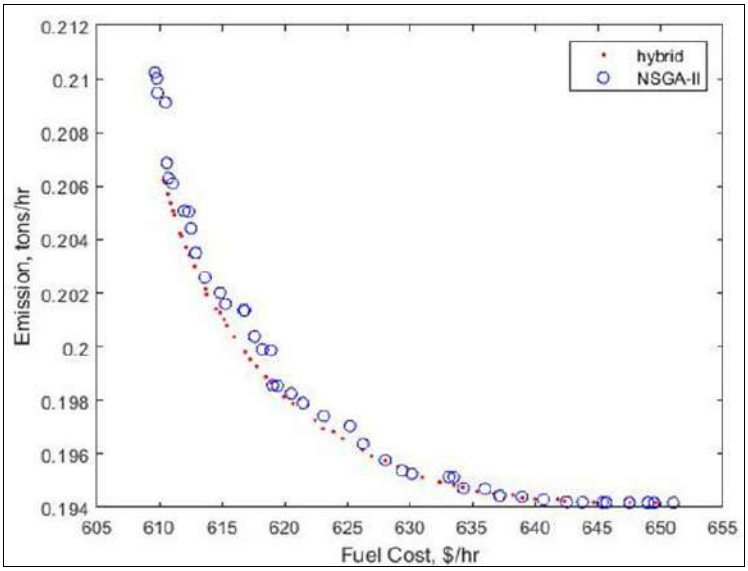

Fig 5: Pareto optimal fronts for best optimization run

Table 1: Parameter settings for IEEE 30-Bus test system

	IEEE 30-bus NSGA-II	NSGA-II/CSEA
Population size, N	50	50
Number of generations, gen	500	450
Crossover probability	0.9	
Mutation probability	1/6	1/6
Number of bins, H		

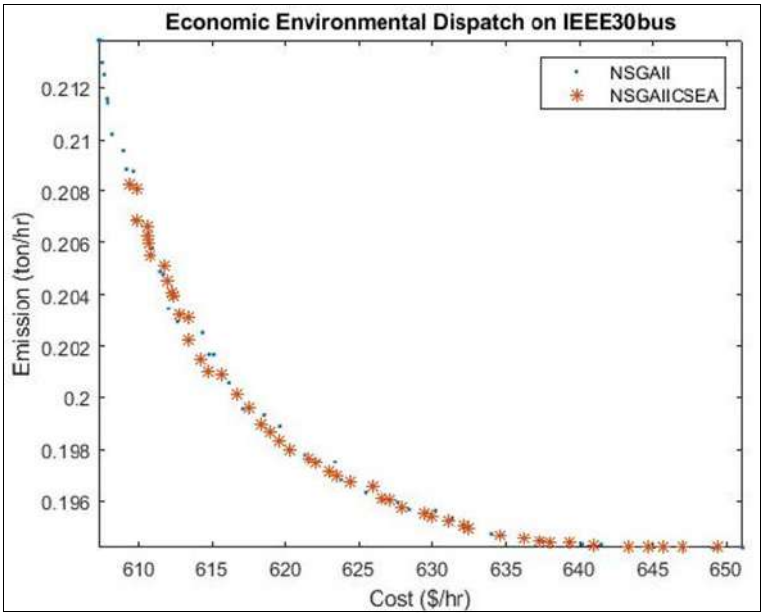

Fig 6: Pareto optimal fronts for IEEE 30 Bus system

Twenty distinct optimization runs were performed for each method and their performance was evaluated by examining their best solutions for minimal fuel cost and minimum emissions in order to build a suitable foundation for comparing NSGA-II and NSGA-II/CSEA algorithms. Additional comparisons were made based on other performance indicators.

Figure 4.4 shows the Pareto-optimal fronts generated by NSGA-II and NSGA-II/CSEA utilizing the IEEE 30 Bus system data in best optimization runs. Thus, it shows that the NSGA II / CSEA may identify solutions that are more convergent while yet maintaining variety. On one hand, there are options in Fig. 4.4 that address both minimal fuel costs and emissions in NSGA II and NSGA II/CSEA.

Table 2: Best solutions out of twenty runs for fuel cost (IEEE 30-BUS)

	NSGA (Abido, 2003)	NPGA (Abido, 2003)	SPEA (Abido, 2003)	NSGA-II/CSEA	NSGA-II
PG1	0.1168	0.1245	0.1086	0.1703	0.0795
PG2	0.3165	0.2792	0.3056	0.2941	0.3698
PG3	0.5441	0.6284	0.5818	0.6060	0.5239
PG4	0.9447	1.0254	0.9846	0.8401	0.9443
PG5	0.5498	0.4693	0.5288	0.5675	0.4974
PG6	0.3964	0.3993	0.3584	0.3794	0.4476
FC	608.245	608.147	607.807	607.9292	608.2219
EM	0.2166	0.2236	0.2202	0.2105	0.2169

Table 3: Best solutions out of twenty runs for emission (IEEE 30-BUS)

	NSGA (Abido, 2003)	NPGA (Abido, 2003)	SPEA (Abido, 2003)	NSGA-II	NSGA-II/ CSEA
PG1	0.4113	0.3923	0.4043	0.4138	0.4134
PG2	0.4561	0.4700	0.4525	0.4663	0.4662
PG3	0.5117	0.5565	0.5525	0.5483	0.5483
PG4	0.3724	0.3695	0.4079	0.3943	0.3937
PG5	0.5810	0.5599	0.5468	0.5485	0.5493
PG6	0.5304	0.5163	0.5005	0.5187	0.5177
FC	647.251	645.984	642.603	650.8678	650.5564
EM	0.19432	0.19424	0.19422	0.1942	0.1942

5. Conclusion

The NSGA-II surrogate-assisted hybrid neural network approach is presented in this study. To address the EED issue, this research employed the NSGA-II/CSEA method, which is based on the IEEE 30-bus test system dataset. There is evidence that the NSGA-II hybrid algorithm, which was created in this study, may improve convergence while keeping the diversity features of the produced solution set, over the stand-alone technique.

This work will provide a basis for more efficient dispatch of power generation (with both economic and environmental benefits) and improved decision making by power system administrators.

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