A Modified Strength Pareto Evolutionary Algorithm 2 based Environmental /Economic Power Dispatch

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ABSTRACT

A Strength Pareto Evolutionary Algorithm 2 (SPEA 2) approach for solving the multi-objective Environmental / Economic Power Dispatch (EEPD) problem is presented in this paper. In the past fuel cost consumption minimization was the aim (a single objective function) of economic power dispatch problem. Since the clean air act amendments have been applied to reduce SO_2 and NO_X emissions from power plants, the utilities change their strategies in order to reduce pollution and atmospheric emission as well, adding emission minimization as other objective function made economic power dispatch (EPD) a multi-objective problem having conflicting objectives. SPEA2 is the improved version of SPEA with better fitness assignment, density estimation, and modified archive truncation. In addition fuzzy set theory is employed to extract the best compromise solution. Several optimization run of the proposed method are carried out on 3-units system and 6-units standard IEEE 30-bus test system. The results demonstrate the capabilities of the proposed method to generate well-distributed Pareto-optimal non-dominated feasible solutions in single run. The comparison with other multi-objective methods demonstrates the superiority of the proposed method.

Keywords: genetic algorithm, multi-objectives optimization, power generation dispatch, power generation economic, pareto distributions

خوارزمية التطور باريتو ٢ لحل ارسالية القدرة الاقتصادية والبيئية

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الخلاصة:

ان الخوارزميةِ التطوّرية الفعالة بمفهوم برتو٢ تقَدَّم في هذا البحث لَحْلَّ مشكلةَ إرسال القدرة بالصورة الإقتصادية متعددةِ الدوال الرفيقة بالبيئيه. في الماضي كان تحقيق الحدّ الأدنى للتكلفةِ الوقودِ المستهلك الهدف (دالة (غاية) موضوعية وحيدة) مِنْ مشكلةَ إرسال القدرة بالصورة الإقتصادية. منذ أقرار قانون الهواء النظيفَ الذي فرض تُخفّضُ انبعاثات غازات SO2 و NO_X مِنْ محطاتِ أنتاج القدرة الكهربائية، غيّر القائمين على ادارة هذه المحطات ستراتيجياتِهم لكي يتم تخفّضَ هذه الانبعاثات وتلوثَ جوّ أيضاً، مضيفين بذالك تحقيق الحدّ من هذه الانبعاثات كدالة موضوعيةَ أخرى و جاعليين إرسال القدرة بالصورة الإقتصادية مشكلة متعددة الدوال الموضوعية ذات أهدافُ متعارضةُ. ان الخوارزميةِ التطوّرية الفعالة بمفهوم برتو٢ هي النسخةُ المُحسَّنةُ من الخوارزميةِ التطوّرية الفعالة بمفهوم برتو بقابلة افضل على تحديد لياقةِ كل فرد وتقدير كثافةِ (توزيع) افضل لكل فرد (حل) مع ألية معدلة لتقليص حجم الأرشيف. بالإضافة

لاستخدام نظرية المجموعات الضبابية (المضببة) لإستخلاص أفضل حَلّ مساومة" بين الدوال. تم عمل عِدّة محاولات لتحقيقِ الأمثلية باستخدام الطريقةِ المُقتَرَحة على النظامِ ذي الثلاثة وحدات توليدية والنظام ذي الست وحدات توليدية (نظامِ IEEE ذي الثلاثون ناقل قدرة القياسي) الاختبارية. النَتائِجُ تَوضح قابلياتَ الطريقة المُقتَرَحةِ لتَوليد حلولِ عملية ليست تحت الهيمنة مُوَزّعة بشكل جيد مثالية بمفهوم بريتو في محاولة واحدة لتحقيقِ الأمثلية. المقارنة بالطرقِ المتعددةِ الاهداف الأخرى تَظهر تفوقَ الطريقة المُقتَرَحةِ.
الكلمات الرئيسية: الخوارزمية الجينية -التضئيل متعدد المعايير- ارسالية قدرة التوليد- توليد القدرة الاقتصادية- توزيعات باريتو

1. INTRODUCTION

The objective of Economic Power Dispatch EPD of electrical power system is to schedule the committed generating unit outputs so as to meet the load demand plus real power transmission loss at minimum operating cost while satisfying all units and system equality and inequality constraints.

The increasing public awareness of environmental protection and the passage of the U.S clean air act amendments of 1990 have forced utilities to modify their design or operational strategies to reduce pollution and atmospheric emission of thermal power plants**, Abido, 2001.**

Strategies as switching to lower emission fuels or installation of pollutant clearing equipment requires considerable capital outlay, while considering emission as a constraint to be satisfied in EPD problem solution, or minimization of emission side by side with fuel cost requires modifying existing dispatching programs to include emission ,**Talaq et al, 1994.** During recent years the last idea received much attention due to development of a number of multi-objective techniques.

Linearly combined fuel cost and the amount of emission as a weighted sum convert the multi-objective EEPD problem to a single-objective optimization problem, **Perez-Guerrero, 2005**. By varying the weights a set of potential solutions Pareto-optimal set were found, unfortunately this requires many runs as many as number of Pareto-front individuals to form the Pareto-optimal solutions as well as the diversity of Pareto-optimal set along Pareto-front depend on the diversity of the weights. Alternatively, many attempts to solve the EEPD were done by handling emission minimization as another objective function using stochastic multi-objective approaches. M. Abido used NSGA ,**Abido, 2001, NPGA ,Abido, 2003a and SPEA Abido, 2003** to solve EEPD problem and obtained the better results using SPEA, although T.F. **Robert, King et al, 2004, and S. Agrawal ,Agrawal et al, 2008** obtains a better results less fuel cost than SPEA using NSGA-II, FCPSO respectively but the corresponding emission amount increased due to conflicting objectives. An extensive evaluation may be done by inserting a real penalty price factor the tax legislated to calculate the overall cost and helping to state the better solution.

SPEA2 which is used in this paper is the improved version of SPEA to solve the multi-objective EEPD problem, SPEA2 uses an archive to store the non-dominated individuals, fitness assignment which takes into account both dominated and dominating other individuals and archive truncation to maintain a constant archive size with good diversity **,Zitzler et al, 2001.** A fuzzy-based mechanism is used to extract a Pareto-optimal solution as the best compromise solution. Two test systems were used to compare and state the superiority SPEA2 with other multi-objective approaches.

2. PROBLEM FORMULATION

The EEPD, involves the simultaneous optimization of fuel cost and emission amount as multi-objective conflicting problem, is generally formulated as follows.

2.1 Problem's Objectives

1. Minimization of fuel cost: The generator consumption fuel cost curves are represented by quadratic functions where the total consumed fuel cost $F(PG)$ in ($/h) can be expressed as

$$F(P_G) = \sum_{i=1}^{n} a_i + b_i P_{Gi} + c_i {P_{Gi}}^2 \qquad (1)$$

Where n is the number of generators, a_i, b_i, and c_i are cost coefficients of the i^{th} generator, and P_{Gi} is the real power output of the i^{th} generator ,**Abido, 2001**.

2. Minimization of emission amount: The total emission $E(PG)$ in (ton/h) of atmospheric pollutants such as sulfur oxides SO_x or nitrogen oxides NO_x caused by fossil-fueled thermal generating units may be expressed as ,**Perez-Guerrero, 2005.**

$$E(P_G) = \sum_{i=1}^{n} \alpha_i {P_{Gi}}^2 + \beta_i P_{Gi} + \gamma_i \quad (2)$$

Or

$$E(P_G) = \sum_{i=1}^{n} \alpha_i + \beta_i P_{Gi} + \gamma_i {P_{Gi}}^2 + \zeta_i \exp(\lambda_i P_{Gi}) \quad (3)$$

Where $\alpha_i, \beta_i, \gamma_i, \zeta_i$ and λ_i are i^{th} generator emission coefficients and P_G is the vector of real power outputs of system generators so,

$$P_G=[P_{G1},P_{G2},\dots,P_{Gn}]^T \quad (4)$$

2.2 Problem's Constraints

1. Generator capacity constraints: The real power output of each generator is restricted by the lower and upper limits as follows:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \text{ for} = 1,2,\dots n \quad (5)$$

2. Power balance constraint: The total generated real power should exactly cover the total demand *PD* and real power loss in transmission lines *PL* as follows, Abido, 2001,

$$\sum_{i}^{n} P_{Gi} - PD - PL = 0 \quad (6)$$

2.3 The EEPD Problem Formulations

The EEPD problem is formulated as:

Minimize [$F(P_G)$, $E(P_G)$]

Subject to:

$g(PG) = 0$ (equality constraint)

$h(PG) \leq 0$ (inequality constraint)

The real power loss in transmission lines *PL* can be considered as another objective function which needs to be minimized, Abido, 2001.

3. MULTI-OBJECTIVE OPTIMIZATION

3.1 Basic Concepts

Multi-objective optimization (MOP) to several objective functions (which are often competing and conflicting objectives) simultaneously obtains a set of optimal solutions (instead of one solution) since none of them are considered better with respect to all objectives. The MOP to N_{obj} objective function can be formulated as ,**Abraham et al, 2005**:

Minimize [$f_1(x), f_2(x), \dots, f_{Nobj}(x)$]

Subject to the *m* equality constraints:

$$g_i(x)=0, \text{ for } i = 1,2,\dots,m \quad (7.a)$$

And the *p* inequality constraints:

$$h_i(x) \leq 0, \text{ for } i = 1,2,\dots,p \quad (7.b)$$

Where $x = [x_1,x_2,..x_n]^T$ is the vector of decision variables. The Pareto-optimality is explained as follows: a vector $x^* \in \mathcal{F}$ is Pareto-optimal if for every other vector $x \in \mathcal{F}$

$f_i(x^*) \leq f_i(x)$ for all $i=1,2,\dots,N_{obj}$ and $f_j(x^*) < f_j(x)$ for at least one j .

Where $\mathcal{F}$ is the feasible set (its elements satisfy **Eqs. (7.a)** and **(7.b),** the vector x* is called non-dominated since there is no such x which dominate it, all non-dominated solutions (vectors) forms Pareto-optimal set.

3.2 The Strength Pareto Evolutionary Algorithm 2 (SPEA2)

E. Zitzler, M. Laumanns, and L. Thiele, had developed SPEA in 1999 ,Zitzler and Thiele, 1999, yet in 2001 they published SPEA2 ,**Zitzler et al, 2001** as enhancement version, by fixing (improving) the potential weakness in fitness assignment, density estimation and archive truncation. Like the earlier SPEA, SPEA2 has external archive to store non-dominated individual and only these individuals form the mating pool. The SPEA2 has an overall algorithm as follow:

Step1: **Initialization**: Generate an initial population $\boldsymbol{P_0}$ and create the empty archive (external set) $\overline{\boldsymbol{P}}_0 = \emptyset$; Set t = 0.

Step 2: **Fitness assignment**: Calculate fitness values of individuals in $\boldsymbol{P_t}$ and $\overline{\boldsymbol{P}}_t$, each individual *i* in the archive $\overline{\boldsymbol{P}}_t$ and the population $\boldsymbol{P_t}$ is assigned a strength value S(*i*), representing the number of solutions (individuals) which it dominates:

$$S(i) = |\{j | j \in (P_t + \overline{P}_t) \wedge i \succ j\}| \quad (8)$$

Where |·| denotes the cardinality of a set (the number of elements in a set), + stands for multi-set union, $\succ$ corresponds to Pareto dominance relation ($i \succ j$ refers to that individual *i* which dominates individual *j*) and $i,j \in \overline{\boldsymbol{P}}_t + \boldsymbol{P}_t$.

On the basis of the *S* values, the raw fitness is determined by the strengths of its dominators in both archive and population, The raw fitness *R*(*i*) of an individual *i* is calculated:

$$R(i) = \sum_{j \in Ag+\bar{A}g, j \succ i} S(j) \tag{9}$$

Since the non-dominated individuals would have the same raw fitness value *R(i)*=0, while a high R(*i*) value means that individual *i* is dominated by many individuals. Therefore additional density information is incorporated to discriminate between individuals having identical raw fitness values. The density estimation technique used in SPEA2 is an adaptation of the k^{th} nearest neighbor method ,**Zitzler et al, 2001,** for each individual *i* the distances (in objective space) to all other individuals *j* in archive and population are calculated and stored in a list. After sorting the list in ascending order, the k^{th} element gives the distance sought. As a common setting, *k* equal to the square root of the entire population size $= \sqrt{N + \bar{N}}$. Where *N* is a population ($\boldsymbol{P}_t$) size and $\bar{N}$ is an archive ($\overline{\boldsymbol{P}}_t$) size.

The distance between the individuals *i* an *k* is denoted as ${\sigma^k}_i$. Density *D*(i) corresponding to *i* is defined by

$$D(i) = \frac{1}{{\sigma^k}_i + 2} \tag{10}$$

By adding *D*(*i*) to the raw fitness value *R*(*i*) of an individual *i* yields its fitness *F*(*i*):

$$F(i)=R(i)+D(i) \tag{11}$$

Step 3: **Environmental selection**: Copy all non-dominated individuals in $\boldsymbol{P}_t$ and $\overline{\boldsymbol{P}}_t$ to $\overline{\boldsymbol{P}}_{t+1}$. If size of $\boldsymbol{P}_{t+1}$ exceeds $\bar{N}$ then reduce $\overline{\boldsymbol{P}}_{t+1}$ by means of the modified truncation operator, so, at each iteration the individual *i* which has the minimum distance to another individual *j* and ${\sigma^k}_i < {\sigma^k}_j$ is chosen for removal; otherwise if size of $\overline{\boldsymbol{P}}_{t+1}$ is less than $\bar{N}$ then fill $\overline{\boldsymbol{P}}_{t+1}$ with dominated individuals in $\boldsymbol{P}_t$ and $\overline{\boldsymbol{P}}_t$, by sorting the multi-set $\boldsymbol{P}_t + \overline{\boldsymbol{P}}_t$ according to the fitness values and copy the first $N - |\boldsymbol{P}_t + 1|$ individuals *i* with *F*(*i*) ≥ 1 from the resulting ordered list to $\overline{\boldsymbol{P}}_{t+1}$.

Step4**: Termination**: If $t = T$ (maximum number of generations) then stop.

Step5: **Mating selection**: Perform binary tournament selection with replacement on $\overline{\boldsymbol{P}}_{t+1}$ in order to fill the mating pool.

Step6: **Variation**: Apply recombination and mutation operators to the mating pool and set $\overline{\boldsymbol{P}}_{t+1}$ to the resulting population. Increment generation counter ($t = t + 1$) and go to step 2.

3.3 Real-Valued (Coded) Genetic Algorithm

The calculations of objective functions many times in the process of the simulation computer program make coding and decoding individuals from and to binary-coded time consuming as well as coding one individual of 3-unit system having the same accuracy obtained in real-valued string needs 3×20 bits, since there are 3 variables of P_G and each variable needs at least 4 digits of 0, 1, assuming the population size is 5. Therefore the genetic algorithm string is represented in a vector of real-valued of power outputs of system generators as:

$$P_G=[P_{G1},P_{G2},\ldots,P_{Gn}]^T$$

1. *Recombination* (*crossover*)*:* A blending crossover operator has been employed. This operator recombines the i^{th} parameter (gene) values of individuals *x*, *y* (selected for recombination), the offspring appear as follows:

$$x = [x_1, x_2, \ldots, x_i', y_{i+1}, \ldots, y_n]$$

$$y = [y_1, y_2, \ldots, y_i', x_{i+1}, \ldots, x_n]$$

Where the offspring are:

$$x_i' = x_i + \beta(y_i - x_i)$$

$$y_i' = y_i - \beta(y_i - x_i)$$

And β is a randomly generated number between 0 and 1.

2. *Mutation:* a non-uniform mutation operator is employed in this study ,**Michalewicz, 1996**, the new

value x_i" of the parameter x_i after mutation at generation *t* is given as:

$$x_i'' = \begin{cases} x_i + \Delta(t, P_i^{max} - x_i) \text{if random binary digit is 0} \\ x_i - \Delta(t, x_i - P_i^{min}) \text{if random binary digit is 1} \end{cases} \quad (12)$$

$$\Delta(t, y) = y * \left(1 - rand^{(1-\frac{t}{T})^b}\right) \quad (13)$$

Due to the imprecise nature of the decision maker's judgment, the i^{th} objective function of a solution in the Pareto-optimal set *Fi* is represented by a membership function μ_i which is a Z-function asymmetrical polynomial curve, defining by:

$$\mu_i = \begin{cases} 1 & Fi \le F_i^{min} \\ \frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} < Fi < F_i^{max} \\ 0 & Fi \ge F_i^{max} \end{cases} \quad (14)$$

Where F_i^{max} and F_i^{min} are the maximum and minimum values of the i^{th} objective function, respectively.

For each non-dominated solution *h*, the normalized membership function μ^h is calculated as:

$$\mu^h = \frac{\sum_{i=1}^{Nobj} \mu_i{}^h}{\sum_{h=1}^{M} \sum_{i=1}^{Nobj} \mu_i{}^h} \quad (15)$$

Whereas *M* is the number of non-dominated solutions. The best compromise solution is the one having the maximum value of μ^h. By arranging all solutions in Pareto-optimal set in descending order according to their membership function will provide the decision maker with a priority list of non-dominated solutions. This will guide the decision maker in view of the current operating conditions. The implementation flow chart of the proposed approach is shown in **Fig.1**

Where *rand* is a random number generator between (0,1), *t* is iteration index, *T* is maximum number of iterations and *b*=5 ,**Michalewicz, 1996.**

3.4 Best Compromise Solution

The solutions obtained for best (minimal) fuel cost and for best (minimal) emission amount were giving an image about the optimized objective functions, but in order to adopt one solution as the best compromise solution to the decision maker's judgment, the proposed approach presents a fuzzy-based mechanism to extract a Pareto-optimal solution as the best compromise solution ,**Abido, 2003**.

4. IMPLEMENTATION OF THE PROPOSED METHOD

To satisfy the problem constraints, the following steps had been made:

(a) The initial population is generated within a capacity limit of each generator as well as the recombination and mutated elements are as follows:

$$P_{Gi} = \left(P_{Gi}{}^{max} - P_{Gi}{}^{min}\right) * rand + P_{Gi}{}^{min} \quad (16)$$

Whereas *rand* is a random number generator between (0, 1).

(b) The power balance constraint is satisfied as follows, the traditional *B*-matrix loss formula is used to calculate the real power transmission loss

$$PL = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{n} B_{io} P_{Gi} + Boo \quad (17)$$

By choosing the r^{th} unit randomly, it's assumed that the r^{th} reference unit power output is responsible of bucking up the remaining load after the other (*n-1*) units have been assigned theirs output power,

$$P_{Gr} = PD + PL - \sum_{\substack{i=1 \\ i \ne r}}^{n} P_{Gi} \quad (18)$$

Rewriting eq. (18) in order to form a polynomial with P_{Gr} is the variable as follows:

$$PL = aP_{Gr}{}^2 + bP_{Gr} + c \quad (19)$$

Where *a* ,*b*, and *c* represent parameters depending on the *B*-matrix coefficients of the power loss equation of the test system used and on the powers of the (*n-1*) generators.

Substituting *PL* from **Eq. (19)** in **Eq. (18),** yields

$$aP_{Gr}{}^2 + (b-1)P_{Gr} + \left(c + PD - \sum_{\substack{i=1 \\ i\neq r}}^{n} P_{Gi}\right) = 0 \quad (20)$$

The roots of the eq. (20) represent the value of P_{Gr} satisfying equality constraint, if neither roots located within unit power capacity limit, other generator is randomly chosen as r^{th} reference unit also, if all units were filed to backup the remaining load another individual is generated randomly to replace this one. After recombination and mutation process each individual is checked for equality constraint violation, it is worth to mention that this process works as another mutation operator. Since, it may vary the value of one gene (generating unit) to achieve equality constraint satisfaction, or it may be the reason of destroying the recombination operator process (if the recombination gene is chosen to be the first or the last in the individual string).

(c) Archive truncation modification

By formulating (a distance matrix) with size [$\overline{\boldsymbol{P}}_{t+1} \times \overline{\boldsymbol{P}}_{t+1}$], this matrix contains each possible pair of two individuals in archive set $\overline{\boldsymbol{P}}_{t+1}$ (before truncation process), reducing the dependency on the k^{th} nearest neighbor method, the process is as follows:

Step1: form the distance matrix, calculating the distance $\sigma^i{}_j$ between each pair of non-dominated individuals (i,j) in multi-objective space.

Step2: searching the matrix for smallest element $\sigma^i{}_j$ (represents the minimum distance between any two individuals i,j) .

Step3: If $\sigma^k{}_i < \sigma^k{}_j$, individual i would be eliminated from archive and its row and column would be eliminated too, else the individual j is chosen for elimination and the size of $\overline{\boldsymbol{P}}_{t+1}$ and distance matrix reduced by one.

Step4: If $\overline{\boldsymbol{P}}_{t+1} = \overline{N}$ then stop, else go to step 2.

5. RESULTS AND DISCUSSION

In this research two systems were adopted in order to investigate the effectiveness and applicability of the proposed method, several simulations runs were done for each test and an identical population and archive sizes were used ,**Zitzler et al, 2001**, the parameters used for all cases are as follows: 200 individuals for each population size and archive size for case (1) and 100 individuals for each population size and archive size for case (2) and the simulations were run for 1000 generations, crossover and mutation probabilities were 1(100%) and 0.01 respectively.

Case (1): Three Generating Units System

The three generators test system whose data are given in **Tables 1, 2** and **3** ,**King, 2003**, the system demand is 850 MW, and the system transmission losses are calculated using a simplified loss expression ,**King, 2003**:

$$PL = 0.00003P_{G1}{}^2 + 0.00009P_{G2}{}^2 + 0.00012P_{G3}{}^2 \quad (21)$$

The coefficients of eq. (19) are

a=B_{rr} , b=0 and $c = \sum_{\substack{i=1 \\ i\neq r}}^{N} \sum_{\substack{j=1 \\ i\neq r}}^{N} P_{Gi} B_{ij} P_{Gj}$

It is important to maintain that the cross-point in the proposed approach applied to solve this test system is fixed in the second gene (second generating unit position) to grantee new individuals generated next population.

Test (1): Fuel Cost and SO_2 Emission Objective Functions:

In this test fuel cost with SO_2 emission were taken as objective functions to be minimized, **Tables 4, 5**, and **6** show the simulation results obtained in one run for best (minimum) fuel cost, minimum emission and best compromise solution in the Pareto front respectively, as compared toTABU search and NSGA-II, while the Pareto-front were plotted in **Fig. 2**.

Table 4 shows a reduction in the consumption fuel cost by more than 100 $ per year than the results obtained by NSGA-II approach. While, **Table 5** shows a reduction in SO_2 harmful emission by 5.6 ton per year than the results obtained by NSGA-II approach for this small system.

The minimum fuel cost and minimum emission solutions were drawn against generations (iterations) in **Fig. 3**. The average simulation run time for this test is 550 second.

The convergence of non-dominated solutions to the true Pareto-optimal front region was done in early stages of the search process (20-30 % of the maximum generations limit), as shown in **Fig. 3**, the later stages is for convergence to the exact solutions (fine tuning).

Test (2): Fuel Cost and NOx Emission Objective Functions:

In this test fuel cost with NOx were taken as objective functions to be minimized, **Tables 7, 8,** and **9** shows the simulation results obtained in one run as compared to TABU search and NSGA-II, while the Pareto-front was plotted in **Fig. 4**. The average simulation run time for this test is 550 second.

Test (3): Fuel Cost, SO2 Emission and NOx Emission objective functions:

In this test fuel cost with SO_2 emission and NOx emission were taken as objective functions to be minimized **Tables 10,** and **11** shows the simulation results obtained in one run as compared to NSGA-II, while the Pareto-front was plotted in **Fig. 5**. The average simulation run time for the test is 780 second.

Although NSGA-II is a new powerful multi-objective technique, the results in the previous tables show that SPEA 2 gave not only better results but also with less population size and less maximum generations number, NSGA-II has population size 500 individuals and was run for 20000 generation ,**King, 2003.**

Case (2): Six Generating Units System

The standard 30-bus IEEE test system with 6-generating units, King, 2004 is used with load demand 2.834 p.u. (100 MW power base), since this system has been already solved and validated by several multi-objective optimization techniques the comparison of SPEA2 with such techniques can show the potential of the proposed method, system data listed in **Tables 12**, and **13**.

Test (1): Fuel Cost and Emission Objective Functions (Real Power Transmission Loss is neglected):

In this test, fuel cost with harm emission were taken as objective functions to be minimized, the system is considered as lossless and the equality constraint is as follows:

$\sum_i^n P_{Gi} - PD = 0$

Tables 14, 15, and **16** show the simulation results obtained in one run as compared to other approaches, while the Pareto-Optimal front was plotted in Figure 6. The average simulation run time for the test is 70 second.

The minimum fuel cost and minimum emission solutions were drawn against generations (iterations) in **Fig. 7**.

The results obtained in **Tables 14** and **15** are clearly demonstrated the superior of SPEA 2 over other multi-objective GA methods and also over the new multi-objective-PSO approach (FCPSO) with reduction in consumption fuel cost more than 190 $ per year than FCPSO approach (table IXV), also the fuel cost corresponding to minimum emission in table XV is less than the fuel cost corresponding to minimum emission FCPSO approach.

Test (2): Fuel Cost and Emission objective functions (transmission loss is included):

The exact value of the system losses can only be determined by means of a power flow solution, but in this research the B-coefficient matrix from, Perez-Guerrero, 2005 is used:

$$B_{ij} = \begin{bmatrix} 0.1382 & -0.02299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}$$

B_{io}=[(-0.0107 0.0060 -0.0017 0.0009 0.0002 0.0030)]

$B_{oo} = 9.8573 \times 10^{-4}$

the coefficient of eq. (19) is

$$a = B_{rr}\ , \quad b = \sum_{\substack{i=1 \\ i \neq r}}^{n} P_{Gi}\, B_{ir} + \sum_{\substack{j=1 \\ j \neq r}}^{n} B_{rj} P_{Gj} + B_{ro}$$

and $c = \sum_{\substack{i=1 \\ i \neq r}}^{n} \sum_{\substack{j=1 \\ i \neq r}}^{n} P_{Gi}\, B_{ij} P_{Gj} + \sum_{\substack{i=1 \\ i \neq r}}^{n} B_{io}\, P_{Gj} + B_{oo}$

Tables 17, 18, and **19** show the simulation results obtained in one run as compared to other approaches, while the Pareto-front was plotted in **Fig. 8**. The average simulation run time for the test is 70 second.

Other researches use load flow solution approach to determine the transmission loss instead of B-coefficient matrix approach, the transmission loss obtained by load flow solution depends on the accuracy of the load flow solution such as in FCPSO approach for example, while the accuracy of the transmission loss obtained by the B-coefficient matrix approach is within 0.25 % of the load demand, which may be accepted when is taking into consideration the computational time which is spent in load flow solution approach compared to those which is using B-coefficient matrix approach.

Test (3) Fuel Cost, Emission and Transmission Loss Objective Functions:

In this test real power transmission loss, fuel cost and harm emission were taken as objective functions to be minimized, **Table 20** shows the three objective functions optimization results as compared with reference ,Wang, 2008, results. While, **Table 21** shows the best compromise solution. The Pareto-front was plotted in **Fig. 9**. The average simulation run time for the test is 90 second.

It is important to mention that the research in ,Wang, 2008, neglects the linear coefficient *Bio* and the constant coefficient *Boo* of the B-matrix used to calculate the power loss *PL* then, in order to obtain a good comparison results these coefficients are neglected in the obtained results in this test only.

All the simulation results obtained in this research were implemented on personal computer Pentium 4, 3.59 GHz with 1GB RAM using MATLAB version 7 programming language.

6. CONCLUSIONS

This paper presents multi-objective environmental/ economic power dispatch (EEPD) solutions using the proposed Strength Pareto Evolutionary Algorithm 2 (SPEA2). The proposed method has a diversity-preserving mechanism to find widely different Pareto-optimal solutions. A distance matrix technique is implemented to provide the decision maker with diverse and manageable Pareto-front without destroying the shape and the boundary of the trade-off front. Moreover, a Fuzzy-based mechanism is employed to extract the best compromise solution over the trade-off curve as in Fig. 1. The Fuzzy system contains a fuzzy inference system, fuzzy controller with a rule base, and a defuzzifier. A triangular membership function is used. The results show that the proposed method is efficient for solving multi-objectives optimization whereas multiple Pareto-optimal solutions can be found in one simulation run. The simulation results of all the tests which were done reveal that SPEA2 presents low computational time (less population size and less generations) and is suitable for on-line EEPD solutions. The proposed method has reliable convergence, high accuracy of solution, and better results than other multi-objective optimization techniques with good Pareto-front diversity regardless of the number of objective functions used.

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Table 1. Fuel cost coefficients.

Unit *i*	a_i	b_i	c_i	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)
1	561	7.92	0.001562	150	600
2	310	7.85	0.00194	100	400
3	78	7.97	0.00482	50	200

Table 2. SO_2 (Sulfur oxide) emission coefficients.

Unit *i*	α_{iN}	β_{iN}	γ_{iN}
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

Table 3. NOx (Nitrogen Oxides) Emission Coefficients.

Unit *i*	α_{iN}	β_{iN}	γ_{iN}
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

Table 4. Best fuel cost.

Unit *i* (MW)	TABU search (King, 2003)	NSGA-II (King, 2003)	SPEA2
P_{G1}	435.69	436.366	435.2538
P_{G2}	298.828	298.187	299.6112
P_{G3}	131.28	131.228	130.9553
Losses(MW)	15.798	15.781	15.8203
Fuel cost($/h)	**8344.598**	**8344.606**	**8344.5935**
Emission (ton/h)	9.02146	9.02083	9.0219

Table 5. Best SO_2 emission.

Unit *i* (MW)	TABU search (King, 2003)	NSGA-II (King, 2003)	SPEA2
P_{G1}	549.247	541.308	551.4131
P_{G2}	234.582	223.249	219.9989
P_{G3}	81.893	99.919	93.10592
Losses(MW)	15.722	14.476	14.5179
Fuel cost($/h)	8403.485	8387.518	8395.8514
Emission(ton/h)	**8.974**	**8.96655**	**8.9659**

Table 6. Best compromise solution.

Unit *i* (MW)	NSGA-II (King, 2003)	SPEA2
P_{G1}	485.886	493.2324
P_{G2}	263.67	259.8824
P_{G3}	115.381	111.7609
Losses(MW)	14.937	14.8757
Fuel cost($/h)	8354.419	8357.442
Emission(ton/h)	8.98383	8.9801

Table 7. Best fuel cost.

Unit *i* (MW)	TABU search (King, 2003)	NSGA-II (King, 2003)	SPEA2
P_{G1}	435.69	435.885	435.2475
P_{G2}	298.828	299.989	299.751
P_{G3}	131.28	129.951	130.8251
Losses(MW)	15.798	15.826	15.8236
Fuel cost ($/h)	**8344.598**	**8344.598**	**8344.593**
Emission(ton/h)	0.09863	0.09860	0.098694

Table 8. Best NOx emission**.**

Unit *i* (MW)	TABU search (King, 2003)	NSGA-II (King, 2003)	SPEA2
P_{G1}	502.914	505.810	508.1853
P_{G2}	254.294	252.951	250.7858
P_{G3}	108.592	106.023	105.7796
Losses(MW)	15.8	14.784	14.7507
Fuel cost($/h)	8371.143	8363.627	8364.8956
Emission(ton/h)	**0.0958**	**0.09593**	**0.095924**

Table 9. Best compromise solution.

Unit *i* (MW)	NSGA-II (King, 2003)	SPEA2
P_{G1}	470.957	464.4353
P_{G2}	280.663	286.072
P_{G3}	113.675	114.9137
Losses (MW)	15.294	15.421
Fuel cost($/h)	8349.722	8348.1913
Emission(ton/h)	0.09654	0.096768

Table 10. Comparison of results for three objective functions.

Unit *i* (MW)	Best fuel cost		Best SO_2 emission		Best NOx emission	
	NSGA-II (King, 2003)	SPEA2	NSGA-II (King, 2003)	SPEA2	NSGA-II (King, 2003)	SPEA2
P_{G1}	431.68	433.73	538.53	552.05	508.37	508.57
P_{G2}	302.93	300.86	227.82	219.62	250.44	250.48
P_{G3}	131.31	131.26	98.185	92.857	105.93	105.70
Losses (MW)	15.919	15.858	14.528	14.518	14.745	14.747
Fuel cost ($/h)	**8344.65**	**8344.6**	8385.1	8396.4	8364.9	8365.1
SO_2 Emission (ton/h)	9.0254	9.0234	**8.9667**	**8.9659**	8.9737	8.9737
NOx Emission (ton/h)	0.0989	0.0988	0.0963	0.0968	**0.0959**	**0.0959**

Table 11. Best compromise solution for three objective functions.

Unit i (MW)	NSGA-II (King, 2003)	SPEA2
P_{G1}	496.328	492.5533
P_{G2}	260.426	259.9366
P_{G3}	108.144	112.3851
Losses (MW)	14.898	14.8749
Fuel cost ($/h)	**8358.896**	**8357.1467**
SO_2 emission (ton/h)	**8.97870**	**8.9804**
NOx emission (ton/h)	**0.09599**	**0.096076**

Table 12. Fuel cost coefficients.

Unit *i*	***ai***	***bi***	***ci***	P_{Gi}^{min} (p.u.)	P_{Gi}^{max} (p.u.)
1	10	200	100	0.05	0.5
2	10	150	120	0.05	0.6
3	20	180	40	0.05	1.0
4	10	100	60	0.05	1.2
5	20	180	40	0.05	1.0
6	10	150	100	0.05	0.6

Table 13. Emission coefficients.

Unit *i*	αi	βi	γi	ζ_i	λ_i
1	4.091e-2	-5.554e-2	6.490e-2	2.0e-4	2.857
2	2.543e-2	-6.047e-2	5.638e-2	5.0e-4	3.333
3	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
4	5.326e-2	-3.550e-2	3.380e-2	2.0e-3	2.000
5	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
6	6.131e-2	-5.555e-2	5.151e-2	1.0e-5	6.667

Table 14. Best fuel cost.

nit *i* (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	NSGA-II (King, 2004)	FCPSO (Agrawal, 2008)	SPEA2
P_{G1}	0.1080	0.1062	0.1059	0.1070	0.10978
P_{G2}	0.3284	0.2897	0.3177	0.2897	0.2993
P_{G3}	0.5386	0.5289	0.5216	0.525	0.52433
P_{G4}	1.0067	1.0025	1.0146	1.015	1.0162
P_{G5}	0.4949	0.5402	0.5159	0.530	0.52457
P_{G6}	0.3574	0.3664	0.3583	0.3673	0.35981
Fuel Cost ($/h)	**600.259**	**600.15**	**600.155**	**600.131**	**600.109**
Emission (ton/h)	0.22116	0.2215	0.22188	0.2223	0.22215

Table 15. Best emission.

Unit *i* (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	NSGA-II (King, 2004)	FCPSO (Agrawal, 2008)	SPEA2
P_{G1}	0.4002	0.4116	0.4074	0.4097	0.40607
P_{G2}	0.4474	0.4532	0.4577	0.455	0.45898
P_{G3}	0.5166	0.5329	0.5389	0.5363	0.53785
P_{G4}	0.3688	0.3832	0.3837	0.3842	0.38308
P_{G5}	0.5751	0.5383	0.5352	0.5348	0.53785
P_{G6}	0.5259	0.5148	0.5110	0.514	0.51017
Emission (ton/h)	**0.19433**	**0.1942**	**0.1942**	**0.1942**	**0.1942**
Fuel Cost ($/h)	639.182	638.51	638.269	638.357	638.264

Table 16. Best compromise solution.

Unit i (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	SPEA2
P_{G1}	0.2696	0.2785	0.11044
P_{G2}	0.3673	0.3764	0.30004
P_{G3}	0.5594	0.5300	0.52349
P_{G4}	0.6496	0.6931	1.0159
P_{G5}	0.5396	0.5406	0.52406
P_{G6}	0.4486	0.4153	0.36009
Fuel Cost($/h)	612.127	610.254	600.1115
Emission(ton/h)	0.19941	0.2005	0.22209

Table 17. Best fuel cost.

Unit i (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	NSGA-II (King, 2004)	FCPSO (Agrawal, 2008)	SPEA2
P_{G1}	0.1245	0.1086	0.1182	0.1130	0.12048
P_{G2}	0.2792	0.3056	0.3148	0.3145	0.28649
P_{G3}	0.6284	0.5818	0.5910	0.5826	0.5822
P_{G4}	1.0264	0.9846	0.9710	0.9860	0.99335
P_{G5}	0.4693	0.5288	0.5172	0.5264	0.5248
P_{G6}	0.3993	0.3584	0.3548	0.3450	0.3523
Fuel Cost ($/h)	**608.147**	**607.807**	**607.801**	**607.786**	**605.998**
Emission (ton/h)	0.22364	0.22015	0.21891	0.2201	0.22076

Table 18. Best emission.

Unit *i* (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	NSGA-II (King, 2004)	FCPSO (Agrawal, 2008)	SPEA2
P_{G1}	0.3923	0.4043	0.4141	0.4063	0.41072
P_{G2}	0.4700	0.4525	0.4602	0.4586	0.46356
P_{G3}	0.5565	0.5525	0.5429	0.5510	0.54474
P_{G4}	0.3695	0.4079	0.4011	0.4084	0.39033
P_{G5}	0.5599	0.5468	0.5422	0.5432	0.54446
P_{G6}	0.5163	0.5005	0.5045	0.4974	0.5155
Emission (ton/h)	**0.19422**	**0.19422**	**0.19419**	**0.1942**	**0.19418**
Fuel Cost ($/h)	645.984	642.603	644.133	642.896	646.190

Table 19. Best compromise solution.

Unit *i* (p.u.)	NPGA (Abido, 2003a)	SPEA (Abido, 2003)	SPEA2
P_{G1}	0.2227	0.2594	0.12048
P_{G2}	0.3787	0.3848	0.28649
P_{G3}	0.5560	0.5645	0.5822
P_{G4}	0.7147	0.7030	0.99335
P_{G5}	0.5500	0.5431	0.5248
P_{G6}	0.4424	0.4091	0.3523
Fuel Cost ($/h)	615.097	616.069	605.9986
Emission (ton/h)	0.20207	0.20118	0.22076

Table 20. Comparison of results of three objective functions optimization.

Unit *i* (p. u.)	Minimum Fuel Cost		Minimum Emission		Minimum Transmission Loss	
	MOPS (Wang, 2008)	SPEA2	MOPS (Wang, 2008)	MOPS (Wang, 2008)	SPEA2	MOPS (Wang, 2008)
P_{G1}	0.1789	0.1115	0.3606	0.1789	0.1115	0.3606
P_{G2}	0.2888	0.2906	0.4568	0.2888	0.2906	0.4568
P_{G3}	0.5776	0.5807	0.5100	0.5776	0.5807	0.5100
P_{G4}	0.9388	0.9940	0.5184	0.9388	0.9940	0.5184
P_{G5}	0.4973	0.5245	0.5598	0.4973	0.5245	0.5598
P_{G6}	0.3770	0.3556	0.4657	0.3770	0.3556	0.4657
Losses (p. u.)	0.0233	0.0231	0.0313	0.0233	0.0231	0.0313
Fuel cost ($/h)	**606.54**	**605.42**	633.70	**606.54**	**605.42**	633.70
Emission (ton/h)	0.2002	0.2209	**0.1953**	0.2002	0.2209	**0.1953**

Table 21. Best compromise solution.

Unit *i* (p. u.)	SPEA2
P_{G1}	0.13811
P_{G2}	0.25129
P_{G3}	0.90012
P_{G4}	0.60386
P_{G5}	0.56767
P_{G6}	0.39051
Losses (p. u.)	0.017558
Fuel cost ($/h)	620.3921
Emission (ton/h)	0.21193

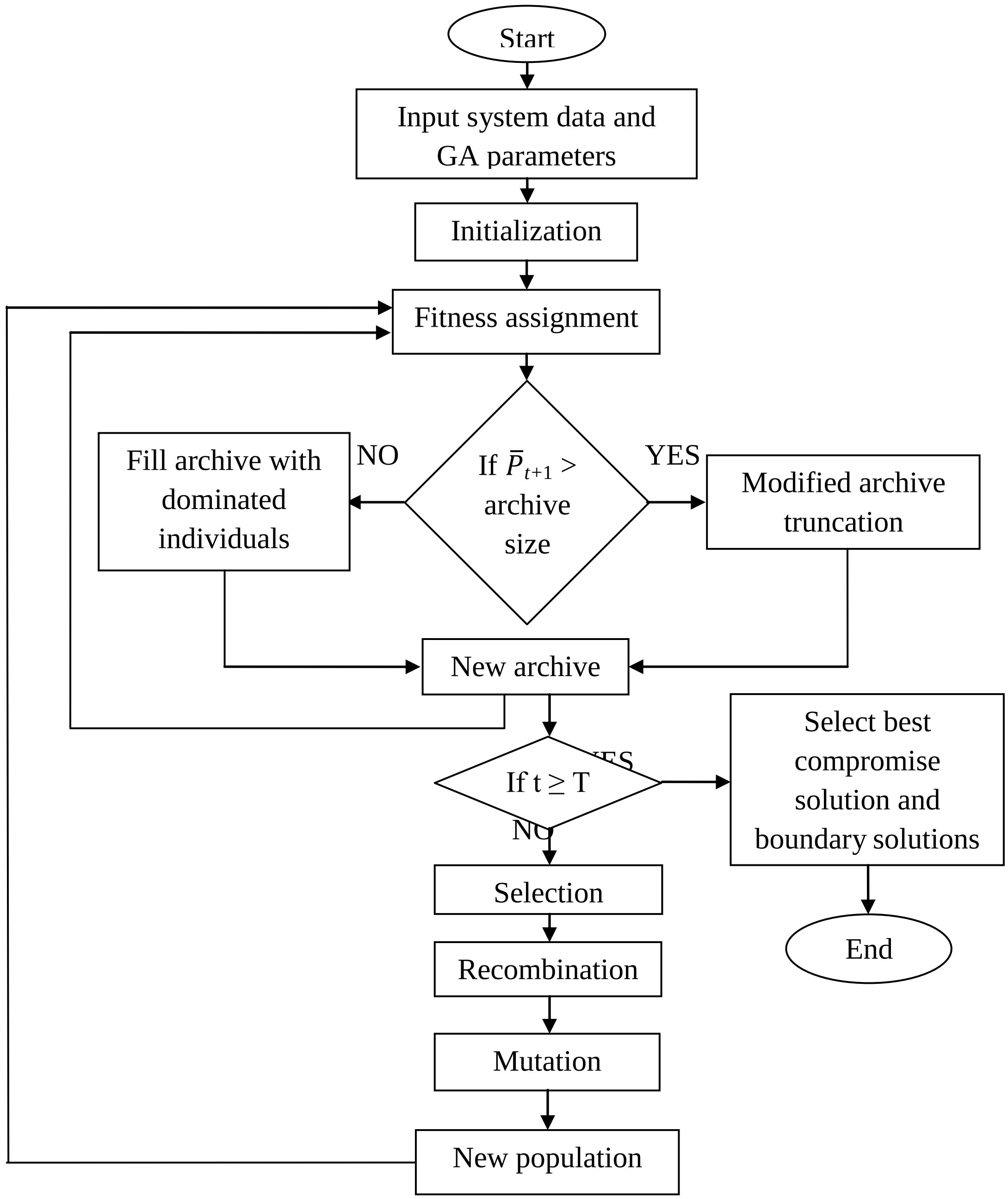

Figure1. The strength pareto evolutionary algorithm 2 flow chart.

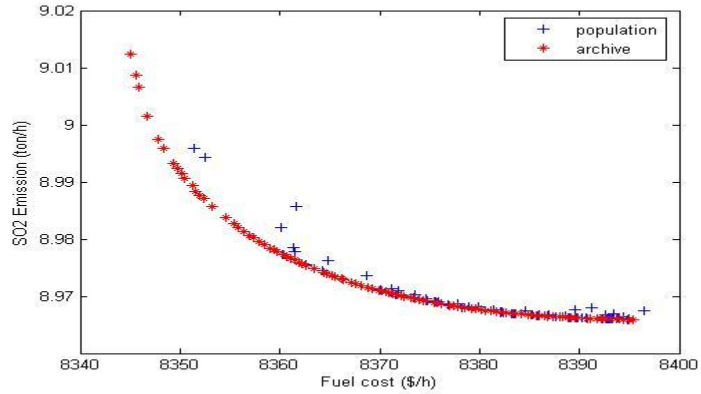

Figure2. Pareto –optimal front for case (1) test (1).

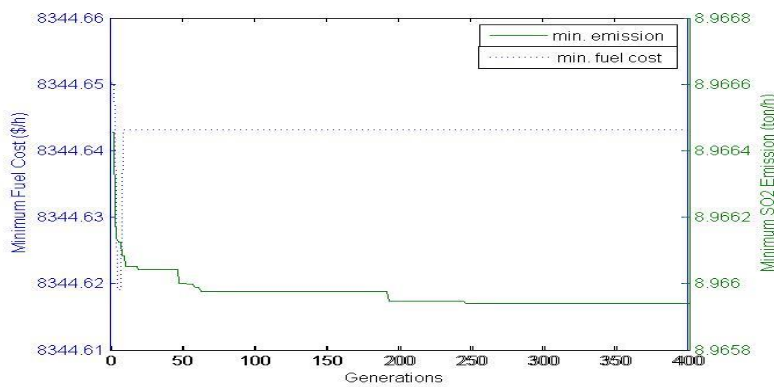

Figure3. Convergence of min. fuel cost and min. emission of the proposed method for system (1), test (1).

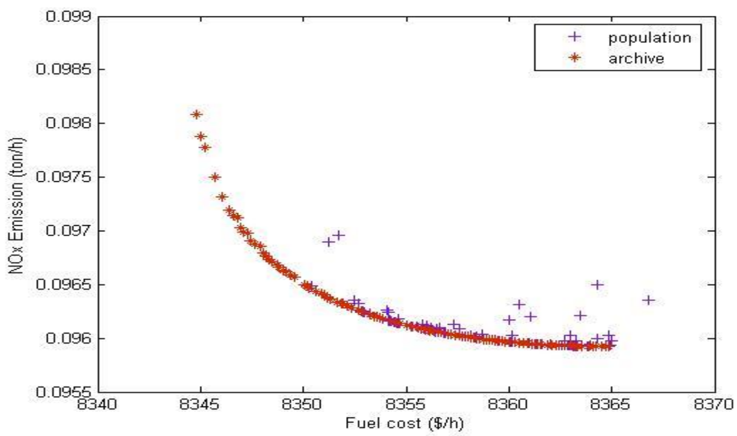

Figure4. Pareto-optimal front for case (1) test (2).

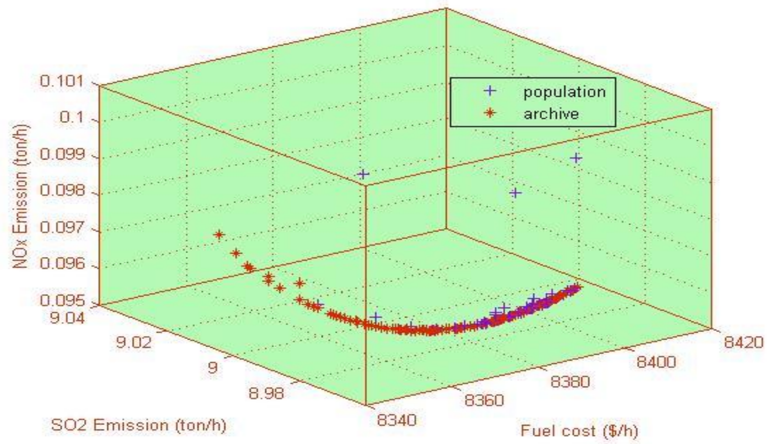

Figure5. Pareto-optimal front for case (1), test (3).

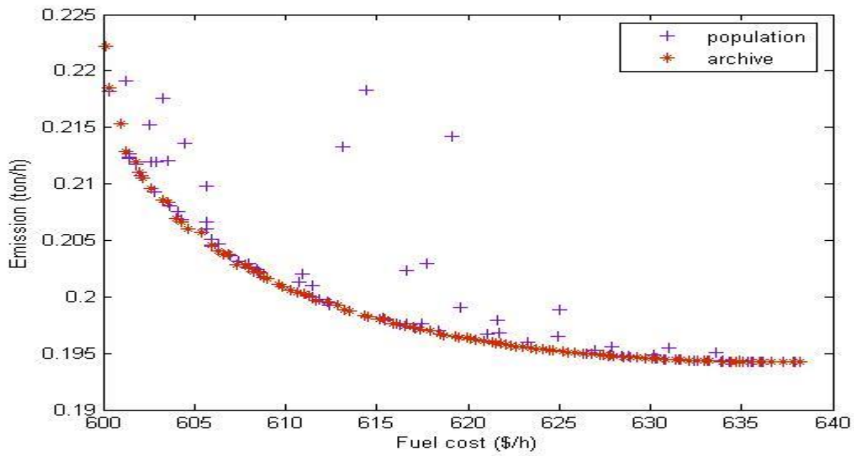

Figure6. Pareto-optimal front for case (2) test (1).

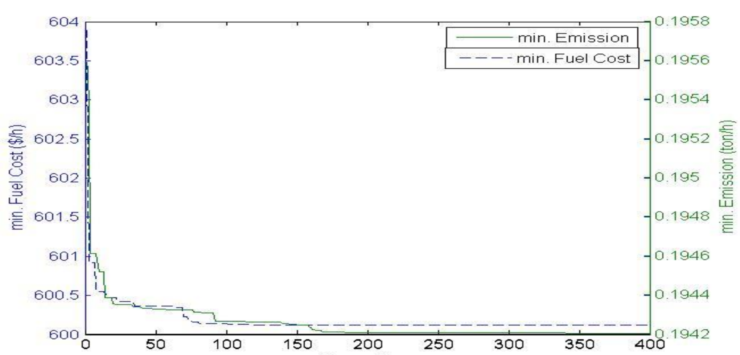

Figure7. Convergence of min. fuel cost and min. emission of the proposed method for system 2, test (1).

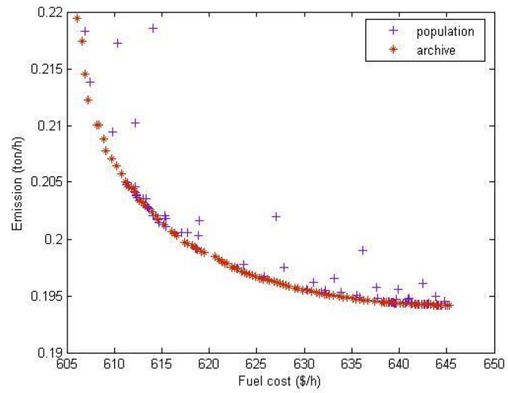

Figure8. Pareto-optimal front for case (2), test (2).

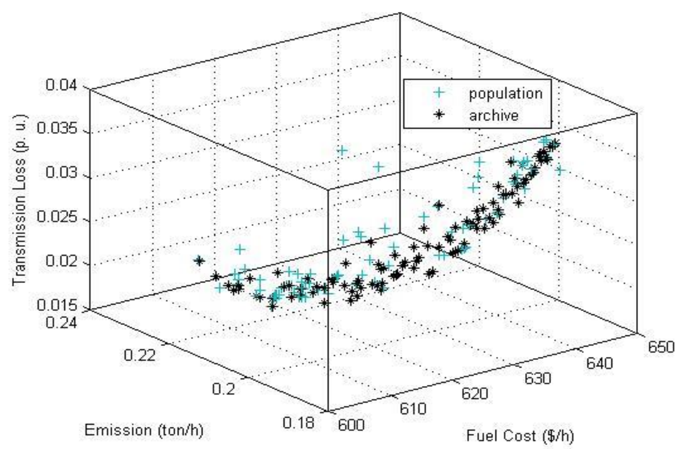

Figure9. Pareto-optimal front for case (2) test (3).