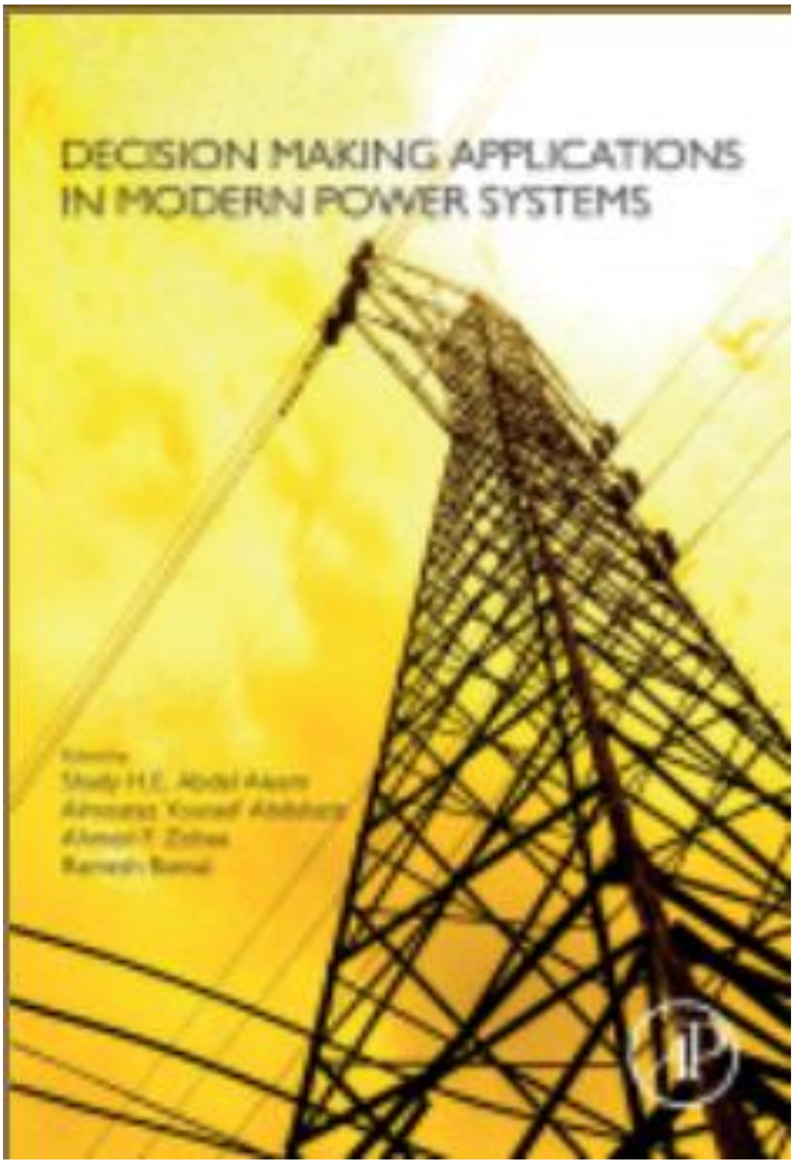
DECISION MAKING APPLICATIONS
IN MODERN POWER SYSTEMS

Chapter 12

Heuristic methods for the evaluation of environmental impacts in the power plants

Jandecy Cabral Leite[1], Jorge de Almeida Brito Júnior[1], Manoel Henrique Reis Nascimento[1], Carlos Alberto Oliveira de Freitas[1], Milton Fonseca Júnior[2], David Barbosa de Alencar[1], Nadime Mustafa Moraes[3] and Tirso Lorenzo Reyes Carvajal[1]

[1]Research Department, Institute of Technology and Education Galileo of Amazon - ITEGAM, Manaus, AM, Brazil, [2]Mauá Generation Department, Generation Eletrobras Amazonas GT Manaus, Amazonas, Brazil, [3]Research Department, University of the State of Amazonas (UEA), Manaus, Amazonas, Brazil

12.1 Introduction

Developing countries seek self-sustainability in the face of current global energy scenario. The reasons for this inclination arise due to the scarcity of fossil fuels in the coming decades, added to the high thermal energy production costs and rising energy consumption, either by developmental reasons or by the misuse of power available. The action strategies to the current national scene need to be updated both with respect to the difficulties observed in the economic and environmental spheres, such as investment in the research of new instruments, methods, and criteria to ensure the effective contribution of the electricity sector in the process of seeking a self-sustainable development [1]. For [2] the electric power generation and shipping problems, the absolute minimum cost is not the only criterion to be fulfilled. Apart from that, environmental considerations have become a major concern for power generation. The limited economic dispatch (ED) problem can be environmentally classified as a multiobjective optimization and a non-linear programming problem. According [3] they argue that since the beginning of the 1970s the dispatch of thermal generation has been proposed as an effective means of dealing with the problem of air pollution. The latest restrictive legislation has led to the adoption of pollution-limiting techniques and/or the use of cleaner fuels. However, an order with restricted emissions

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is even more necessary when the weather conditions are adverse to the diffusion of effluents. The authors present a dynamic dispatch procedure, which is able to hold the integral nature of the restrictions of issue. So, the environmental economic dispatch (EED) in thermal plants is a very important task to ensure the power demand, which is to make a distribution to all the mill engines, ensuring that the cost is minimal.

In this chapter a model and a mathematical method for EED tools using evolutionary algorithms (EAs) [nondominated sorting genetic algorithm (GA) II (NSGA-II)] to reduce both the cost of energy production in thermal power plants (TPPs) and the environmental impact are applied. The identification of different ways of evaluating the emissions produced by power plants suggests mathematical models and computational tools to be used for the assessment of the economic (cost generation and fuel consumption) and environmental (emissions) variables, considering the pollution generated as well as the permissibility of each pollutant in the atmosphere to allow the construction of different simulation scenarios. It also formulates the optimization of bi-objective EED problem, using a computational tool (NSGA-II-EA) analysis for the selection of the configuration of independent and dependent variables of the mathematical model, considering the demanded power and the environmental impacts.

12.2 Materials and methods

12.2.1 Heuristic optimization techniques

The use of heuristic methods increases to quickly get tools to give solutions to actual problems. It is important to note that these methods do not guarantee the best optimization solution found, although the purpose is to find the solution next to the optimal solution in a reasonable time. Fig. 12.1 shows the classification of global optimization methods [4,5].

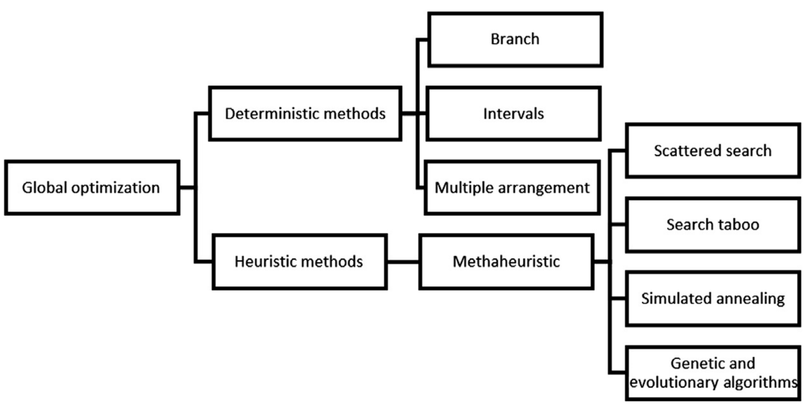

FIGURE 12.1 Global optimization methods.

The heuristic optimization techniques can be of exhaustive and nonexhaustive types. The comprehensive or exhaustive techniques, such as algorithmic schemes, Backtracking and Branch & Bound, have the advantage of finding the optimal solution always, using the worst case—the entire solution space is huge. It is difficult to narrow the search by the use of heuristic techniques and, therefore, may result in inefficient algorithms for medium-to-large problems.

The nonexhaustive techniques are known by the name of metaheuristics, which can be algorithmic schemes based on different ideas in many outlets, occasions, and the workings of nature, which is a common approach of problem-solving by successive improvements of a solution or set of solutions, with an exploration of broader solution space and with some random factor [6,7].

In this work the metaheuristic techniques, specifically GAs, will be used. It is taken into consideration that the types of optimization problems have a very complex resolution space; therefore exploring it completely may not be feasible for certain applications. In this type of technique, what is done is to work with a solution or a set of solutions for new responses that are closer to the optimal in order to avoid the great places and, iteratively, to achieve a high-quality convergence. In this way, it is possible to guarantee the quality of the solution, as this will comply with the criteria found.

12.2.2 Genetic algorithms

GAs are adaptive heuristic search algorithms that are based on evolutionary ideas of natural selection and genetics. As such, they represent an intelligent exploitation of a random search used to solve optimization problems. Although randomized, GAs are not random, instead, exploit historical information to direct the search for the best performance region within the search space. The basic techniques of GAs are designed to simulate processes in natural system necessary for evolution, especially those that follow the principles established by Charles Darwin first—"survival of the fittest," where, in nature, in competition among individuals for scarce resources, the more capable individuals dominate over the weak.

It is better than conventional techniques of artificial intelligence (AI) that is more robust. Unlike older systems, AI, they don't break easily even if the inputs change slightly, or in the presence of reasonable noise. In addition, when searching a large state space, multimodal state space, or n-dimensional surface, a GA can provide significant benefits on the types of most typical search engine optimization techniques (linear programming, heuristic depth-first search width, and praxis) [9].

GAs mimic the survival-of-the-fittest individuals from every successive generation of a problem to solve. Each generation consists of a population of strings of characters that are similar to chromosome that we see in DNA.

Each individual is a point in a search space and a possible solution. The individuals of the population are made to go through a process of evolution.

GAs are based on analogy with the genetic structure and behavior of chromosomes within a population of individuals using the following bases [8]:

- The individuals in a population compete for resources and mates.
- The most successful individuals in each "competition" will produce more offspring than those who have a poor performance.
- The genes of individuals "good" spread throughout the population so that two good parents sometimes produce offspring that are better than either parent.
- Thus each succeeding generation becomes more suitable to their environment.
- The simplest form of GA has the following three types of operators [10]:
- Selecting and playing: This operator drains chromosomes among the population to make the play. The more capable is the chromosome, the more often will be selected to reproduce.
- Crossing: This is an operator who has to choose a place of function and change the sequences before and after that position between two chromosomes, to create a new offspring (e.g., 10,010,011 and 11,111,010 chains can cross after the third place to produce offspring 10011010 and 11110011), and mimics the biological recombination between the haploid organisms.
- Mutation: This operator produces random variations in a chromosome (e.g., the chain can exchange 00011100 its second position for the current 01,011,100). The mutation can take place in each position of a bit in a string, with a probability typically very small (e.g., 0.001). As can be seen, the GAs are different from traditional methods of search and optimization in four key areas.
- They seek a population of points, not a single point. Maintaining a population of well-adapted sampling points, the probability of falling into a false peak is reduced.
- Employing the objective function and it doesn't need derivatives or other information complementary, because sometimes they are very hard to be achieved. Thus they gain in efficiency and generality.
- They use stochastic transition rules, not deterministic. The GAs use random operators to guide the search to the best spots; it may seem strange, but the nature is full of precedents in this regard.

12.2.3 Nondominated sorting genetic algorithm II

For the development the multiobjective algorithms require mathematical methods optimization on a population of solutions because the NSGA-II was chosen as proposed, due to its diversity and reliability characteristics. However, an overview should be maintained to enable the use of other procedures, such as ant colonies, simulated annealing, and the particle swarm.

The NSGA-II, the first version based on GAs, is classified as an elitist type, since it incorporates a preservation mechanism of the dominant solutions through several generations of a GA.

The process starts from a set of size N solutions (couple) obtained randomly or methodically. Later generations are determined using modified mechanisms of selection, crossover, and mutation defined by classic GA.

12.2.3.1 Selection process, crossover, and mutation

On the current population (pair), randomly selected N pairs of solutions are selected. Each pair competes in a tournament in winning alternative that belongs to the category of best quality. If the dominance of alternatives belongs to the same front, then winning it introduces a greater degree of diversity to all that are under construction. The winners of each tournament are allowed only for seed; the crossover and mutation are handled in the same way as shown by the classic GA.

Thus what is expected is that the genetic information of the dominant alternative be present in the following generations and attract the rest of the population to their respective neighborhoods.

12.2.3.2 Stacking operator

The multiobjective algorithms seek to find a big number of solutions that belong to the Pareto front. Therefore it is necessary that the population be kept as much diverse as possible. The stacking operator quantifies the space around an alternative that is not occupied by any other solution. This is due to calculating the perimeter of the cuboid formed by neighboring solutions that have the same category of the alternative dominance i, which is described by the following equation:

$$d_i = \sum_{m=1}^{M} \left| \frac{f_m^{\left(I_{i+1}^m\right)} - f_m^{\left(I_{i-1}^m\right)}}{f_m^{\max} - f_m^{\min}} \right| \tag{12.1}$$

where I^m is a vector indicating the nearby alternative solution alternative i, $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values in the function of the solution space object m, respectively, and M is the number of optimized objective functions.

12.2.3.3 Selection by tournament second stacking operator

This procedure replaces the selection used in traditional GA. They consist of comparing two solutions; each one of them has two attributes:

- A range of nondomination r_i, according to the Pareto front.
- A local stacking distance, d_i.

The selection returns to winning solution i based on two fundamental criteria:

- If j has better hierarchy, $r_i < r_j$.
- If j has the same hierarchy, but i has a better stacking distance, $d_i > d_j$.

12.2.3.4 Determination of final set descending

Before finalizing a generation of algorithm, a process of preselection and preservation of elite solutions is performed, which involves getting the set of solution parents and offspring obtained through the selection of operators, crossover, and mutation.

Thus the present population increases to double the initial population of individuals. It is necessary to classify the full set of fronts in their respective dominance and preserve individuals who belong to the best quality fronts, as is shown in Fig. 12.2.

If it is not possible to enter all the alternatives of a particular forward, then those individuals are disposed with a smaller distance to the crowd.

12.2.3.5 Pseudocode for the nondominated sorting genetic algorithm II

The steps used in NSGA-II are as follows:

1. Generate a population of size N.
2. Identify the dominance of fronts and evaluate stacking distances on every front.
3. Using selection, crossover, and mutation generates a downward population, the same size as P.
4. Parents and children together in a set of $2N$ rank the dominance fronts.
5. Determine the final set down by selecting the fronts of the best features or hierarchy. If exceeded the threshold population of N, eliminate solutions with the shortest distance across stacking the last selected.
6. With the fulfillment of convergence criterion, the process ends, if not, return to step 3.

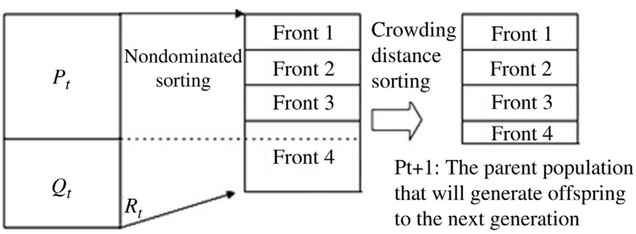

FIGURE 12.2 Determination of new population. In the figure, P_t is the current population, Q_t is the offspring population, and R_t is the population after recombination.

In this chapter the EED problem will be used as NSGA-II with two objective functions—one is the cost of fuel and the other, emission index.

12.2.4 The emission ratio as a parameter to assess the environmental contamination

The production of energy by fossil fuels, industrial processes, and means of transport has a great influence on the environment, due to the deforestation and emissions (CO_2, NO_x, SO_x, C_xH_y, particulates, etc.); it is considered the main anthropogenic sources of pollution.

The Kyoto Protocol resulted from the meeting of 160 nations in 1997 in Japan to reduce emissions of gases that cause the greenhouse effect (CO_2, CH_4, etc.) and encourage the development of new technologies and the implementation of clean sources power. Since then, the right to trade emissions (primarily CO_2 resulting from the burning of fossil fuels, whose use in developed countries is intensive) is gaining strength as a political strategy.

The air pollutants originate mainly from incomplete combustion of fossil fuels. Those are classified into two types: primary and secondary. Primary pollutants are those emitted directly from sources to the atmosphere, highlighting particulate matter (smoke, dust, and mist), carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxides (NO and NO_2), sulfur compounds (H_2S and SO_2), hydrocarbons, and chlorofluorocarbons [11−13].

With the introduction of emissions and ecological taxation market for the electricity sector, the development of decision-making methods for emissions trading or emission restrictions is becoming increasingly important, and many studies may decide to program generators for operation [14−18].

Although there are many studies on CO_2 restrictions, they focus primarily on the problem of deciding the output level of each generator during the ED.

However, to obtain an optimal solution, it is important to consider not only the dispatch level of each generating unit, but also the schedule (on/off), since the power minimum output, restrictions, and start-up influence the final solution of the cost/emission. So it is essential to consider the restriction problem of each unit in decision-making methods. In addition, most generating unit studies, including CO_2 restrictions, are focusing on programming the solution that maximizes earnings per unit [24,25] but not in optimal solutions Pareto in reducing CO_2 [14,26,27].

According [28], CO_2 emission allowances are usually given for a period of 1 year, while the time frame for programming is scheduled of 24 hours for several days, and restrictions have an effect only when the value of CO_2 emissions became high. According [29] they believe that maximum profit is

TABLE 12.1 Data to determine the emission index of gas engines.

Pollutant	Primary standard CONAMA (g/m^3)	Specific weight permissible	Value of influence
Total particulate matter	240	0.00592885	0.99407115
Carbon monoxide	40,000	0.98814229	0.01185771
Nitrogen dioxide	320	0.00790514	0.99209486
Hydrocarbons	160	0.00395257	0.99604743
Total	40,480	1	3

important but the trade-off of cost reduction and CO_2 should not be taken into consideration.

12.2.5 Emission index of gas engines

To evaluate the environmental pollution caused by gas engines, the emission rate is established by the author of this work, considering the value of the first data table. To develop the mathematical expression, the emission index limits were considered and the air quality was determined by CONAMA and the weighted value of each pollutant in the air quality [30] expressed in Table 12.1.

The influence of the amount of CO_2 to 1 is considered. The equation for calculating the emission index from gas engines is expressed by (12.2).

$$I_{emg} = CO_2 + 0.99407115MP + 0.01185771CO + 0.99209486NO_2 + 0.99604743C_XH_y \tag{12.2}$$

As gas engines also emit nitrogen monoxide, it was decided to include them in the expression with the same amount of influence as NO_2, in the following formula:

$$I_{emg} = CO_2 + 0.99407115MP + 0.01185771CO + 0.99209486(NO_2 + NO) + 0.99604743C_XH_y \tag{12.3}$$

To calculate the emission index or rate of emissions, all emission values must be in the same system of units, which is necessary to perform conversions of the same according to the companies that make the control of these

TABLE 12.2 Conversion factors.

Parameter	Initial units	Multiply by	End units
PM	mg/m^3	1	mg/m^3
Nitrogen dioxide (NO_2)	mg/m^3	1	mg/m^3
Nitrogen monoxide (NO)	mg/m^3	1	mg/m^3
Carbon dioxide (CO_2)	%	18,000	mg/m^3
Carbon monoxide (CO)	ppm	1.25	mg/m^3
Hydrocarbons (C_xH_y)	%	17,960	mg/m^3

PM, Particulate matter.

TABLE 12.3 Molecular weights.

Sustenance	Molar weight (g/mol)
W	12
O_2	32
O	16
CO_2	44
CO	28
N	14
N_2	28
H	1
Methane (CH_4)	16
Hexane (C_6H_{14})	86

emissions. Table 12.2 shows the emission values as the thermal plant and the conversion factors.

To perform conversions, molecular weights of the components were considered, according to the following procedures and amounts (see Table 12.3):

$$\mathrm{mg}/m^3 = \frac{\mathrm{ppm} \times \mathrm{PM}}{24.45} \tag{12.4}$$

Thus the expression to calculate the emission rate of gas engines is given by

TABLE 12.4 Typical emissions from gas engines.

Typical emissions of a gas engine (UGGN 12)	Original *U*	3% mg/m^3
Particulate material (mg/m^3)	76.57	76.57
Nitrogen dioxide (mg/m^3)	315.07	315.07
% Oxygen (mg/m^3)	12.3	80,490.7975
Carbon dioxide (CO_2)% to mg/m^3	4.8	86,400
Carbon monoxide CO (ppm mg/m^3)	286	327.525562
Nitrogen monoxide (mg/m^3)	105	105
Hydrocarbons (C_xH_y) (ppm mg/m^3)	861.64	1688.8144
Nitrogen oxides (NO_x as NO_2) (ppm mg/m^3)	213	400.44

$$I_{emg} = 18,000\ \mathrm{CO_2} + 0.99407115\ \mathrm{MP} + 0.01185771 \times 1.25\ \mathrm{CO} + 0.99209486(\mathrm{NO_2} + \mathrm{NO}) + 0.99604743 \times 17,960\mathrm{C}_x\mathrm{H}_y \text{ in } \mathrm{mg}/m^3 \quad (12.5)$$

In expression (12.5), CO_2 and C_xH_y are expressed in % in ppm CO and the other data in mg/m^3.

Table 12.4 shows the typical emissions of a plant gas engine in Manaus.

12.2.6 Index engine emissions of heavy fuel oil

In this case the developed procedure was the same as for gas engines but taking into account the emissions of such engines (see Table 12.5).

Table 12.6 shows the conversion values:

$$I_{\mathrm{emHFO}} = 18,000 \times \mathrm{CO_2} + 0.9941\mathrm{MP} + 1.25 \times 0.0265\mathrm{CO} + 0.992(\mathrm{NO_2} + \mathrm{NO}) + 0.991\mathrm{SO_2} + 0.9961 \times 17,960\ \mathrm{C}_x\mathrm{H}_y\ (g/m^3) \quad (12.6)$$

Table 12.7 shows the typical emissions of a motor heavy fuel oil (HFO), the plant in Manaus.

12.2.7 Contamination caused by plant

The thermal plant studied lies in Manaus and has a generating capacity of 173 MW. It contains 23 Jenbacher gas engines of 3.5 MW and 5 engines of HFO of 18.5 MW; but for the use of optimization engines, 10 were used.

TABLE 12.5 Data to determine the emission index of the heavy fuel oil engines.

Pollutant	Primary standard CONAMA (g/m^3)	Specific weight permissible	Value of influence
Total particulate matter	240	0.0059	0.9941
Carbon monoxide	40,000	0.9735	0.0265
Nitrogen dioxide	320	0.0078	0.9922
Sulfur dioxide	365	0.0089	0.9911
Hydrocarbons	160	0.0039	0.9961
Total	*41,085*	*1*	*4*

TABLE 12.6 Conversion factors in the case of engines heavy fuel oil.

Parameter	Initial units	Multiply by	End units
PM	mg/m^3	1	mg/m^3
Nitrogen dioxide (NO_2)	mg/m^3	1	mg/m^3
Nitrogen monoxide (NO)	mg/m^3	1	mg/m^3
Carbon dioxide (CO_2)	%	18,000	mg/m^3
Carbon monoxide (CO)	ppm	1.25	mg/m^3
Sulfur dioxide	mg/m^3	1	mg/m^3
Hydrocarbons (C_xH_y)	%	17,960	mg/m^3

PM, Particulate matter.

To analyze the contamination caused by the plant, we studied the data of exhaust emissions from the years 2011 and 2012. In addition, to compare the contamination of gas engines with the contamination of HFO engines, data from HFO engines at the same level of oxygen were converted to the data from gas engines.

To convert data to different % oxygen, the following expression was used:

$$C_c = C_{\mathrm{GAS}} \times \frac{(21 - O_{\mathrm{REF}})}{(21 - O_{\mathrm{MED}})} \tag{12.7}$$

where C_c is the corrected concentration expressed % to specified oxygen, C_{GAS} is the concentration of gas corrected (values obtained with checks),

TABLE 12.7 Typical emissions of an engine heavy fuel oil (HFO).

Typical emissions from a motor HFO (MAN 1)	U original	7% mg/m^3	3% mg/m^3
Particulate material (mg/m^3)	156.65	156.65	201.407143
Sulfur dioxide (mg/m^3)	287.42	287.42	369.54
% Oxygen (mg/m^3)	13.7	179,304.703	230,534.619
Nitrogen dioxide (mg/m^3)	315.07	315.07	405.09
Carbon dioxide (CO_2)% to mg/m^3	5.5	98,977.5051	127,256.792
Carbon monoxide CO (ppm mg/m^3)	66.66	76.3386503	98.1496933
Nitrogen monoxide (mg/m^3)	1167	1167	1500.42857
Nitrogen oxides (NO_x as NO_2) (mg/m^3)	1843	1843	2369.57143
Total hydrocarbons (C_xH_y) from the % (mg/m^3)	0.03	588	756

TABLE 12.8 Emissions in the different systems of units.

Gas	mg/m^3 ppm
CO	1.25
At the	1339
NO_2	2054
NO_x (as NO_2)	2054
SO_2	2857

O_{REF} is the oxygen reference, that is, it is noted as the measurements, O_{MED} is the average oxygen during measurements.

It was necessary to establish the same system of units for some values as presented in Table 12.8.

For the engine emissions to index HFO, the plant was carried out similarly to the gas engine, that is, measurements were carried out in the chimney values of engines of different pollutants and statistically processed results. With the average values, emission index for each motor HFO plant was calculated, shown in Fig. 12.3.

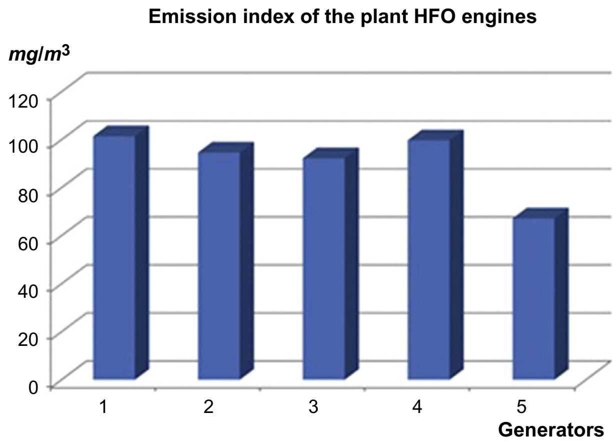

FIGURE 12.3 The emission index of the plant HFO engines. *HFO*, Heavy fuel oil.

The figure can be seen that the emission rate of the HFO power plant engines has values very close to each other, which are almost similar, that is, are not so different as in the case of gas engines. In this case, the contamination of these motors is lower than that of the gas engines; the explanation for this contradiction is that the technical state of the gas engine is lower than the roadworthiness of motor HFO.

12.2.8 Specific emission index

To better evaluate, emission indexes were divided by the power generated by the engines, thus obtained specific emission index. Table 12.9 shows a comparison between the specific index emissions from gas engines and engines HFO, and Fig. 12.4 shows a comparison according to the emission power supplied to the gas engines and fuel oil engines.

The graph in Fig. 12.4 shows the specific emission index for each type of pollutant.

In the graph of Fig. 12.4, it can be seen that in this case, the motors HFO contaminate the environment more than the gas engine, especially the emissions of carbon dioxide; these results are in agreement with those established in the literature but the rest of emissions should behave similarly. Gas engines emit more NO_2 than the engines HFO, but this fact has to do with two things, the first is the LENOX device that has these engines that regulate them for maximum efficiency, and this is achieved when the NO_2 emissions are highest. The other aspect that influences the technical state of gas engines is mentioned above.

12.2.9 Permissible values of emission Index

In the literature referred to for EED, only permissible values or restrictions for the emission of TPPs appear, which reinforces the need of emission using

TABLE 12.9 Comparison of emissions between gas engines and heavy fuel oil (HFO) engines in relation to power supplied.

Specific emission index g/m^3, kW	HFO	Gas
Particulate matter	10.6564	22.32
Sulfur dioxide	19.5523	0
Oxygen	121.975	234.66
Nitrogen dioxide	21.4333	91.85
Carbon dioxide (CO_2)	673.16	251.89
Carbon monoxide (CO)	6.41	11.8
Nitrogen monoxide (NO)	79.3877	30.61
Nitrogen oxides (NO_x as NO_2)	125.374	116.74
Total hydrocarbons (C_xH_y)	40	49.36

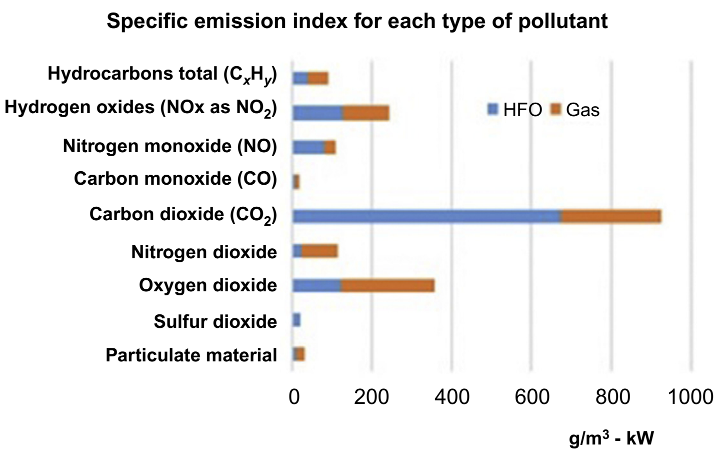

FIGURE 12.4 Specific emission index for each type of pollutant.

a parameter, which constricts the operation of a TPP. In most cases the authors estimate the amount of emissions and sometimes convert these values in cash [35] Developed by emission factors for the case of the use of coal, but not limited to these emissions [36]. Developed a complex mathematical procedure to determine the allowable CO_2 emissions, but this procedure being very complex includes only CO_2 emissions. According [37] they made an inventory of NO_x and CO through several years of observation and concluded that they should be restricted.

The emission index developed in this work presents a great advantage because it brings restrictions, which was developed from the damage that the emissions cause. However, if desired greater precision, you can set a maximum rate of emissions that would be the sum of all allowable values for [38] adding permissible values of CO_2 emissions, which are not provided by this standard.

According to these considerations, the maximum pollutant emission index (MPEI) would be

$$MPEI = 58.48\ \mathrm{mg}/m^3$$

It can be seen from the analyses carried out in this chapter that the various engine emission indexes ever exceed this value, which shows something that is already known and that the thermal plants greatly harm the environment.

12.2.10 Obtaining primary data

For the emission index from gas engines, plant measurements were performed in the chimney values of engines of different pollutants and statistically processed results. With the average values, the emission index for each gas engine of the plant was calculated.

To get the raw data in expectation to calculate emission index, it develops the following:

- They were placed at all plant engines operating at different power levels with respect to maximum power (20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and 100%).
- For each of the power levels, emissions of various pollutants were measured, both in volume and type of pollutants in $\mathrm{mg/m^3}$.
- For each of the power levels of each motor, emission rate according to Eqs. (12.5) or (12.6) was calculated, depending on whether it is a gas engine or HFO engine.
- With the emission index of each engine, power curve versus emission index was obtained. In the graphs of this chapter, indexes emissions at full power were placed.
- With the curve of the emission index of each engine and using a regression software, equation index emissions from all power plant engines were obtained. We also calculated the coefficients d, e, and f to be used in the function emission index.

12.2.11 Price of carbon emissions

Carbon credits are a financial instrument envisaged in the Kyoto Protocol to try to mitigate the threats that cause the greenhouse effect. Each credit is equivalent to 1 t of carbon dioxide that was allowed to emit into the atmosphere. They may be generated through the mechanisms established in the Kyoto Protocol. As the mechanism exists, different types of credits are provided [39,40].

In other words, these credits are used to make it easy to calculate the amount of gases that are released into the air and offset their emissions. It is part of an international plan, probably the largest, that has been created in human history, to reduce global warming and effects. It is even the total amount of emissions that can be released by a company or business. If there is an excess amount of gases that are emitted, there is a monetary value assigned to that excess and can be traded, especially for projects that offset pollution, that is, to renew dioxide that has been emitted into the atmosphere, such as reforestation projects (usually in poor or developing countries).

It is well known that some companies think if they can bribe, they would be illegally allowed to pollute. In addition, there are credits that are bought and sold in international markets. So, this may be the object of speculation and does not have to be used to care for the environment.

By convention, 1 t of carbon dioxide (CO_2) represents 1 carbon credit. This credit can be negotiated in international market. Reducing the emission of other gases, also generators of greenhouse effect, it can also be converted to carbon credits, using the concept of carbon equivalent (carbon dioxide equivalent) [41].

A ton of CO_2 equivalent corresponds to a carbon credit. The CO_2 equivalent is the result of multiplying the tons of greenhouse effect emitted by its global warming potential. The global warming potential of CO_2 was set to 1. The global warming potential of methane is 21 times greater than CO_2 potential, so the CO_2 equivalent of methane is equal to 21. Therefore a reduced ton of methane corresponds to 21 carbon credits [18,42,43].

Global warming potential of greenhouse gases is as follows [44, 45]:

- CO_2—carbon dioxide = 1
- CH_4—methane = 21
- N_2O—nitrous oxide = 310
- HFCs—hydrofluorocarbons = 140−11,700
- PFCs—perfluorocarbons = 6500−9200
- SF_6—sulfur hexafluoride = 23,900

Since 2008 the price of carbon credits traded to sell to the developed countries in America (CO_2 Certificate of Emission Reduction) fell 98%, from 23 euros per ton to only 35 cents of euro per ton. The value of securities is traded in the domestic market in Europe—European Union Allowance. In turn, it fell from 30 to 4 euros [40]. Basically, considering the concept of supply and demand, there is currently an excess of credit carbon, which is a problem. In fact, the latest figures estimate that the market is saturated in about 1700 million tons of carbon credits.

Second [45], the cost per ton of emissions of CO_2 has varied between 9 and 24 euros. These authors as mentioned earlier also make an equivalence between the tons of other pollutants and tons of CO_2. Considering the above criteria, you can calculate the cost using the emission index by the following approximation:

$$\text{Cost}_{\text{emissions}} = 24 \times I_{em} \text{ in euros} \tag{12.8}$$

12.3 A mathematical model for the optimization of EED considering the emission index

Optimizing the EED is one of the most important tasks in power plants with internal combustion engines. The ED energy with a single goal cost of fuel only considers the one objective, that is, the question of generation. It has given way to multiobjective orders because of the environmental issues that arise from emissions from thermal plants. The purpose of this chapter is to analyze a new solution optimizing the EED by the technique of NSGA-II but using the new concept of emission index instead of using emissions as a cost or as much of greenhouse gases.

The EED of the problem is to minimize the total cost of generation and emission levels while at the same time to satisfy the demand of generation plants.

Thermal power generation is one of the sources of significant carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) that create air pollution [13]. The classic problem generating ED is to provide the required amount of power at the lowest cost, to meet the demand and operational restrictions.

This is a very complex problem to be solved for its high dimensionality, a nonlinear objective function, and many restrictions. Various techniques, such as Integer Programming [46], Dynamic Programming [47], Newton's method for [48], and the functions of Lagrange by [49], have been used to solve the problem EED generation.

To solve the EED problem, other optimization methods, such as the method of simulated annealing (simulated annealing goal attainment) pointed to by [50], particle swarm used by [51], the Game Theory used by [52], and the approach using the technique for order preference by a similarity of the ideal solution (TOPSIS) [53].

Various methods have also been developed on the basis of mathematical approaches to offer a quicker solution to the ED [54]. EAs have also been applied to the ED of the problem in question [55]. The research has also been developed to minimize the costs, including emission restrictions to solve the ED of generation and selection of generators [56]. Recently, it has been successfully employed by a combination of gravitational search algorithms modified by NSGA-II [57] and NSGA-III [58] that are convenient to solve the generation of EED optimization problems.

Therefore all previous models for EED only take into account the emissions and the amount of emissions. This work presents the degree of influence of each type of emissions on the environment. In the coming sessions, we develop a novel mathematical model that accurately classifies emissions according to their impact on the environment and this will be one of the functions to be optimized within the template.

12.3.1 Mathematical model for environmental economic dispatch

In the mathematical formulation of the multiobjective problem of EED, two important goals in a thermal system of power generation have to be considered, which are economic and environmental impacts [52,59,60].

12.3.1.1 Minimizing costs

The fuel cost of a thermal unit is considered as an essential criterion for economic viability. The fuel cost curve is assumed to be approximated by a quadratic function of the output power of the generator P_i [52,59,61,62]. The function to be used to minimize the cost is

$$F_1(P_i) = \sum_{i=1}^{n} \left(a_i + b_i P_i + c_i P_i^2\right) \ \$/\mathrm{h} \tag{12.9}$$

where a_i, b_i, c_i, and P_i are the fuel cost coefficients of the ith generating unit, and n is the number of generators and the active power of each generator.

However, despite the great financial benefit of classical dispatch strategy described by Eq. (12.9), whose fuel cost versus power generated curve is shown in Fig. 12.5, it tends to produce high amount of SO_2 and NO_x.

The fuel cost function of each thermal generating unit considering the valve-point effect is expressed as the sum of a quadratic function and a sine function [64,65]. The total cost of fuel in terms of active power can be expressed as

$$F_1 = \sum_{m=1}^{M} \sum_{s=1}^{N_S} t_m \left[a_s + b_s P_{sm} + c_s P_{sm}^2 + \left|d_s \sin\left\{e_s(P_s^{\min} - P_{sm})\right\}\right|\right] \tag{12.10}$$

12.3.1.2 Minimizing the environmental impact

The generators with fossil fuels are the main source of emissions of nitrogen, oxides, and other pollutants. Currently, there are strong constraints of environmental protection agencies to reduce the emission of nitrogen oxides (NO_x) being important from the point of view of environmental conservation.

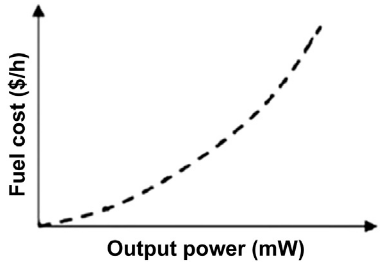

FIGURE 12.5 Cost of fuel versus output power.

There are various alternatives to consider and minimize the environmental impact of power plants, which are as follows:

- A dispatch alternative strategy that must meet environmental requirement is to minimize the cost of operation under environmental restrictions.
- Control of emissions may be included in conventional ED, adding the environmental cost to generation costs [2,66]. Emissions are modeled as a cost to the environment, which are later added to the cost of generation. The objective function is expressed as follows:

$$\text{minimize } C = w_0 \cdot F + w_1 \cdot E_S + w_2 \cdot E_N \tag{12.11}$$

where E_S and E_N is the emission function of SO_2 and NO_x, respectively. w_0, w_1, and$w_2$are the cost of weight in relation to the fuel (F) and the emissions of SO_2 and NO_x, respectively. F is the function of the cost of fuel, which is another variation to consider emissions into a single objective function, where particular weightage is given to NO_x and SO_2 emissions.

The functions of the function in emission cost curves of the active power generated included in function (12.11) can be expressed as follows:

$$E_s = \sum_{i=1}^{n} (d_i + e_i P_i + f_i P_i^2) \tag{12.12}$$

$$E_N = \sum_{i=1}^{n} (g_i + h_i P_i + k_i P_i^2) \tag{12.13}$$

where d_i , e_i ,f_i , g_i , h_i, and k_i are the estimated parameters based on the results of the emission tests generating unit, and P_i is the power of each generator.

In this model, when the emission weights are 0, the objective function becomes a classic problem of ED. In this case the goal is to minimize costs and total system output. For SO_2 emission, the weights w_0 and w_2 are equal to 0 and w_1 is equal to 1. For SO_2, the goal is to minimize the emission. For NO_x emission, the weights w_0 and w_1 are 0 and w_2 is equal to 1, where the problem lies in the minimization of NO_x emissions. On the contrary, when the weights are not 0, minimizing both the cost of fuel and emissions at the same time becomes the problem.

For [67], the amount of emission of each generator is given as a function of its output, which is the sum of a quadratic function and an exponential function. The total emission system can be expressed as

$$F_2 = \sum_{m=1}^{M} \sum_{s=1}^{N_S} t_m \left[\alpha_s + \beta_s P_{sm} + \gamma_s P_{sm}^2 + \eta_s \exp(\delta_s P_{sm}) \right] \tag{12.14}$$

where $\alpha_s, \beta_s, \gamma_s, \eta_s,$ andδ_s are the coefficients of the emission characteristics of each generator, and P_{sm} is the power of each generator.

According [68], the multiobjective problem of dispatch emissions and combined economic can be converted into an optimization problem of a single goal by introducing a factor h penalty price as follows:

$$\text{Minimize } F = F_C + h_i \times \text{EC} \tag{12.15}$$

where F_C is the fuel cost function and EC is the total amount of emissions.

Expression (12.15) is subject to the equations and power flow restrictions. The price of the penalty factor h combines the issue with the cost of fuel and F is the total operating cost in \$/h. The price penalty factor is the ratio of the maximum cost of fuel and the emission maximum of the corresponding generator h_i [68]:

$$h_i = \frac{F_C\left(P_{g_i}^{max}\right)}{EC\left(P_{g_i}^{max}\right)} \tag{12.16}$$

where F_C is the fuel cost function, EC is the total amount of emissions and g_i is the power in generator ith.

The emissions that are considered most important in the power generation industry due to their effects on the environment are sulfur dioxide (SO_2) and nitrogen oxides (NO_x) [13,69]. These emissions can be modeled by associating functions with emission power production for each unit. One approach to represent the emissions of SO_2 and NO_x is to use a combination of polynomial terms [68,70]:

$$\text{EC}\left(P_g\right) = \sum \left(\alpha_i P_{g_i}^2 + \beta_i P_{g_i} + \gamma_i \right) + \varepsilon_i \exp\left(\lambda_i P_{g_i}\right) \tag{12.17}$$

where $\alpha_i, \beta_i, \gamma_i, \varepsilon_i,$ andλ_i are the emission characteristics of the coefficients of the total power generated, P_g, which is the power of each generator.

Second [71], the total emission $F_2(P_i)$ of air pollutants such as sulfur dioxide, SO_2, and nitrogen oxides, NO_x, caused by the combustion of fuel in thermal units may be expressed as

$$F_2(P_i) = \sum_{i=1}^{n} \left(d_i + e_i P_i + f_i P_i^3 \right) \ \text{m}^3/\text{h} \tag{12.18}$$

where d_i, e_i, and f_i are the coefficients of emission characteristics for each generating unit.

12.3.1.3 Load dispatch restrictions considering emissions

In this section, a number of restrictions are considered:

- An equal restriction of active power balance generated

  The following equation is the power balance constraint [72,73]:

$$\sum_{i=1}^{n} P_i - P^D - P^L = 0 \tag{12.19}$$

  where P_i is the output power of each i generator, P^D is the load demand, and P^L are transmission losses.

  In other words, the total power generation has to meet the total demand, P^D, and the loss of active power transmission lines, P^L:

$$\sum_{i=1}^{n} P_i = P^D + P^L \tag{12.20}$$

  The calculation of power losses involves the solution of the load flow problem, which has equal restrictions on active and reactive power in each bar as follows [74]:

$$P^L = \sum_{i=1}^{n} B_i P_i^2 \tag{12.21}$$

  To model the transmission loss, each function generator loss through the derivatives of formula Kron coefficients for loss is set to output.

$$P^L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{M} B_{0i} P_{Gi} + B_{00} \tag{12.22}$$

  where $B_{ij}, B_{0i}, \text{and} B_{00}$ are the power loss coefficient in the transmission line. A reasonable accuracy can be obtained when the actual operating conditions are close to the base case where the coefficients B were obtained [75].

- An inequality constraint in terms of generation capacity

  For stable operation, the active power generated by each generator is limited by the upper and lower limits. These restrictions in the generation limits are expressed by

$$P_{\min,i} \le P_i \le P_{\max,i} \tag{12.23}$$

  where P_i is the output power of the generator, $i, P_{\min,i}$ is the minimum power of the generator, i, and $P_{\max,i}$ is the maximum generator power.

- An inequality constraint in terms of fuel supply

At each time interval the amount of fuel supplied to each generator F_{im} must be within its lower limit, $F_i^{\min}$, and its upper limit, $F_i^{\max}$, [59] such that

$$F_i^{\min} \le F_{im} \le F_i^{\max}, \quad i \in N, \ \ m \in M \tag{12.24}$$

where F_{im} is the fuel supplied to the engine in the interval m, $F_i^{\min}$ is the minimum quantity of fuel supplied to the machine, $F_i^{\max}$ is the maximum quantity of fuel supplied to the machine.

- An inequality constraint in terms of fuel storage limits

Each unit of fuel storage volume in each interval, V_{im}, should be within its lower limit, $V_{\min}$, and the upper limit, $V_{\max}$, [59] so that

$$V_{\min} \le V_{im} \le V_{\max} \tag{12.25}$$

$$V_{im} = V_{(m-1)} + F_{im} - t_m\left[\eta_i + \delta_i P_i + \mu_i P_i^2\right] \quad i \in N, \ \ m \in M \tag{12.26}$$

where $\eta_i, \delta_i,$ andμ_i are the fuel consumption coefficients for each generating unit.

Although a strong review in the literature is made on the restrictions of emissions comparing them with a ceiling which cannot be achieved, there were no mathematical expressions of equal or unequal restriction emissions.

12.3.1.4 Objective functions

The objective function used to minimize the cost of fuel was expressed in Eq. (12.9). It is important to note that to apply this equation; the coefficients $a_i, b_i,$ andc_i of each engine were first calculated by putting all the engines of power plants operating at different power values, which result in the power curve versus the cost of each engine. Subsequently, regression equation methods and their respective coefficients were obtained.

The function used to minimize the emission index is given by the following equation:

$$I_{em}(P_i) = \sum_{i=1}^{n} \left(d_i + e_i P_i + f_i P_i^3\right) \ \ \mathrm{mg/m^3} \tag{12.27}$$

where $d_i, e_i,$ andf_i are the coefficients of the characteristics of the emission index for each unit.

12.3.2 Order environmental economic load: case studies

12.3.2.1 Problem formulation

Two plants to the case studies were chosen to examine the feasibility of the proposed solution; we used a set of 10 thermal generating units of TPP in

TABLE 12.10 Characteristic data of the case study of the plant generators.

Generator	c_i (\$/MW)	b_i (\$/W)	a_i (\$)	P_{min} (MW)	P_{max} (MW)
PG1	0.15247	38.53973	756.79886	0.76	3.36
PG2	0.10587	46.15916	451.32513	0.76	3.36
PG3	0.02803	40.3965	1049.9977	0.76	3.36
PG4	0.03546	38.30553	1243.5311	0.76	3.36
PG5	0.02111	36.32782	1658.5596	0.76	3.36
PG6	0.01799	38.27041	1356.6592	0.76	3.36
PG7	0.02682	45.27041	1260.6592	0.76	3.36
PG8	0.02700	46.27041	1266.6592	0.76	3.36
PG9	0.02754	47.27041	1287.6592	0.76	3.36
PG10	0.02799	48.27041	1290.6592	0.76	3.36

$$B_m = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\ 0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000014 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\ 0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.000036 & 0.000012 & 0.000012 & 0.000014 & 0.000015 \\ 0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\ 0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\ 0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\ 0.000020 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044 \end{bmatrix}$$

FIGURE 12.6 Symmetric matrix with the transmission loss coefficients.

the city of Manaus and the test system with 10 generating units [76]. The characteristics of the generators are shown in Table 12.10. For the determination of the coefficients, a_i, b_i, and c_i, a trial operation test was conducted by running generators for different powers and measuring the fuel consumed. Then the power curves versus fuel costs were plotted and a regression method was acquired. Demand for energy used was 20 MW in the case of 10 generators.

The transmission loss coefficients (B_m) are given by a square matrix of dimension $n \times n$, where n is the number of engines. The loss matrix B_m, for a plant with 10 units (all figures should be multiplied by e^{-2}), as shown in Fig. 12.6 having the symmetric matrix defined by the following: a square matrix, $S = [a_{ij}]$, is symmetric if and only if $S^T = S$. If $S = [a_{ji}]$ is a

TABLE 12.11 Emission coefficients for the 10 generators of the plant.

Generator	f_i [(Mg/m^3 h)/(MW)]	e_i [(Mg/m^3 h)/(MW)]	d_i (Mg/m^3 h)
PG1	0.00419	1.32767	73.85932
PG2	0.00419	0.32767	13.85932
PG3	0.00683	− 0.54551	40.2669
PG4	0.00683	− 0.54551	40.2669
PG5	0.00461	− 0.51116	42.89553
PG6	0.00461	− 0.51116	42.8955
PG7	0.00461	− 0.51116	42.8955
PG8	0.00461	− 0.51116	42.8955
PG9	0.00061	− 0.51116	10.8955
PG10	0.00461	− 0.51116	42.8955

All values are multiplied by e^{-2}.

symmetric matrix, the elements arranged symmetrically with respect to the main diagonal are equal, $a_{ij} = a_{ji}$. In this case the product of a square matrix S by its transpose S^T is also a symmetric matrix.

Table 12.11 shows the emission coefficient for 10 generators of the plant.

To develop the whole optimization process, NSGA-II was used, known as GA elitist ordination, and not dominated, which has the following characteristics [77,78]:

The multiobjective optimization problem [56,79], considered in this chapter is defined as

$$\text{Minimize}[F_1(P),\ \ F_2(P)] \tag{12.28}$$

where $F_1(P)$and$F_2(P)$ are the objective functions to be minimized over admissible decision set, that is, the vector P.

In this case the function $F_1(P)$ of Eq. (12.10) and the function $F_2(P)$ of Eq. (12.18) are used.

There are two stages to solve multiobjective problems: determining the set of nondominated solutions and selecting the best feasible solution. The execution procedure is explained in the following steps [79]:

Step-1: Power demand being supplied by the plant ($P_d = 20$ MW).
Step-2: The selection of the minimum number of more efficient generators that satisfy the active power demand.
Step-3: Set the parameters of the algorithm:
 Population size;
 Number of generations.

Step-4: Initialize the population, P_t.
Step-5: Create a young population or descendants Q_t of the current population P_t
Step-6: Combine the two populations Q_t and P_t to form R_t where $R_t = P_t \cup Q_t$.
Step-7: Find the nondominated Pareto fronts $F_i$andR_t.
Step-8: Start the new population $P_{t+1} = 0$ and the count for inclusion $i = 1$.
Step-9: While $P_{t+1} + F_i \leq N_{\text{pop}}$ do: $P_{t+1} \leftarrow P_{t+1} \cup F_i$, where $i \leftarrow i + 1$.
Step-10: Order the last front F_i using the distance agglomeration in descending order and choose the first elements $\left(N_{\text{pop}} - P_{t+1}\right)ofF_i$.
Step-11: Use the selection of operators, crossover, and mutation to create the young population or the descendants of the new population Q_{t+1}.

12.3.3 Analysis and discussion of results

The solution report presents the input parameters to run the program, such as the energy demand, the minimum and maximum power of the engines and the results of the total cost of fuel, total power loss, and optimal power for each machine in the plant to meet the load demand.

Table 12.12 shows the results of the case study of the plant located in the city of Manaus (first case study). These results were obtained after the execution of the program for a power demand of 20 MW.

As can be seen from Table 12.12, there is a certain difference between the levels of emission of generators, and the power demand is distributed among all generators with lower values assigned to the generators 2 and 10. It can also be seen that the power is not always the maximum power that is related to the maximum emission.

Table 12.13 shows the results for the case study of the IEEE test system [75]. These results were obtained after the execution of the program for a 1036 MW power demand, which is the power between the maximum and minimum power of this system. This system has 10 units.

As is shown in Table 12.13, there are some differences between the emission index of the engine test system.

This is mainly due to the power difference between the engines of this system. This also leads to different emission index of generators.

Fig. 12.7 shows the trade-off between emission index and the fuel cost of the first case study after the application of NSGA-II, generated by MATLAB.

Fig. 12.8 shows the trade-off between emission index and the fuel cost of the test system IEEE 118-bars after applying NSGA-II, generated by MATLAB.

TABLE 12.12 Nondominated sorting genetic algorithm II (NSGA-II) final programming of Manaus test system.

Solutions to environmental economic dispatch using NSGA-II			
Power demand		20 MW	
Minimum power		0.76 MW	
Maximum power		3.36 MW	
Power losses		0.135 MW	
Fuel cost		6684.72 \$/h	
Power values and each generator emission index			
Power (Pm_i)	MW	Emission index (Em_i)	g/m^3
Pm_1	1.72	Em_1	41.24
Pm_2	3.01	Em_2	42.96
Pm_3	2.35	Em_3	41.64
Pm_4	0.92	Em_4	43.37
Pm_5	0.76	Em_5	43.29
Pm_6	0.76	Em_6	43.29
Pm_7	0.76	Em_7	43.29
Pm_8	3.34	Em_8	44.78
Pm_9	3.02	Em_9	44.57
Pm_{10}	3.36	Em_{10}	43.12
Total	20.00	Total	431.55

Pm_i is the signed power of every ith generator and Em_i is the emission level of each ith generator.

Fig. 12.9 shows a comparison of the active power generator for each plant in the first case study where it can be seen that the generators (12.6)–(12.8) produce less power.

Fig. 12.10 shows the comparison graph of active power output of each generator to the test system.

Fig. 12.11 shows a graph comparing the cost of each generator of the first case study, in which it is noted that the highest cost is incurred by generators (12.9) and (12.10).

Fig. 12.12 shows the graph comparing the cost of each generation to the test system.

TABLE 12.13 Nondominated sorting genetic algorithm II (NSGA-II) Final Programming of IEEE test system.

Solutions to environmental economic dispatch using NSGA-II		
Power demand	1036 MW	
Minimum power	10 MW	
Maximum power	470 MW	
Power losses	0.0377 MW	
Fuel cost	55,485.25 $/h	
Power values and each generator emission index		
Power	MW	Emission index (g/m^3)
Un1	0	0
Un2	0	0
Un3	293.62	4,291,234.13
Un4	299.99	4,376,989.15
Un5	157.25	3,333,188.65
Un6	156.38	3,330,974.55
Un7	75.78	3,320,000.42
Un8	57.66	3,308,745.27

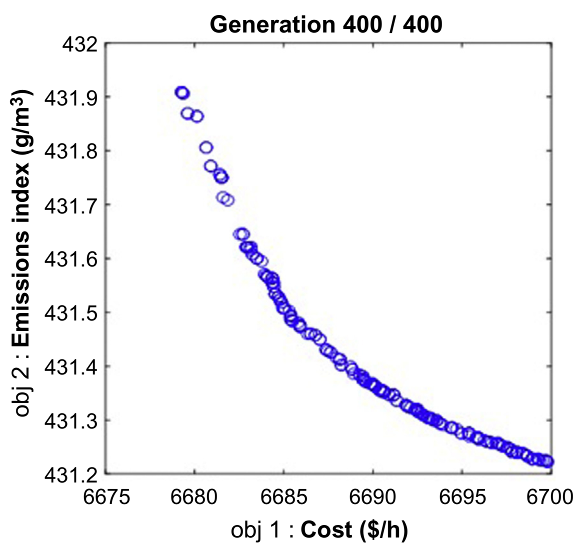

FIGURE 12.7 Trade-off between emission level and the cost of fuel after the application of the NSGA-II, 10 generator system. *NSGA-II*, Nondominated sorting genetic algorithm II.

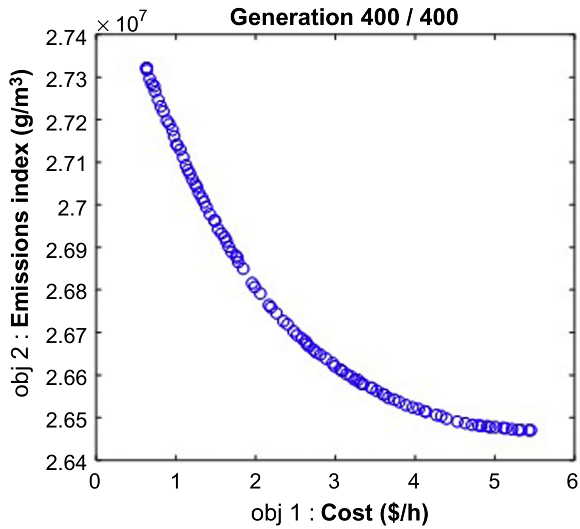

FIGURE 12.8 Trade-off between emission level and the cost of fuel after applying the NSGA-II for the test system 118-bars IEEE. *NSGA-II*, Nondominated sorting genetic algorithm II.

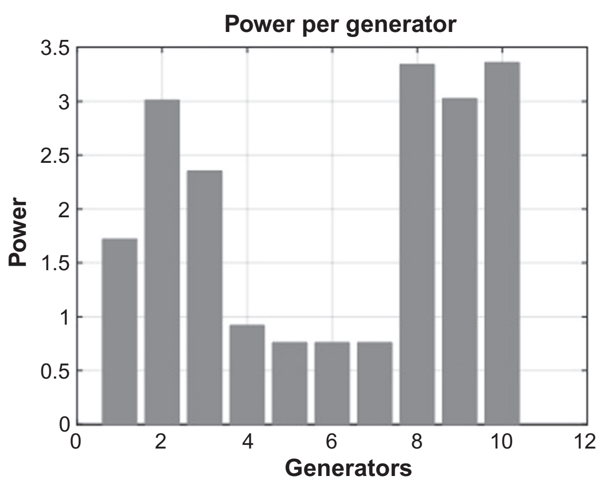

FIGURE 12.9 Power of each generator in the first case study.

Fig. 12.13 shows the comparison graph of the emission index of each generator of the first case study, and it was observed that generators (12.9) and (12.10) are generating the highest emission rates.

Fig. 12.14 shows a graph comparing the emission index of each generator to the test system where it can be seen the difference between the emission index of each generator according to their respective power.

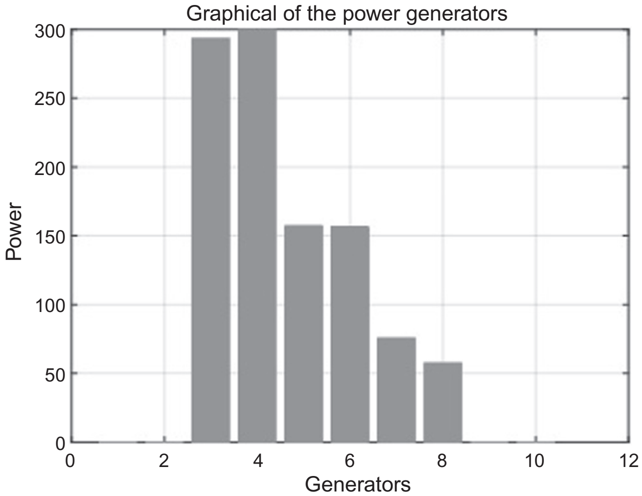

FIGURE 12.10 Output powers of the generator to the test system.

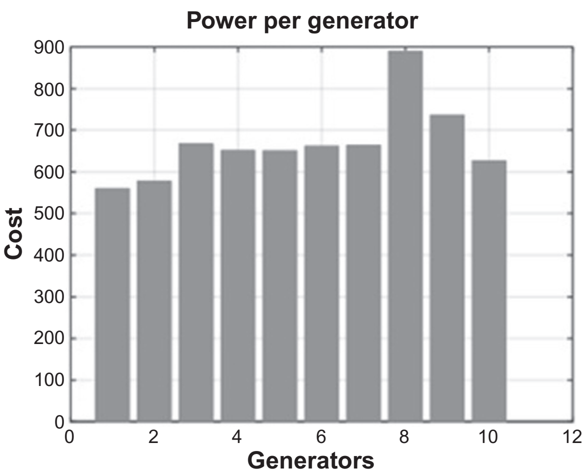

FIGURE 12.11 Generation costs of each generator of the first case study.

The developed procedure was applied satisfactorily to both cases in a TPP Manaus and testing system. These two cases were used to validate this approach.

In the case of the TPP, emission indexes are not so different as in the case of the 118-bus test system. It is widely known that this system of power generators is very different. In both the cases the power allocated to each generator corresponds to the values that guarantee the minimum cost of TPP and at the same time the minimum emission level is guaranteed.

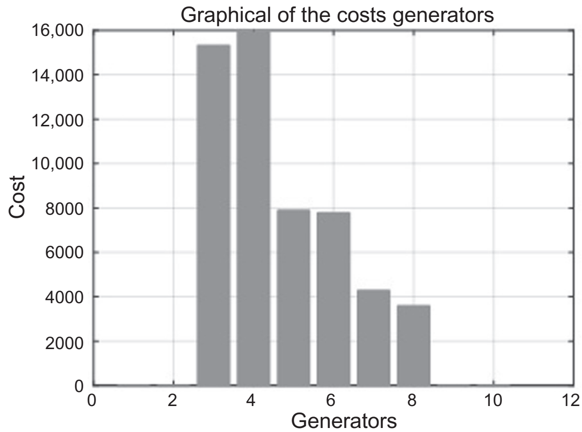

FIGURE 12.12 Cost of each generation to the test system.

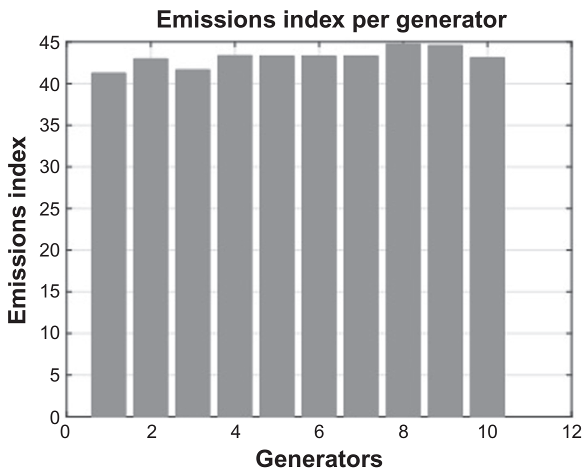

FIGURE 12.13 Generators of emission index of the first case study.

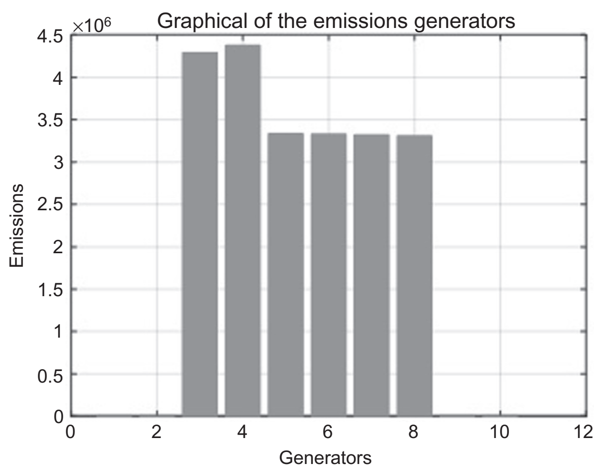

FIGURE 12.14 Issue of generators indexes for the test system.

12.4 Conclusions

The EED optimization problem in electric distribution systems is formulated as a multiobjective problem that considers the economic benefits in the operation of electric networks and the reduction of environmental pollution by inserting the emission index calculation on the system in relation to the minimization of the function emission index. In addition, the formulation presented considers the relevant restrictions imposed by Brazilian standards in relation to electrical and environmental specifications.

From the results obtained in this study, the model and mathematical method for the EED using EA NSGA-II tools reduce the cost of energy production from TPPs and environmental impact. The use of NSGA-II allows the computational tool to establish the solution to this formulation. It has determined the Pareto optimal solutions to the problem and allows the professional to determine the most effective solutions.

According to the analysis of the old EED in relation to the methodology used in this work forward, a new mathematical approach to assess emissions from generators and at the same time reducing the cost of fuel is a new possibility of identifying the different ways of evaluating the emissions produced by power plants, in relation to mathematical models with the implementation of computational tools to evaluate the economic and environmental variables, considering the permissibility of each pollutant in the atmosphere.

The mathematical procedure developed has been applied to the case study of a power-generating plant in the city of Manaus, Amazonas, and also to the test system. The relevant results of this study based on examples and practical analyses show the advantages and validate all developed procedures.

It was seen from the case study, the value of the emission index varies for different plant engines. Their values vary from 54 to 102 g/m^3 for maximum power.

The gas engine emission rate in the mill case study is quite different from all the engines of the plant. Furthermore, gas engines emit particulate matter, something that, according to the literature, is not permissible. In the indicated situation, due to technical conditions of gas engines, a huge number of burning oil particles are mixed with gas and so exist in the exhaust gas.

In the case of HFO engines, the emission index difference among various engines is not as significant as in the case of gas engines. It can be seen that, in general, the HFO engines have a specific emission index lower than that of gas engines, that is, engines emit less pollutants HFO in relation to the power they deliver. For the 10-engine test system, the results showed a discrepancy among emission levels in relation to the characteristics of the respective generators as the power supplied.

An extensive literature review of the EED was presented, among which numerous techniques solve the problem in reducing emissions due to power generation. However, all the techniques for this purpose were searched for a solution that requires less investment to run, which is ED with minimal emissions.

A new methodology was developed to evaluate the environmental pollution caused by a TPP. This method, unlike the other ones in the literature, does not assign a cost value to emissions but use a general index that considers not only the cost but also the impacts on the environment caused by the production. To make comparisons among different engines and fuels, the concept of specific emission index was developed, which is simply the emission index divided by the power generated by each engine.

The results of the current study, considering the emission index and using the NSGA-II optimization procedure, were significant and can be applied to any TPP that makes the use of the new approach possible to give support to professionals in the field to reduce the cost and emission involved in generation.

References

[1] A.I.S. Kumar, K. Dhanushkodi, J.J. Kumar, C.K.C. Paul, Particle swarm optimization solution to emission and economic dispatch problem, in: Paper Presented at the IEEE Conference Tencon, 2003.

[2] A. Vourc'h, M. Jimenez, Enhancing environmentally sustainable growth in Finland, in: OECD Economics Department Working Papers, No. 229, 2000, OECD Economics Department Working Papers, Finland, 2000.

[3] L. Albright, Albright's Chemical Engineering Handbook, CRC Press, 2008.

[4] P.R. Arévalo, Optimización del diseño y rediseño de procesos químicos complejos bajo incertidumbre mediante cooperación de técnicas de programación matemática y metaheurísticas, Universidad Politécnica de Madrid, 2005.

[5] N. Aversano, T. Temperini, El Calentamiento Global: Bonos de Carbono, una alternativa. Modelización y Simulación de Sistemas Económicos, 2006. Available from: <https://www.ingenieriaquimica.org/articulos/bonos_de_carbono>.

[6] A.K. Awopone, A.F. Zobaa, W. Banuenumah, Techno-economic and environmental analysis of power generation expansion plan of Ghana, Energy Policy 104 (2017) 13−22. Available from: https://doi.org/10.1016/j.enpol.2017.01.034.

[7] J.F. Bard, Short-term scheduling of thermal-electric generators using Lagrangian relaxation, Oper. Res. 36 (5) (1988) 756−766.

[8] M. Basu, A simulated annealing-based goal-attainment method for economic emission load dispatch of fixed head hydrothermal power systems, Int. J. Electr. Power Energy Syst. 27 (2) (2005) 147−153.

[9] M. Basu, Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II, Int. J. Electr. Power Energy Syst. 30 (2) (2008) 140−149.

[10] M. Basu, Economic environmental dispatch using multi-objective differential evolution, Appl. Soft Comput. 11 (2) (2011) 2845−2853. Available from: https://dx.doi.org/10.1016/j.asoc.2010.11.014.

[11] M. Basu, Fuel constrained economic emission dispatch using nondominated sorting genetic algorithm-II, Energy 78 (0) (2014) 649−664. Available from: https://dx.doi.org/10.1016/j.energy.2014.10.052.

[12] C. Palanichamy, N.S. Babu, Day-night weather-based economic power dispatch, IEEE Trans. Power Syst 17 (2) (2002) 469−475.

[13] J.C.O. Carretero, D.G. Cánovas, F.D.Q. Pereira, Técnicas Heurísticas para Problemas de Diseño en Telecomunicaciones, 2008.

[14] J.P.S. Catalao, S.P.S. Mariano, V.M.F. Mendes, L.A.F.M. Ferreira, Profit-based unit commitment with emission limitations: a multiobjective approach, Power Tech. (2007). 1417−1422.

[15] S. Chaturvedi, Right to Pollute? An Understanding on the Implications of International Carbon Trading Market, 2014.

[16] F. Chen, J. Zhou, C. Wang, C. Li, P. Lu, A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching, Energy 121 (2017) 276−291. Available from: https://doi.org/10.1016/j.energy.2017.01.010.

[17] Conama, Padroes de Qualidade do ar. Portal Saude., 2017. Available from: <https://portal.saude.gov.br/portal/arquivos/pdf/conama_03_90_padroes_de_qualidade_do_ar.pdf>, 1990 (retrieved 01.01.17).

[18] R. Conama, 357, de 17 de Março de 2006. Conselho Nacional do Meio Ambiente-CONAMA, 357, 2006.

[19] J. Curtis, M.Á. Lynch, L. Zubiate, Carbon dioxide (CO_2) emissions from electricity: the influence of the North Atlantic Oscillation, Appl. Energy 161 (2016) 487−496. Available from: https://doi.org/10.1016/j.apenergy.2015.09.056.

[20] N. Daryani, K. Zare, Multiobjective power and emission dispatch using modified group search optimization method, Ain Shams Eng. J. (2015). Available from: https://doi.org/10.1016/j.asej.2016.03.001.

[21] E. Delarue, K. Van den Bergh, Carbon mitigation in the electric power sector under cap-and-trade and renewables policies, Energy Policy 92 (2016) 34−44. Available from: https://doi.org/10.1016/j.enpol.2016.01.028.

[22] D. Ashish, D. Arunesh, P. Surya, A.K. Bhardwaj, A traditional approach to solve economic load dispatch problem of thermal generating unit using MATLAB programming, Int. J. Eng. Res. Technol. (IJERT) 2 (9) (2013) 3147−3152.

[23] J. Dhillon, S.K. Jain, Multi-objective generation and emission dispatch using NSGA-II, IACSIT Int. J. Eng. Technol. 3 (5) (2011) 460.

[24] J. English, T. Niet, B. Lyseng, K. Palmer-Wilson, V. Keller, I. Moazzen, et al., Impact of electrical intertie capacity on carbon policy effectiveness, Energy Policy 101 (2017) 571−581. Available from: https://doi.org/10.1016/j.enpol.2016.10.026.

[25] B.A.D. Fernández, K. Dowsland, Diseño de heurísticas y fundamentos del recocido simulado, Inteligencia Artif.: Rev. Iberoam. Inteligencia Artif. 7 (19) (2003) 93−102.

[26] C.A. Floudas, Deterministic Global Optimization: Theory, Methods and Applications, vol. 37, Springer Science & Business Media, 2013.

[27] L.L. Garver, Power generation scheduling by integer programming—development of theory, IEEE Trans. Power Apparatus Syst. PAS 82 (3) (1963) 730−735.

[28] A. Ghasemi, M. Gheydi, M.J. Golkar, M. Eslami, Modeling of Wind/Environment/Economic Dispatch in power system and solving via an online learning meta-heuristic method, Appl. Soft Comput. 43 (2016) 454−468. Available from: https://doi.org/10.1016/j.asoc.2016.02.046.

[29] G. Grande-Acosta, J. Islas-Samperio, Towards a low-carbon electric power system in Mexico, Energy Sustain. Dev. 37 (2017) 99−109.

[30] G. Granelli, M. Montagna, G. Pasini, P. Marannino, Emission constrained dynamic dispatch, Electr. Power Syst. Res. 24 (1) (1992) 55−64.
[31] D.W. Green, Perry's Chemical Engineering Handbook, McGrawHill Professional Publ, 2007.
[32] H.Y. Yamin, Q. Ei-Dwairi, S.M. Shahidehpour, A new approach for GenCos profit based unit commitment in day-ahead competitive electricity markets considering reserve uncertainty, Electr. Power Energy Syst. 29 (2007) 609−616.
[33] B. Hassler, B.C. Mcdonald, A. Borbon, K. Civerolo, C. Granier, G.J. Frost, et al., The application of long-term observations of NO_x and CO to constrain a global emissions inventory, in: Paper Presented at the IGAC 2016 Science Conference (International Global Atmospheric Chemistry), 2016.
[34] J.S. Holladay, J. LaRiviere, The impact of cheap natural gas on marginal emissions from electricity generation and implications for energy policy, J. Environ. Econ. Manage. 85 (2017) 205−227. Available from: https://doi.org/10.1016/j.jeem.2017.06.004.
[35] B. Hong, E. Slatick, Carbondioxide emission factors for coal, Q. Coal Rep. (1994) 7.
[36] I. Kockar, A. Conejo, R. Mcdonald, Influence of the emissions trading scheme on generation scheduling, Electr. Power Energy Syst. 3 (1) (2009) 465−473.
[37] L. Jebaraj, C. Venkatesan, I. Soubache, C.C.A. Rajan, Application of differential evolution algorithm in static and dynamic economic or emission dispatch problem: a review, Renew. Sustain. Energy Rev. 77 (2017) 1206−1220. Available from: https://doi.org/10.1016/j.rser.2017.03.097.
[38] X. Jiang, J. Zhou, H. Wang, Y. Zhang, Dynamic environmental economic dispatch using multiobjective differential evolution algorithm with expanded double selection and adaptive random restart, Int. J. Electr. Power Energy Syst. 49 (2013) 399−407.
[39] A.M. Jubril, O.A. Olaniyan, O.A. Komolafe, P.O. Ogunbona, Economic-emission dispatch problem: a semi-definite programming approach, Appl. Energy 134 (2014) 446−455.
[40] M.P. Kasmaei, Despacho ótimo de potências ativa e reativa de sistema elétricos multiáreas considerando restrições físicas, econômicas e ambientais = : environmentally constrained active-reactive optimal power flow-a compromising strategy for economic-emission dispatch and a multi-area paradigm, 2015.
[41] A.G. Kök, K. Shang, S. Yücel, Impact of electricity pricing policies on renewable energy investments and carbon emissions, Manage. Sci. 64 (2016) 1−493.
[42] E.T. Lau, Q. Yang, G.A. Taylor, A.B. Forbes, P.S. Wright, V.N. Livina, Optimisation of costs and carbon savings in relation to the economic dispatch problem as associated with power system operation, Electr. Power Syst. Res. 140 (2016) 173−183. Available from: https://doi.org/10.1016/j.epsr.2016.06.025.
[43] Y. Li, M. Li, Q. Wu, Energy saving dispatch with complex constraints: prohibited zones, valve point effect and carbon tax, Int. J. Electr. Power Energy Syst. 63 (2014) 657−666.
[44] X. Liu, B. Lin, Y. Zhang, Sulfur dioxide emission reduction of power plants in China: current policies and implications, J. Cleaner Prod. 113 (2016) 133−143. Available from: https://doi.org/10.1016/j.jclepro.2015.12.046.
[45] G. Lobos, O. Vallejos, C. Caroca, C. Marchant, El Mercado de los Bonos de Carbono ("bonos verdes"): Una Revisión, RIAT, 1 (1) (2005).
[46] X. Ma, Y. Wang, C. Wang, Low-carbon development of China's thermal power industry based on an international comparison: review, analysis and forecast, Renew. Sustain. Energy Rev. 80 (2017) 942−970. Available from: https://doi.org/10.1016/j.rser.2017.05.102.

[47] N.M. Moraes, Modelo matemático para otimização multiobjetivo do despacho econômico ambiental de usinas térmicas usando o NSGA-II. UNIVERSIDADE FEDERAL DO PARÁ INSTITUTO DE TECNOLOGIA PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA, 2017.

[48] E. Muela, J. Secue, Environmental economic dispatch with fuzzy and possibilistic entities, Rev. Fac. Ingeniería 59 (2012) 227−236.

[49] M. Muslu, Economic dispatch with environmental considerations: tradeoff curves and emission reduction rates, Electr. Power Syst. Res. 71 (2) (2004) 153−158.

[50] N. Mustafa-Moraes, U. Holanda-Bezerra, J.L. Moya-Rodríguez, J. Cabral-Leite, The emission index as a parameter for assessing the environmental pollution from thermal power plants. Case study, Dyna 83 (199) (2016) 218−224.

[51] R. Muthuswamy, M. Krishnan, K. Subramanian, B. Subramanian, Environmental and economic power dispatch of thermal generators using modified NSGA-II algorithm, Int. Trans. Electr. Energy Syst. 25 (8) (2015) 17.

[52] E. Naderi, A. Azizivahed, H. Narimani, M. Fathi, M.R. Narimani, A comprehensive study of practical economic dispatch problems by a new hybrid evolutionary algorithm, Appl. Soft Comput. (2017). Available from: https://doi.org/10.1016/j.asoc.2017.06.041.

[53] N.I. Nwulu, X. Xia, Multi-objective dynamic economic emission dispatch of electric power generation integrated with game theory based demand response programs, Energy Convers. Manage. 89 (0) (2015) 963−974. Available from: https://dx.doi.org/10.1016/j.enconman.2014.11.001.

[54] I. Pavic, T. Capuder, I. Kuzle, Low carbon technologies as providers of operational flexibility in future power systems, Appl. Energy 168 (2016) 724−738. Available from: https://doi.org/10.1016/j.apenergy.2016.01.123.

[55] B. Purkayastha, N. Sinha, Optimal combined economic and emission load dispatch using modified NSGA-II with adaptive crowding distance, Int. J. Inform. Technol. Knowl. Manage. 2 (2) (2010) 553−559.

[56] B.Y. Qu, J.J. Liang, Y.S. Zhu, Z.Y. Wang, P.N. Suganthan, Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm, Inform. Sci. 351 (2016) 48−66. Available from: https://doi.org/10.1016/j.ins.2016.01.081.

[57] B.Y. Qu, Y.S. Zhu, Y.C. Jiao, M.Y. Wu, P.N. Suganthan, J.J. Liang, A survey on multi-objective evolutionary algorithms for the solution of the environmental/economic dispatch problems, Swarm Evol. Comput. (2017). Available from: https://doi.org/10.1016/j.swevo.2017.06.002.

[58] I.J. Raglend, S. Veeravalli, K. Sailaja, B. Sudheera, D.P. Kothari, Comparison of AI techniques to solve combined economic emission dispatch problem with line flow constraints, Electr. Power Energy Syst. 32 (2010) 592−598.

[59] N.G. Rahul Dogra, H. Saroa, Economic load dispatch problem and Matlab programming of different methods, in: International Conference of Advance Research and Innovation (ICARI-2014), 2014.

[60] A. Rajan, T. Malakar, Optimum economic and emission dispatch using exchange market algorithm, Int. J. Electr. Power Energy Syst. 82 (2016) 545−560. Available from: https://doi.org/10.1016/j.ijepes.2016.04.022.

[61] S. Rebennack, B. Flach, M.V. Pereira, P.M. Pardalos, Stochastic hydro-thermal scheduling under CO_2 emissions constraints, IEEE Trans. Power Syst. 27 (1) (2012) 58−68.

[62] P.T. Rodríguez-Piñero, Introducción a los algoritmos genéticos y sus aplicaciones: Universidad Rey Juan Carlos, Servicio de Publicaciones, 2003.

[63] S. Sahoo, K. Mahesh Dash, R.C. Prusty, A.K. Barisal, Comparative analysis of optimal load dispatch through evolutionary algorithms, Ain Shams Eng. J. 6 (1) (2015) 107−120. Available from: https://dx.doi.org/10.1016/j.asej.2014.09.002.

[64] K. Sastry, D.E. Goldberg, G. Kendall, Genetic Algorithms Search Methodologies, Springer, 2014, pp. 93−117.

[65] S. Sayah, A. Hamouda, A. Bekrar, Efficient hybrid optimization approach for emission constrained economic dispatch with nonsmooth cost curves, Int. J. Electr. Power Energy Syst. 56 (2014) 127−139.

[66] D.C. Secui, A new modified artificial bee colony algorithm for the economic dispatch problem, Energy Convers. Manage. 89 (2015) 43−62.

[67] P.K. Sharma, C.P. Verma, Carbon Credit Accounting. Dear Academicians & Research Scholars, Journal of Management Value & Ethics consistently stepping up towards their target groups day by day. Our Journal published many research papers from across the world, some of them from USA, Thailand, Indonesia, Saudi Arabia and other counties. Some of the most renowned academic personalities from USA, Uzbekistan, 2013.

[68] R. Sivaraj, T. Ravichandran, A review of selection methods in genetic algorithm, Int. J. Eng. Sci. Technol. 1 (3) (2011) 3792−3797.

[69] W.L. Snyder, H.D. Powel, J.C. Rayburn, Dynamic programming approach to unit commitment, IEEE Trans. Power Syst. 2 (2) (1987) 339−350.

[70] J. Talaq, F. El-Hawary, M. El-Hawary, A summary of environmental/economic dispatch algorithms, IEEE Trans. Power Syst. 9 (3) (1994) 1508−1516.

[71] V.L. Toache, J.R. Amado, G.T. Bertollini, S.G. Sánchez, Bonos de carbono: financiarización del medioambiente en México Carbon credits: Mexico's environment financialization, Estud. Soc. Rev. Alimentación Contemp Desarrollo Reg. 25 (47) (2016) 189−214.

[72] D.G. Victor, J.C. House, S. Joy, A Madisonian approach to climate policy, Science 309 (5742) (2005) 1820−1821.

[73] K. Wang, Y.-M. Wei, Z. Huang, Potential gains from carbon emissions trading in China: a DEA based estimation on abatement cost savings, Omega 63 (2016) 48−59.

[74] L. Wang, C. Singh, Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm, Electr. Power Syst. Res. 77 (12) (2007) 1654−1664. Available from: https://dx.doi.org/10.1016/j.epsr.2006.11.012.

[75] T. Yalcinoz, H. Altun, Environmentally constrained economic dispatch via a genetic algorithm with arithmetic crossover, in: Paper Presented at the African Conference in Africa, IEEE AFRICON, Sixth, 2002.

[76] X. Yuan, H. Tian, Y. Yuan, Y. Huang, R.M. Ikram, An extended NSGA-III for solution multi-objective hydro-thermal-wind scheduling considering wind power cost, Energy Convers. Manage. 96 (2015) 568−578.

[77] R. Zhang, J. Zhou, L. Mo, S. Ouyang, X. Liao, Economic environmental dispatch using an enhanced multi-objective cultural algorithm, Electr. Power Syst. Res. 99 (2013) 18−29.

[78] Y. Zhang, D.-W. Gong, Z. Ding, A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch, Inform. Sci. 192 (2012) 213−227.

[79] Z. Zhu, J. Wang, M.H. Baloch, Dynamic economic emission dispatch using modified NSGA-II, Int. Trans. Electr. Energy Syst. (2016). Available from: https://doi.org/10.1002/etep.2228.