Best Suitable Cogeneration Power for Factories from Multi-Objective Data Analysis

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Abstract: *The cogeneration systems in the industrial sector have become an essential part due to their global efficiency and reduced pollution. These systems may operate from conventional fuel sources, as well as from renewable energy sources (biomass, solar, fuel cell).*

Cogeneration systems could be installed as a distributed generation and on-site generation source in order to take advantage from the produced heat. The utility can motivate factories to install such systems by permitting them to link and sell their residual production capacity to the electrical grid.

This work presents a new technique to find the best solution from multi-objective optimization results, using a sensitivity and data analysis method. Genetic Algorithm (GA) optimization method is used with the data analysis method: Multiple Linear Regression (MLR).

Keywords: *Combined Heat and Power (CHP), energy management, Genetic Algorithm (GA), sensitivity analysis, multiple linear regression.*

1. Introduction

Cogeneration or CHP (Combined Heat and Power) is defined by the simultaneous production of electric power and heat. The cogeneration system consists normally of a prime mover, a generator, a heat recovery system and electrical interconnections. Its thermal power is produced from the heat released by the fuels combustion in the system.

When compared to a separated conventional generation system with efficiency about 58%, the cogeneration system efficiency is much more than 85% (Fig. 1). Then the integration of these systems is economically and environmentally viable.

A cogeneration system may operate from conventional fuel sources, as well as from renewable energy sources (biomass, solar, fuel cell).

Cogeneration is installed as distributed generation and on-site generation to profit from the produced heat. In fact, it is good to invest in such systems in the factories because of the utility support that can be translated by permitting them to link their residual production capacity to the electrical grid.

In the previous works, T s a y et al. [1] have calculated the power that must be imported to get the minimum production cost and the power that must be imported to get the minimum polluting emissions. They have proposed a dispatch strategy that could be suitable for the decision makers. In [2] and [3] they have also considered the environmental constraints. They have calculated the optimal costs during peak, semi-peak and off-peak periods in [2]. In [3] they deduced that a minimum production cost corresponds to maximum pollution and conversely. F r a n g o p o u l o s et al. [4] have used the Genetic Algorithm (GA) with sensitivity analysis to find the number of cogeneration systems to be installed for given capacities, without considering the environmental issues. In fact, the systems capacities were specified, so they only selected the systems quantity. In F u r u s a w a et al. [5] have studied the production cost under environmental constraints. They deduced that even if the installed cogeneration systems are large, they are always efficient in reducing the primary energy consumption and the polluting emissions (CO_2). F r e s c h i et al. [6] have found trade-off solutions by applying the weighted sum method on the economic and the environmental assessments.

As shown in the previous works, there is not a clear viewpoint of concerning the best power to be installed when having environmental constraints. In this work the goal is to find the best suitable cogeneration capacity to be installed in a factory considering the environmental constraints. The multi-objective optimization is executed using the GA method, and the best result selection is performed using the sensitivity analysis method: the Multiple Linear Regression (MLR).
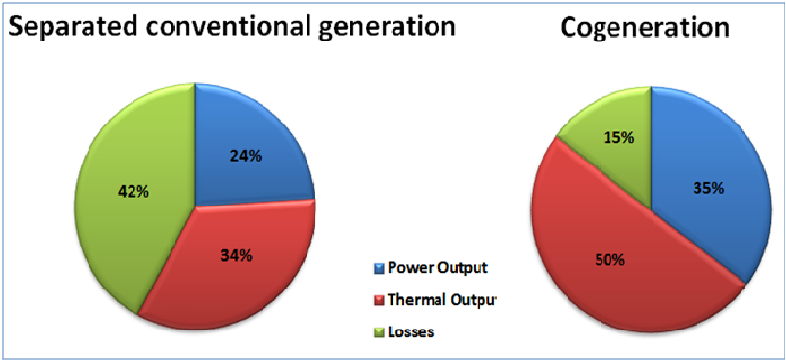

Fig. 1. Efficiency comparison between separated conventional generation and cogeneration

In Section 2 the mathematical models will be settled. In Section 3 we will represent the multi-objective optimization and the main factors. In Section 4 the sensitivity analysis method will be discussed. Finally, in Section 5 we will discuss and analyze the results obtained.

2. Mathematical formulation

In this section, the mathematical models are presented and discussed as objective functions.

These objective functions represent the economic and environmental issues.

2.1. Economic objective function

The economic objective function corresponds to the total of cogeneration systems integration into a smart-grid.

The total cost function to be minimized is presented by

(1)
$$F_{\text{total}} = \sum_{j=1}^{N}\left(H_b c_j\right) - \sum_{j=1}^{N} t_j\, a_j + \sum_{j=1}^{N} \alpha_j c_{mj} -$$

$$- \left(\sum_{j=1}^{N}\left(Pt_j - E_{j\,\text{load}}\right)\left[\max\left(Pt_j - E_{j\,\text{load}}, 0\right)\left(\frac{n-1}{Pt_j - E_{j\,\text{load}}}\right) + 1\right]\right)\text{tariff} +$$

$$+ \text{InvCost} + \sum_{j=1}^{N}\left(Pt_j - E_{j\,\text{load}}\right) c_t,$$

with:

$$\sum_{j=1}^{N} t_j\, a_j + \sum_{j=1}^{N} \alpha_j c_{mj} -$$

$$- \left(\sum_{j=1}^{N}\left(Pt_j - E_{j\,\text{load}}\right)\left[\max\left(Pt_j - E_{j\,\text{load}}, 0\right)\left(\frac{n-1}{Pt_j - E_{j\,\text{load}}}\right) + 1\right]\right)\text{tariff} =$$

$$= \text{Exchanged energy cost,}$$

$\sum_{j=1}^{N}\left(H_b c_j\right) = $ Produced energy cost;

$\sum_{j=1}^{N} \alpha_j c_{mj} = $ Maintenance cost;

$\sum_{j=1}^{N} t_j\, a_j = $ Attrition cost;

$\sum_{j=1}^{N}\left(Pt_j - E_{j\,\text{load}}\right) c_t = $ Transmission cost;

N.B: $\max\left(Pt_j - E_{j\,\text{load}}, 0\right)\left(\frac{n-1}{Pt_j - E_{j\,\text{load}}}\right) + 1 = 1$ or n.

Thus:

$$F_{\text{total}} = \text{Produced energy cost} - \text{Exchanged energy cost} + \text{Maintenance cost}$$
$$- \text{Attrition cost} + \text{Investment cost} + \text{Transmission cost.}$$

2.2. Notations

N – number of time intervals;

P – power produced by the cogeneration system, MW;

$(P = P_{\text{electrical}} + P_{\text{thermal}})$;

t_j – production time of the cogeneration system at j-th time interval, h;

$E_{j\,\text{load}}$ – load demand at j-th time interval, MW.h;

tariff – electricity tariff, € per 1 MW.h;

n – incentive or motivation factor when consumer sells the utility (usually $1 \leq n \leq 4$);

H_b – fuel enthalpy in the boiler of the cogeneration system, MW.h;

$P = P_\text{thermal} + P_\text{electrical}$ or $H_\text{b} = Pt_j + \text{Losses}$;

c_j – fuel cost of the cogeneration system at j-th time interval, € per 1 MW.h;

α_j – deterioration factor of the cogeneration system at j-th time interval ($0 \leq \alpha \leq 1$; $\alpha = 0$ for ideal cogeneration system and $\alpha =1$ for damaged one);

c_{mj} – average maintenance cost of the cogeneration system at j-th time interval, €;

InvCost – Investment Cost of the cogeneration system (proportional to the Power), €;

a_j – attrition cost of the conventional extinct generator at j-th time interval due to cogeneration system integration, € per 1 h;

c_t – transmission cost, € per 1 MW.h;

D_j – pollution rate of fuel in the boiler of the system at j-th time interval, kg/(MW.h);

Dam_j – pollution due to Damaging of the system at j-th time interval, kg;

Pol_j – Pollution of the extinct generator at j-th time interval, kg/h.

2.3. Environmental objective function

The environmental objective function corresponds to the polluting emissions of the cogeneration systems integration into a smart-grid.

The polluting emissions function to be minimized is presented by:

(2) $\qquad F_\text{pollution} = \sum_{j=1}^{N}\left(H_\text{b}D_j\right) + \sum_{j=1}^{N} \alpha_j \text{Dam}_j - \sum_{j=1}^{N} t_j\, \text{Pol}_j,$

with:

$\sum_{j=1}^{N}\left(H_b D_j\right) = \text{fuel pollution}$;

$\sum_{j=1}^{N} \alpha_j \text{Dam}_j = \text{pollution due to system deterioration}$;

$\sum_{j=1}^{N} t_j\, \text{Pol}_j = \text{pollution due to conventional extinct generator}$,

thus:

$\qquad F_\text{pollution} = \text{Fuel pollution} + \text{Pollution due to system deterioration} -$
$\qquad\qquad - \text{Pollution due to conventional extinct generator}.$

3. Multi-objective optimization

The objective functions of the previous section are contradictory in terms of solutions. As mentioned in [3], the operational cost, which is related to the total cost, is inversely related to pollution. Thus, the system consisting of these two functions must be solved using a multi-objective optimization tool. For this reason, we chose the Genetic Algorithm (GA) multi-objective optimization method. The

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latter is applied using Matlab R2011b, on an Intel Core I7 PC with a CPU speed of 3.4 GHz.

3.1. What is multi-objective optimization?

Anyone might need to formulate problems with more than one objective, since a single objective with several constraints may not adequately represent the problem being faced. If so, there is a vector of objectives, $F(x) = [F_1(x), F_2(x), ... , F_m(x)]$, that must be traded off in some way. The relative importance of these objectives is not generally known until the system's best capabilities are determined and tradeoffs between the objectives are fully understood. As the number of objectives increases, the tradeoffs are likely to become complex and less easily quantified.

In our case, we have F(Power) = [Total_cost (Power), Polluting_emissions (Power)]. Thus we need to evaluate the system we are studying by its economic and environmental performance. In addition, we only have two objectives which means that we do not have the tradeoffs complexity problem.

3.2. Genetic algorithm

GA concept was developed by Holland and his colleagues in the 1960-ies and 1970-ies [7]. It is inspired by the evolutionist theory explaining the species origin [8].

The proposed GA procedure works through the following steps:
1) creation of a random initial population;
2) evaluation of the individuals and application of the penalty function method;
3) ranking of the individuals, calculation of the fitness and registration of the best individuals;
4) registration of all non-dominated individuals in the Pareto set filter operator;
5) selection of the pairs of individuals as parents;
6) crossover of the parents to generate the children;
7) replacement of the individuals using the niche operator;
8) genetic mutation;
9) replacement of the individuals using the elitism operator [9].

3.3. Elitist multi-objective Genetic algorithm

The multi-objective GA function uses a controlled elitist genetic algorithm (a variant of NSGA-II [10]).

In fact, a controlled elitist GA prefers individuals affecting the diversity increase of the population even if they have a lower fitness value, while an elitist GA always prefers individuals with better fitness value only. The diversity of population is maintained for convergence to an optimal Pareto front. This is done by controlling the elite members of the population as the algorithm progresses. Two options are used to control the elitism: "ParetoFraction" and "DistanceFcn". The Pareto fraction option limits the number of individuals on the Pareto front (elite members or best solutions), whereas the distance function option helps to maintain

diversity on a front by preferring individuals that are relatively far away on the front [11].

In our work we apply the GA to the economic and environmental functions simultaneously. We have on the Pareto front, individuals corresponding to a power for given values of the total cost and the polluting emissions.

Then we can deduce from this multi-objective optimization a set of proposals described by the triplet (Total_cost; Polluting_emissions; Power).

3.4. Integration levels

The multi-objective optimization is carried out considering two industrial energy levels. The first corresponds to an average energy level pharmaceutical factory. This has 77000 MWh as consumption (electrical + thermal) in the first year, and 76000 MWh in the second year. The second one corresponds to a high energy level paper mill which consumption is 200 000 MW.h (electrical + thermal) in the first year and 210 000 MW.h in the second year.

The study concerns two years of integration of the cogeneration systems with an average of 8000 hours of operation per year. Thus, the number of time intervals is $N = 2$. The data that will be obtained correspond to the functions values after two years of operation.

The inequality constraint concerning the first level is: $P \leq 15$ MW; 1 MW is the lower bound and 15 MW is the upper bound of $P = P_{\text{thermal}} + P_{\text{electrical}}$.

The inequality constraint concerning the second level is: $P \leq 50$ MW; 16 MW is the lower bound and 50 MW is the upper bound of $P = P_{\text{thermal}} + P_{\text{electrical}}$.

3.5. Main factors

The motivation factor n is considered equal to 2; it means that the factory sells the utility of its residual energy (electrical + thermal) at twice the tariff.

The efficiency of a cogeneration system is considered 85%, thus:
$$Pt_j = 0.85 H_{\text{b}} \implies H_{\text{b}} = \frac{Pt_{ij}}{0.85}.$$

- For the pharmaceutical factory, we have:
cm = [120 000; 130 000], €;
a = [15; 15], €per 1 h;
D = [300; 280] $\times 10^{-3}$, kg/(MW.h);
Dam = [2000; 2100] $\times 10^{-3}$, kg;
Pol = [75; 76] $\times 10^{-3}$, kg/h;

- For the paper mill, we have:
c_{m} = [200 000; 300 000], €;
a = [25; 25], €per 1 h;
D = [500; 480] $\times 10^{-3}$, kg/(MW.h);
Dam = [3000; 3100] $\times 10^{-3}$, kg;
Pol = [90; 96] $\times 10^{-3}$, kg/h;

- The other parameters for both factories are:

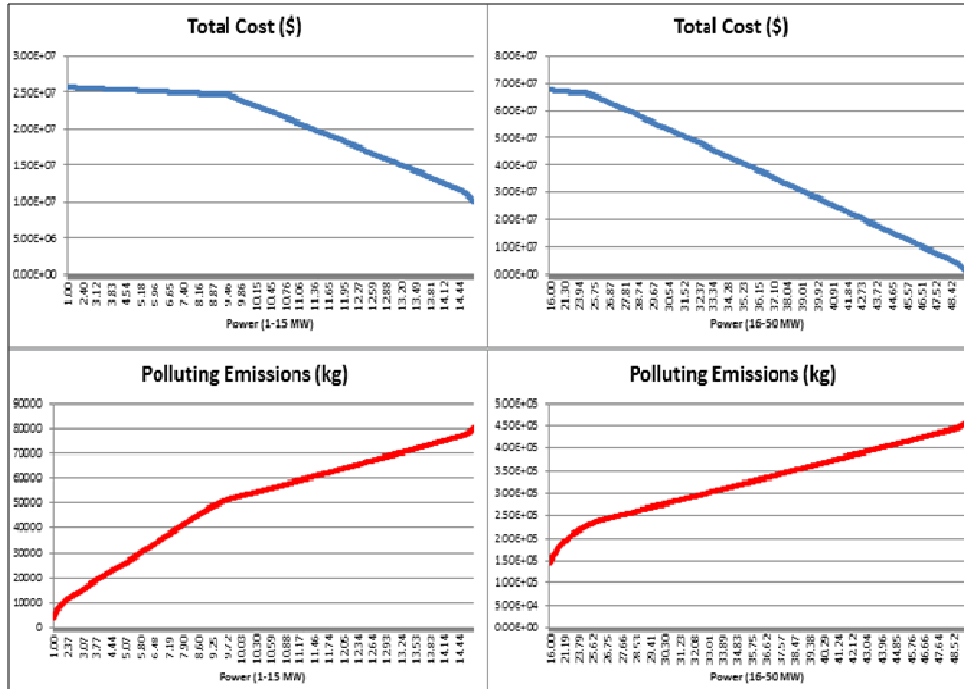c = [85; 90], €per 1 MW.h;

c_t = 10, €per 1 MW.h.

Fig. 2. Total cost vs. pollution variations in function of power

4. Data analysis

GA is a heuristic method; at each simulation the solution changes. Thus, the obtained solution is not guaranteed to be the best. The simulations number is then selected to be 1000 (i.e., 1000 solutions). And to select the best solution, we use the multiple linear regression (MLR) as a sensitivity analysis method.

4.1. Multiple linear regression

If we have two or more variables in a linear function, the MLR will be an excellent method to fit the data corresponding to the system [12].

In our work we have two correlated variables: the total $\text{cost}(x_1)$ and the pollution(x_2). The predicted value of the power function is $\hat{y}$. Then we have the MLR model:

$$(3) \qquad \hat{y} = \alpha_0 + \alpha_1 . x_1 + \alpha_2 . x_2 + \varepsilon.$$

The parameter α_0 is the intercept of the power. The parameters α_1 and α_2 are referred to as partial regression coefficients. Parameter α_1 represents the change in the mean response corresponding to a unit change in x_1 when x_2 is held constant.

Parameter α_2 represents the change in the mean response corresponding to a unit change in x_2 when x_1 is held constant. ε is the random error [13].

4.2. Data selection

The difference between the observed value of the dependent variable (y) and the predicted value ($\hat{y}$) is called a residual (e). Each data point has one residual.

$$(4) \qquad\qquad\qquad e = y - \hat{y},$$

$$\text{Residual} = \text{Observed value} - \text{Predicted value}.$$

In our work we consider the nearest observed value to the predicted one as the best solution. It means that the data point with the lowest residual value corresponds to the best power.

5. Results and discussions

After the multi-objective optimization, the sensitivity analysis was carried out for each data series. So we applied the MLR on the data in an Excel sheet. 10171 and 10268 observations were analyzed for the first and the second data series respectively, knowing that these values are distinct from each other because we removed the duplicates. The data number for each series is largely greater than the simulations number 1000, because of the different suggested solutions at each simulation (Pareto front).

Fig. 2 presents the variations of the total cost and the pollution in function of the power. As remarked, the total cost is inversely related to the power capacity while the pollution is directly related to it. In addition, the total cost corresponding to the highest power capacity (15 MW) in the pharmaceutical factory is widely smaller than that corresponding to the smallest power capacity (16 MW) of the paper mill. In fact, these values correspond to two years of integration of the cogeneration systems, thus it is the resulting cost after these two years. Particularly, if we compare the energy consumption for each factory we could realize that the exchanged energy cost is negative for the first one (i.e., benefits) and positive for the second one.

5.1. Multiple linear regression models

The MLR model of the first data series is:
$$\hat{y} = 0.22306 - 9.21590. 10^{-3}x_1 + 0.00019x_2 + 0.00022.$$
The MLR model of the second data series is:
$$\hat{y} = 0.16204 - 2.84781. 10^{-3}x_1 + 0.00011x_2 + 0.00043.$$

As mentioned in the previous section, the data point with the lowest residual value corresponds to the best power. The latter corresponds to the best compromise between the economic and environmental issues. In fact, the best economic performance corresponds to the highest power installed in both cases, because the energy produced will be greater than the energy demanded. Thus, the factory can sell its residual energy and have a lower total cost. Besides, the best pollution performance corresponds evidently to the lowest power installed.

Figs 3 and 4 represent the total cost and the polluting emissions fitting plots for the MLR, for the first and the second data series respectively.

5.2. Best suitable powers

Tables 1 and 2 represent the best residuals values for the first and the second data series respectively. Each residual value corresponds to a data point, particularly to a power (thermal+ electrical).

As shown in Table 1, the best nominal power to be installed in the pharmaceutical factory is 8.78 MW (3.62 MW electrical and 5.16 MW thermal). From Table 2 we can also deduce that the best nominal power for the paper mill is 45.54 MW (18.75 MW electrical and 26.79 MW thermal).
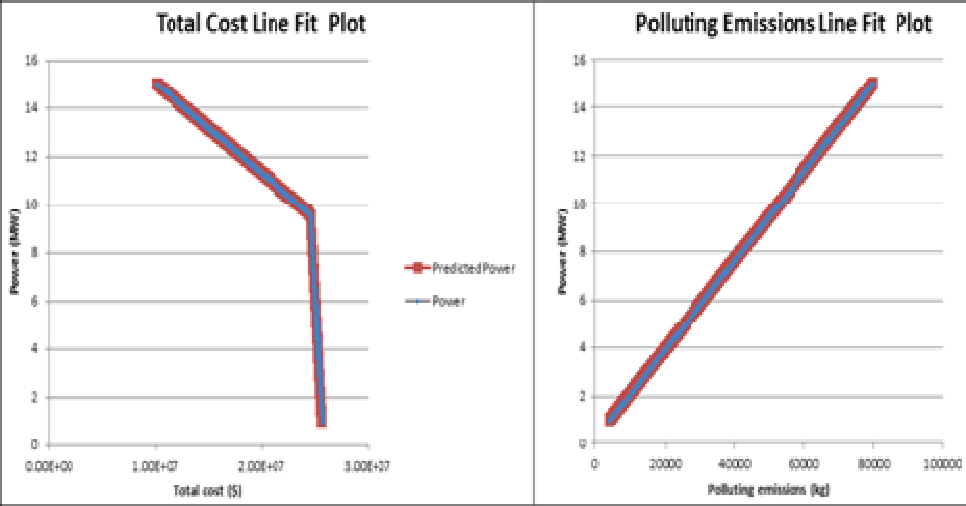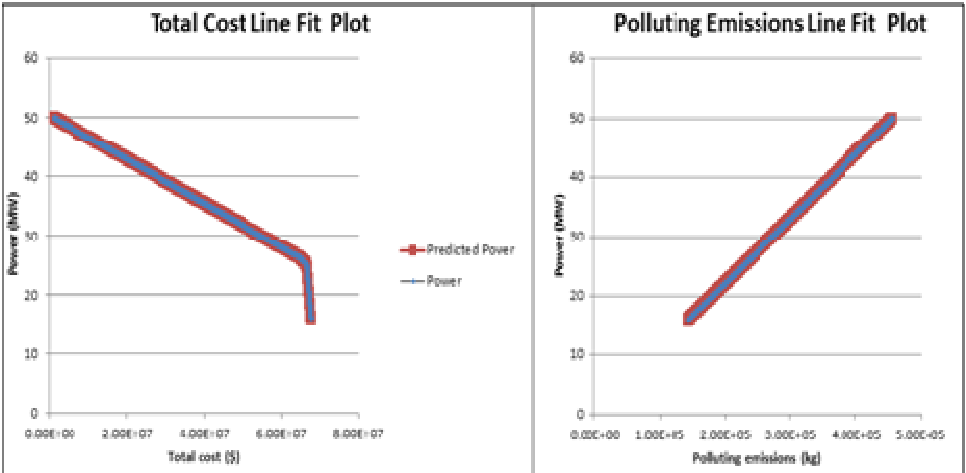

Fig. 3. Predicted power vs power (1-15 MW)

Fig. 4. Predicted power vs. power (16-50 MW)

Table 1. Best residuals values for the first data series

Predicted power (MW)	Residuals	Absolute value of residuals
8.781599931	6.92814×10^{-8}	6.92814×10^{-8}
9.99709993	7.04118×10^{-8}	7.04118×10^{-8}
8.586100095	-9.52529×10^{-8}	9.52529×10^{-8}
8.56910011	-1.0964×10^{-7}	1.0964×10^{-7}
3.387800136	-1.36326×10^{-7}	1.36326×10^{-7}
9.946099852	1.47978×10^{-7}	1.47978×10^{-7}

Table 2. Best residuals values for the second data series

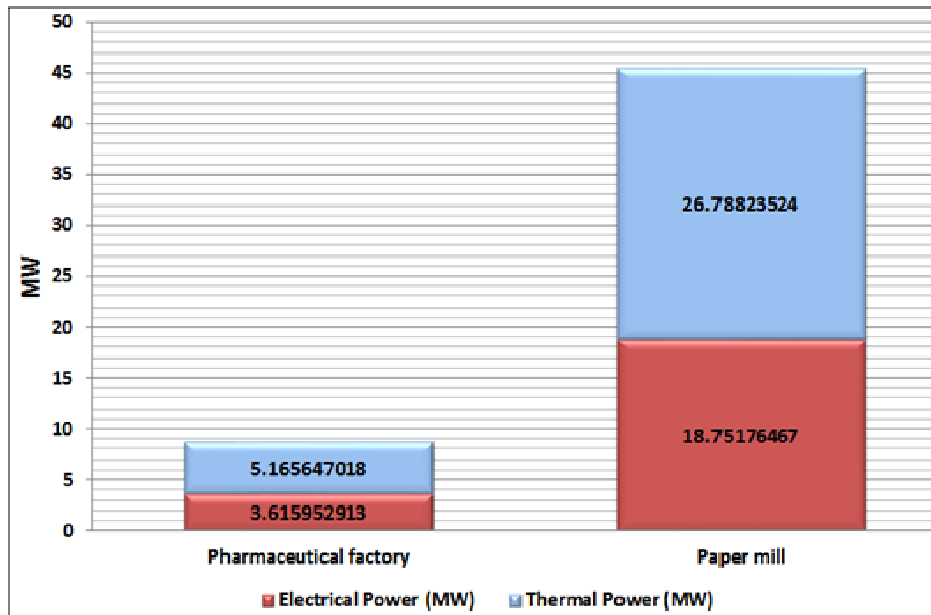| Predicted power (MW)	Residuals	Absolute value of residuals
45.5399999	9.3504×10^{-8}	9.3504×10^{-8}
44.9450001	-9.7538×10^{-8}	9.7538×10^{-8}
45.8799998	2.0251×10^{-7}	2.0251×10^{-7}
45.9649998	2.2976×10^{-7}	2.2976×10^{-7}
44.4350003	-2.6133×10^{-7}	2.6133×10^{-7}
44.2650003	-3.1612×10^{-7}	3.1612×10^{-7}

Fig. 5. Best electrical and thermal powers for the pharmaceutical factory and the paper mill

Fig. 5 represents the best suitable and nominal electrical and thermal powers to be installed in the pharmaceutical factory and the paper mill. The red blocks correspond to the electrical power and the blue blocks correspond to thermal power.

6. Conclusion

Nowadays the industrial sector depends more and more upon cogeneration systems due to their global efficiency and reduced pollution.

In this work we have presented a study concerning the optimized cogeneration capacities to be installed in a pharmaceutical factory and a paper mill. These two samples represent two different power levels from the industrial sector.

The main goal from this study is to find the best compromise between the economic and the environmental issues. The economic issues are related more and more to the environmental constraints due to the global warming and the climate change.

In this work, the optimized cogeneration capacity was calculated and selected using the Genetic algorithm multi-objective optimization method and the multiple linear regression as a sensitivity analysis method.

This study could be applied in many other sectors as it could be suitable for small industries and residential buildings.

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