Multi-Objective Optimization for CCHP Systems Based on Regressions Considering Economic and Environmental Aspects

Chawki Lahoud, Marwan Brouche, Jad Dakroub and Joseph Al Asmar
Saint Joseph University, ESIB, Beirut 2753, Lebanon

Corresponding Author:
Chawki Lahoud
Saint Joseph University, ESIB, Beirut 2753, Lebanon

Abstract: CHP (Combined Heating and Power) and CCHP (Combined Cooling, Heating and Power) systems defined by a high energy efficiency and a fewer polluting emissions in comparison to the separated energy generation leads to a high attention during the last decade. In order to combine these systems into a grid, the economic aspect and an environmental aspect must be studied. In this study, a multi-objective optimization is developed to study these aspects. This optimization is based on the economic and the environmental challenges of a trigeneration system that produces cooling, heating and electricity simultaneously. Due to the complexity of the system a Genetic algorithm is used to find the optimal solution. Then, a new decision-making strategy for the optimal power of the CCHP system that must be integrated in any sector based on Mathematical regressions is introduced. Different load levels were studied in order to demonstrate the effectiveness of this proposed optimization.

INTRODUCTION

During the last decades, the installation of CHP and CCHP systems is increasing because of their high efficiency and less polluting emissions. The cogeneration and trigeneration systems are proven to be systems that achieve energy savings and reduces polluting emissions at the same time. First, their installation was focused in industries, later installation was made in commercial and even in residential buildings. For cooling production an absorption or an adsorption chiller can be used in the CCHP system.

Generally, as any system the first design of a CHP/CCHP system is not the final design since it can be improved by applying the proper modifications to get in the end the final design. Therefore, the optimization is the

key for the improvement of the main design which can be in cost saving, increasing efficiency and decreasing polluting emissions. The optimization process can be applied on the prime mover, the heat recovery system, the operation strategy and on the energy storage system. Many researches are carried out on the optimization of a CHP or a CCHP system. There are many ways of optimization like the Mixed-Integer Linear Programming (MILP), the Mixed-Integer Non-Linear Programming (MINLP), the Stochastic optimization, the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO).

From the above, the design of a trigeneration system is a complex multi-objective optimization problem. The scope of this research is to introduce a method of optimization of a trigeneration plant taking into

consideration the environmental and economic criteria. The set of optimal solutions is grouped and then a decision-making technique is introduced to choose the best solution.

A single multi-constraint objective for a CCHP system cannot adequately represent the problem being faced. For this reason, there is a need to formulate the problem with two or more objectives. Therefore, the multi-objective optimization method is applied to solve the problem.

A multi-objective optimization optimizes many objectives simultaneously in an area of multi-criteria decision making. It is also called Pareto optimization. When these objectives are contradictory, the optimal solution of one function may exclude those of other functions. Then, the new optimum will be the compromise between the objectives. The set of Pareto optimal points in the objective space form the Pareto front.

The relative importance of the objectives is generally not known until the system is well defined and the trade-offs between objectives are well understood. As the number of objectives increases, the tradeoffs will likely become complex and less easy to quantify.

In this research, we consider the following system: F (Power) = [Total_cost (Power), Polluting_emissions (Power)]. Next, we must evaluate the system we are studying by its economic and environmental performance.

In former studies, Tsay *et al.*[3] found the optimal power that corresponds to the minimum cost of production and the optimal power that corresponds to the minimum polluting emissions each one separately. They proposed also a distribution strategy for policymakers[1]. They calculated as well the minimum cost in 3 cases (Peak, half-peak and off-peak) by considering environmental constraints[2, 3]. Lastly by Tsay[3] they concluded that the cost of production and the polluting emission are inversely correlated. Frangopoulos *et al.*[4] utilized the Genetic Algorithm (GA) with a sensitivity analysis to obtain the optimal number of CHP to be integrated for a given power, without taking into consideration the environmental limitations. Thus, for a given system, the decision makers only have to find the number of cogeneration systems that needs to be installed[4]. Furusawa etc, took into consideration the environmental constraints in their study to find the cost of production. They found that the cogeneration systems even with big capacities reduces the primary energy consumption and the polluting emissions mainly the emissions. Freschi etc, adopted the weighted sum method for economic and environmental evaluations. As a result, they obtained many solutions as compromise solutions[5]. This method is not considered evident and accurate because different solutions can be obtained by changing the weights factors.

As a conclusion from the above cited studies, the decision-making strategy of the optimal power of a CHP/CCHP system is taking into consideration a compromise between the economy and the environment issues.

On another side, many decision-making techniques utilizedthe multi-objective optimization. To design a hybrid energy system, Perera *et al.*[6] adopted the Fuzzy TOPSIS technique of multi-criteria decision making[6, 7]. This technique is combined with Pareto multi-objective optimization. Applying this technique with a weighting decision matrix the solution is obtained. Thus, TOPSIS Fuzzy technique is based on estimation of the weight factors. Chaudhuri and Deb[8] utilized an interactive multi-criteria decision-making method that is founded on the weighted sum approach, the function-based approach of the distribution service and the Chebycheff function approach. The optimal solution based on estimations of the decision makers is found. Pedrycz and Song[9] used the methods of AHP (Analytic Hierarchy Process) and granularity information[10-14]. Due to the importance of the objective studied the weighting factor is assigned to it from a fuzzy set theory defined by Huang[15]. A fuzzy decision algorithm defined by Niknam *et al.*[16] based on the selection of the weight factors by the decision makers due to the importance of the objective studied. By Miettinen *et al.*[17] used a method that finds the optimal solutions of Pareto obtained by selection of preference information in the form of classifications by the user. This method is a NIMBUS multi-objective optimization[18-20]. Gunawan and Azarm tested a set of robust designs which is considered as a set of optimal solutions (Pareto solutions)[21]. Dowhan *et al.*[22] applied the analytic hierarchy process method combined with Pareto multi-objective optimization. Yang and Wang converted the multi-objective problem to a single objective problem using the weighted aggregation approach method defined by the multiplication of the objective by a weighting factor estimated by the user and the decision maker[23]. Dufo-Lopez, etc., calculated the optimal solution of the Pareto front by using many control strategies in order to produce energy[24].

All the above-mentioned studies are based on decision-making techniques that adopt estimations and suggestions of the users and the decision makers while using the multi-objective optimization. Not very often, these techniques are appropriate because the decision maker has a predicted result that must be confirmed by the method. But in general, the results must be based on a scientific method and not assumptions.

Al Asmar *et al.*[25] have proposed a scientific method of multi-objective optimization and decision-making to calculate the best power of a cogeneration system to be

installed in several sectors based on the multilinear regression as a function of total cost and polluting emissions[25-27].

Rabbani *et al.*[28] used Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to find the optimal solution between the economic aspect represented by the capital cost, operational cost and energy consumption and the pollutant emissions represented by the emissions following five different load strategies and by applying different weight factors chosen by the user[28].

In this research, we propose a new method for selecting the best solution calculated by a heuristic multi-objective optimization. This method is applied to find the optimal power of a trigeneration system to be installed in any sector, respecting the economic-environmental conflict.

First of all, we find the best regression fitted with the Pareto set previously calculated. The minimum residual for the selected regression corresponds to the optimal solution.

Model of performance of the trigeneration system: In this study, a mathematical formulation of a trigeneration system with gas turbine as a prime mover and an adsorption chiller will be carried out. Two objective functions will be considered, the first function corresponds to the total cost which represent the economy objective function. And the second function corresponds to the emissions due to integration of trigeneration system into a grid which represents the environmental objective function. The objective function that represent the total cost to be optimized is represented as follow by (Eq. 1)[25-27, 29, 30]:

F_{total} = Produced energy cost-exchanged energy cost+maintenace cost-Attrition cost of conventional extinct generator+investment cot transmission cost. Which can be represented mathematically as follows:

$$F_{total} = \sum_{j=1}^{N}(H_b.c_j) - \sum_{k=0}^{k}\left(\sum_{j=1}^{N}t_j.a_{jk}\right) + \sum_{j=1}^{N}(\alpha_j.c_{mj}) -$$

$$\left(\sum_{j=1}^{N}(P.t_j+P_c.t_{cj}-E_{jload})\right) * \left[\begin{array}{c} Max(P.t_j+P_c.t_{cj}-E_{jload},0)* \\ \left(\dfrac{n-1}{P*t_j+P_c*t_{cj}-E_{jload}}\right) \\ +1 \end{array}\right] *$$

$$tariff + Inv.cost + \sum_{j=1}^{N}(P.t_j+P_c.t_{cj})$$

The objective function that represent the pollutant emissions (CO_2) to be optimized is represented as follow by Eq. 2[25-27, 29, 30]:

$F_{pollution}$ = Fuel pollution+pollution due to system deterioration

-pollution due to conventional extinct generator

+pollution due ro the fabricatio of the units of the CCHP

Which can be represented mathematically as follows:

$$F_{pollution} = \sum_{j=1}^{N}(H_b*D_j)\sum_{j=1}^{N}\alpha_j*Dam_j - \sum_{k=0}^{k}$$
$$\left(\sum_{j=1}^{N}t_{ij}*Pol_{jk}\right) + fam*\sum_{i}NIN(i)*CO_2I(i)$$

The total cost and CO_2 emissions functions are contradictory but need to be solved simultaneously to find the optimal solution of the CCHP studied. Therefore, the system composed from these two objective functions can be solved using a multi-objective optimization tool. In this study the multi-objective genetic algorithm solver of MATLAB 2018b is used.

Integration level: Three energy load levels are considered in this study: residential, commercial and industrial. For the residential load level, six medium apartments in a building are considered. Their electrical and thermal consumption is 57000 and 56000 kWh for 2 years, respectively. The inequality constraint of this level is: P15 kW; the lower bound is 5 kW and the upper bound is 15 kW[25].

For the commercial load level, 17 shops are considered. Their electrical and thermal consumption is 100000 and 105000 kWh for 2 years, respectively. The inequality constraint of this level is: P30 kW; the lower bound is 16 kW and the upper bound is 30 kW[25].

For the industrial level integration, it corresponds to a high energy level paper mill. Its electrical and thermal consumption is 200000 and 210000 MWh for 2 years, respectively. The inequality constraint of this level is: P50 MW; the lower bound is 16 MW and the upper bound is 50 MW[25].

Main factors: For the three load levels the system studied is a CCHP system with gas turbine as a prime mover and an absorption chiller.

The efficiency of the cogeneration system is considered to be 85% and the coefficient of performance of the absorption chiller is 0.8. This study corresponds to two years of integration of trigeneration systems and 2 values for the integration system n (1.1 and 1.5) with an average of 8000 operating hours per year for the cogeneration system and an average of 3200 operating hours per year for the absorption chiller. Then the number of time intervals is j = 2. Thus, the number of traditional generators extinct because of this integration is k = 1. The calculated power: $P = P_{thermal}+P_{cooling}+P_{electrical}$. All the data required are represented below for each load level[25] (Table 1).

Table 1: Factors of different load levels

Factors	Residential sector	Commercial sector	Industrial sector
E (kWh)	[67000;66000]	[120000;125000]	$[77000;76000].10^3$
Tariff (€/kWh)	0.17	0.17	0.17
c (€/kWh)	[0.1:0.11]	[0.1:0.11]	[0.085 0.090 ;0.085 0.090 ;0.090 0.095]
alpha	[0.2;0.3]	[0.2;0.3]	[0.2 0.3 ; 0.3 0.3 ; 0.31 0.3]
cm (€)	[2000;2100]	[4000;4100]	[120000 130000; 170000 180000;150000 140000]
a (€/h)	[0.1;0.12]	[0.2;0.18]	[15 14 15; 15 15 14]
ct (€/kWh)	0.01	0.01	0.01
D (kg/MWh)	[40;41]	[60;61]	[300 280; 275 273; 270 270]
Dam (kg)	[320;360]	[480;460]	[2000 2100; 2100 2150; 2000 2170]
Pol (kg/h)	[4.5;4.6]	[6.5;6.6]	[75 76 75; 76 75 74]
fam	0.1	0.1	0.1

MATERIALS AND METHODS

The Pareto set of solutions will change at each simulation on MATLAB. Therefore, there is no ideal solution but there is a preferred solution using the multi-objective optimization. This multi-objective simulation is executed on MATLAB 1000 times for each level in order to get a more accurate result.

All the Pareto sets obtained are assembled to obtain the resulting Pareto set. In this study as a novelty different regression method will be introduced and compared in order to select the best solution. We will use the resulting Pareto set to represent the different regressions. The best solution will correspond to the best regression and the closest one to the regression selected.

Multiple linear regression: Multiple linear regression is used to model the relationship between a response or a dependent variable and two or more explanatory or independent variables by fitting a linear equation to the observed data.

This study considers two explanatory variables: the total cost (x_1) and the CO_2 emissions (x_2). The response value is the predicted value $\hat{y}$. The MLR applied to the model from the multi-objective optimization obtained is as follow:

$$\hat{y} = \alpha_0 + \alpha_1.x_1 + \alpha_2.x_2 + \varepsilon$$

Where:
α_0 = Intercept of the power
α_1 and α_2 = The partial regression coefficients
ε = The random error of the studied regression[31]

Multiple polynomial regression: Multiple polynomial regression is used to model the relationship between a response or dependent variable and two or more explanatory or independent variables by fitting a polynomial equation to the observed data.

This study considers two explanatory variables: the total cost (x_1) and the CO_2 emissions (x_2). The response value is the predicted value . The MPR applied to the model from the multi-objective optimization obtained is as follow:

$$\hat{y} = \alpha_0 + \alpha_1.x_1 + \alpha_2.x_2 + \alpha_3 x_1^2 + \alpha_4 + x_2^2 + \alpha_5.x_1.x_2 + \varepsilon$$

With α_0 intercept of the power α_1, α_2, α_3, α_4 and α_5 are the partial regression coefficients. ε is the random error of the studied regression.

Multiple Log-Level regression: Multiple Log-Level regression is used to model the relationship between a response or dependent variable and two or more explanatory or independent variables: the total cost (x_1) and the CO_2 emissions (x_2). The response value is the predicted value $\hat{y}$. The Multiple Log-Level applied to the model from the multi-objective optimization obtained is as follow:

$$\text{Ln } \hat{y} = \alpha_0 + \alpha_1.x_1 + \alpha_2.x_2 + \varepsilon$$

With α_0 intercept of the power α_1 and α_2 are the partial regression coefficients. ε is the random error of the studied regression.

Multiple level-log regression: Multiple level-log regression is used to model the relationship between a response or dependent variable and two or more explanatory or independent variables: the total cost (x_1) and the CO_2 emissions (x_2). The response value is the predicted value $\hat{y}$. The Multiple level-log applied to the model from the multi-objective optimization obtained is as follow:

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

With α_0 intercept of the power α_1 and α_2 are the partial regression coefficients. ε is the random error of the studied regression.

Multiple log-log regression: Multiple Log-Log regression is used to model the relationship between a response or dependent variable and two or more explanatory or independent variables: the total cost (x_1) and the CO_2 emissions (x_2). The response value is the predicted value $\hat{y}$. The Multiple Log-Log applied to the model from the multi-objective optimization obtained is as follow:

$$\ln \hat{y} = \alpha_0 + \alpha_1.\mathrm{Ln}(x_1) + \alpha_2.\mathrm{Ln}(x_2) + \varepsilon$$

With α_0 intercept of the power α_1 and α_2 are the partial regression coefficients. ε is the random error of the studied regression.

Method of selection of the best regression and best solution: In statistics, the standard deviation represents the measure of dispersion of a set of data values studied. In our study, the standard deviation is calculated for the residual of each solution obtained by the multi-objective optimization tool. The lowest the standard deviation of the residuals is the fitter is the data with the regression studied.

In this study, the regression selected is the best regression that fits the data which means that it will be the regression with the lowest standard deviation of the residuals. Once the regression is selected, the best power needs to be found inside this regression. For this purpose, the observed power that have the smaller residual will be considered as the best power of trigeneration system to be integrated into the grid for each load level. Note that each data point has one residual defined by:

$$e = |y - \hat{y}|$$

$$\mathrm{Residual} = |\mathrm{Observed\ value} - \mathrm{Predicted\ value}|$$

RESULTS AND DISCUSSION

In this study, the numerical results of the "multi-objective" optimization that was simulated 1000 times is represented. The number of solutions obtained for each series is far greater than the number of simulations (15210 for the residential case and 38251 for the industrial case). We have eliminated duplicates to obtain an equiprobable data set, knowing that regressions are not affected by repeated solutions. The table below shows the value of standard deviation for different regression types and for all the studied load levels (Table 2).

Since, the standard deviation for the log-log regression is the lowest, therefore we will choose the predicted values for the power from this regression. The difference between the observed value of the dependent variable (y) and the predicted value ($\hat{y}$) is called the residual (e). Each given point has a single residual which is represented by equation:

$$e = |y - \hat{y}|$$

$$\mathrm{Residual} = |\mathrm{Observed\ value} - \mathrm{Predicted\ value}|$$

The equation obtained from the regression is considered as an empirical relation (equation) between the power, the total cost and the polluting emissions. This equation depends on the characteristics of the system and the energy demand. The power corresponding to the smallest residual is considered as the optimal power to be integrated into the grid[1, 25, 29].

The series corresponding to the residential and commercial load levels when n = 1.1 did not provide an optimal solution unlike where all the other series an optimal solution is provided. These solutions are between the lower and the upper boundaries of each load level. Therefore, we chose the log-log regression analysis (lowest standard deviation) between all the regressions in order to select the optimal solution. The equations obtained by the log-log regression for each data series obtained from the multi-objective optimization are as follow (Table 3):

Residential load level for n = 1.5:

$$\ln(\hat{y}) = -2.830438081 - 0.01594476 \ln(x_1) + 0.987802028 \ln(x_2) + 1.304173.10^{-5}$$

Commercial load level for n = 1.5:

$$\ln(\hat{y}) = -3.054455338 - 0.005238329 \ln(x_1) + 0.993966735 \ln(x_2) + 8.692974.10^{-6}$$

Industrial load level with n = 1.1:

$$\ln(\hat{y}) = -3.339671947 - 0.05481179 \ln(x_1) + 0.98765487 \ln(x_2) + 2.862607.10^{-5}$$

Industrial load level with n = 1.5:

$$(\hat{y}) = -3.767117075 + 0.992521052 \ln(x_1) - 0.000180406 \ln(x_2) + 9.179882.10^{-5}$$

Table 3 represents the observed power having the smallest absolute residual which represents the optimal

Table 2: Standard deviation of different regressions for all load levels studied

SD	Type of regression	MLR	MPR	Level-log	Log-level	Log-log
Residential	n = 1.5	0.000239897	0.000207113	0.016346958	0.002233927	$8.11452.10^{-6}$
Commercial	n = 1.5	0.000205999	0.000205983	0.008012557	0.003170067	$5.05672.10^{-6}$
Industrial	n = 1.1	0.00031029	0.00031029	0.01447069	0.010237925	$1.62644.10^{-5}$
	n = 1.5	0.00180465	0.00179916	0.50982296	0.010306197	$5.61441.10^{-5}$

Table 3: Results of the multi-objective optimization

Integration levels	Total cost (€)	Pollution (kg of CO₂)	Power (KW)	Residuals
Residential (n = 1.5)	24187	7893.7	9.299	5.84782E-11
Commercial (n = 1.5)	36770	34287	26.878	3.37081E-09
Industrial (n = 1.1)	23142000	286700	44333	2.35507E-11
Industrial (n = 1.5)	9773600	131580	20447	5.79290E-09

power for each case. It also represents the total cost and the polluting emissions of each system in function of the motivation factor n. For the residential and the commercial load levels, the multi-objective optimization has provided only one solution (the lower boundary of the power). And thus, there is no need to calculate the residuals.

As shown in the above table, the pollution factor affects the solution. In fact, if this factor is not taken into consideration the best power could be chosen according to the highest power obtained by the optimization (the best economic power). Therefore, this study can highlight the fact that due to the log-log regression, the best economic-environmental power is obtained.

Nevertheless, the motivation factor and the total cost are inversely proportional (if n increases, the total cost decreases and vice versa). Furthermore, the integrated power is directly related to the motivation factor which is economically viable for the user.

Moreover, the integration of trigeneration systems in an industrial load level is very advantageous. In fact, at both motivation factors, the results were satisfactory. However, for the residential and commercial integration level, the results were only satisfactory with the highest motivation factor. Finally, the parameters of the objective functions affect the results of the optimization. Between all the parameters the most affecting one is the energy consumption. Thus, the results could vary according to the energy load on the grid.

CONCLUSION

In this research, our interest was to install a trigeneration system into an electrical grid for different energy loads level taking into consideration the economic and the environmental issues.

The innovation in this study was to introduce a new decision-making strategy that is used to find the optimal trigeneration power that respects the economy and the environment issues. This innovation is divided into four stages. The first corresponds to a multi-physical modeling, associated with economy and environment, of the integration of trigeneration systems in an electrical network. The second corresponds to the heuristic multi-objective optimization (Genetic algorithm) dealing with the total cost and emissions objective functions in order to obtain the Pareto front which generates the optimal solutions set. The third is the application of a new decision-making strategy by

choosing the best regression fitted to the model. The fourth corresponds to the selection of the best trigeneration power adapted to the level of integration required that corresponds to the smallest residual of the chosen regression. This power illustrates the best compromise between the total cost and emissions.

Finally, the above cited is applied on three load levels (residential, commercial and industrial). The results were significant showing the benefit of integrating a CCHP into each network. This study could be applied to any multi-objective optimization method. In addition, it could be applied to several integration levels and trigeneration system types. Being dependent on energy consumption, the best suitable trigeneration power varies according to the system's application.

List of Nomenclatures:

M = Number of cogeneration systems
N = Number of time intervals
K = Number of conventional extinct generators
P_i = Power produced by ith cogeneration system (MW)
$P_{c,I}$ = Power produced by ith absorption chiller system (MW)
$t_{i,j}$ = Production time of the ith cogeneration system at jth time interval (h)
$t_{c,ij}$ = Cooling production time of the ith absorption chiller at jth time interval (h)
$E_{j\,Load}$ = Load demand at jth time interval (MWh)
Tariff = Electricity tariff (€)
N = Incentive or motivation factor when consumer sells the utility (usually
H_{bij} = Fuel enthalpy in the boiler of the ith cogeneration system at jth time interval (MWh)

$P_i = P_{ithermal} + p_{1electrical}$ or

$$H_{bij} = P_i * t_{ij} + p_{c,i} + Losses$$
$$0 \leq Loseses \leq 0.5H_{bij}$$

c_{ij} = Fuel cost of the ith cogeneration system at jth time interval (€/MWh)
α_{ij} = Deterioration factor of the ith cogeneration system at jth time interval ($0 \leq \alpha_i \leq 1$; α_i = for ideal cogeneration system and for damaged one)
c_{mij} = Average maintenance cost of the ith cogeneration system at jth time interval (€)
Inv. Cost = Investment cost of the trigeneration system. (€)

a_{jk}	=	Attrition cost of the kth conventional off-generator at jth time interval due to cogeneration system integration. ($€$/h)
S_t	=	Total steam demand (Ton)
c_w	=	Cost of water ($€$/Ton)
c_t	=	Transmission cost ($€$/MWh)
D_{ij}	=	Pollution rate of fuel in the boiler of the ith system at jth time interval (Ton/MWh)
Dam_{ij}	=	Pollution due to damaging of the ith system at jth time interval (Ton)
pol_{jk}		Pollution of the kth off-generator at jth time interval (Ton/h)
Fam	=	Amortization and maintenance factor
NIN	=	Number of pieces of equipment installed
CO_2l	=	CO_2 emission associated with the construction of the unit

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