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Effects of uncertainties on the stability of the results of an optimal sized modular cogeneration plant

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Abstract

In the last decades, the growing concerns about global warming and climate changes effects led to specific Directive, especially in Europe, promoting the use of primary energy saving techniques. In particular, a more widespread adoption of cogeneration systems has been obtained. However, distributed energy systems do not ensure the achievement of primary energy and cost savings without a proper sizing and operation of the plant. Therefore, vector optimization algorithms could play a key role to identify optimal solutions even when conflicting goals are pursued. The potential of the proposed methodology is demonstrated showing the results achieved from a specific application.

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Keywords: *Combined Heat and Power; Multi-Objective Optimization; Robust Design Optimization; Hospital Facility.*

1. Introduction

The balance between energy supply and energy demand is a critical issue to address, especially in developed countries, as extensively discussed in [1]. Human activities have required 13699 Mtoe (≈159327 TWh) of primary energy worldwide in 2014 [2], which corresponds to an annual hourly average power supply of approximately 18 TW. Therefore, the development of innovative technologies in future [3]-[4] and traditional engines [5]-[6], the use of alternative and clean fuels [7]-[10], a more efficient use of energy [11]-[12] and an increasing use of renewable

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energy sources [13] are still mandatory to face the challenges imposed by the world energy balance and recognized by Paris Agreement on climate change. In this scenario, a key role for primary energy saving and greenhouse gas emission reduction could be played by cogeneration systems [14]-[17]. The strategic role of CHP plants to achieve the Paris Agreement goals is leading the transition from centralized energy generation to a mature distributed, small and medium scale energy generation. However, due to the decrease in thermal efficiency and the increase in specific investment costs with the reduction of the plant size, the study of an effective utilization of the recovered heat is a fundamental issue to identify solutions that maximize the relevant energetic and economic objectives (e.g., primary energy saving, simple payback period, CO_2 emission, etc.) through a suitable use of the recovered thermal power and generated electricity [1]. Moreover, the proposed methodology enables the design of a CHP plant when energetic, economic, regulatory or market scenarios change. In fact, many studies ignore uncertainties that could alter the outcome of the optimizations, as stated in [18]. For example, most of the researches considered fixed energy prices, electricity tariffs, grid carbon intensity, etc., while these and other quantities can vary through the plant life. Moreover, most of the proposed models do not provide real-life solutions because CHP units size obtained from the numerical solution of the optimization problem could not be available in the market, as stated in [19] and [20]. Therefore, objective of this research paper is to highlight, with reference to the load profiles of an Italian hospital facility, the key role that advanced mathematical methods have for the optimal design of CHP systems and the effects of uncertainties on the stability of the results of an optimal sized modular cogeneration plant.

Nomenclature

std dev	Standard deviation of the considered quantity
Abbreviations	
CHP	Combined heat and power
DII	Department of industrial engineering of the University of Naples Federico II
ICE	Internal combustion engine
h	Generic hour of the year [h]
MOGA	Multi-objective genetic algorithm
SPB	Simple payback period
TPES	Total (or technical) primary energy savings

2. Methodology

Starting from the load profiles of the reference hospital facility (Fig. 1), whose details are reported in [21], one of the goals of the proposed study was the calculation of the potential energetic and economic benefits achievable over the useful life of the CHP plant, which is estimated to be 10 years long. For this reason, with the goal of optimizing specific target quantities, a constrained optimization problem was solved to find optimal modular plant configurations (i.e., CHP engine size and number) adopting a multi-objective approach. Vector optimization [22]-[27] can be useful for deducing general results by conducting a predictive investigation on a large number of possible plant configurations, especially with regard to possible tradeoffs between energetic and economic objectives. In fact, most optimization problems are characterized by several objectives, which are usually conflicting real functions to be maximized or minimized. Generally, these problems, also called multi-objective optimization problems, can be formalized as follows [28]:

$$min\boldsymbol{F}(\boldsymbol{x}) = min(F_1(\boldsymbol{x}), F_2(\boldsymbol{x}), \dots, F_k(\boldsymbol{x})) \qquad (1)$$

where: $\boldsymbol{x} \in X$ $\quad F_i: R^n \to R \quad i = 1, \dots, k \quad k \geq 2$

where R^k is called the objectives space, while R^n represents the decision variable space. Therefore, vector $x \in R^n$ is a vector decision variable, while $y = F(x) \in R^k$ is a vector of objectives. Obviously, it is assumed that the functions $F_1(x), F_2(x), \dots, F_k(x)$ are, at least partly, conflicting.

Table 1 shows decision variables and objective functions of the optimization problem. The number of CHP units has been considered variable in the range 1-9. The optimal solutions in the multi-objective optimization can be defined from the mathematical concept of partial ordering, and the search for the minimum in the above problem is solved on the basis of the Pareto non-dominance criterion.

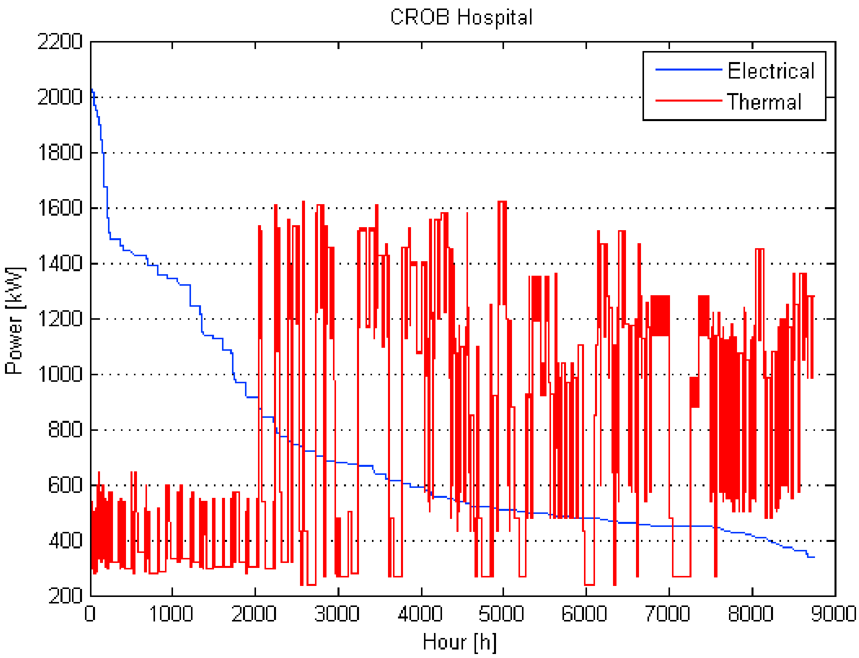

Fig. 1: Thermal and electric load profiles for CROB hospital.

Typically, there is no single global solution but rather a set of optimal solutions complying with the definition of Pareto optimality.

DECISION VARIABLES		OBJECTIVE FUNCTIONS		CONSTRAINTS	
VARIABLE	RANGE	OBJECTIVE	TARGET	VARIABLE	RANGE
CHP size	150 – 1000 kW	TPES	maximize	-	-
CHP number	1 – 9	SPB	minimize		

Table 1 - Decision variables and objective functions for the considered optimization problem.

The methodology adopted involved coupling a coded calculation algorithm with a commercial optimization solver. The optimization problem has been solved using the evolutionary algorithm MOGA II, belonging to the class of genetic methods. Statistical multi-objective optimization algorithms such as the considered algorithm can be effectively used when a large and discrete decision variable space is considered to find solutions that are probably close to the global optimum. In fact, while classical gradient-based methods are faster, stochastic methods are very robust but slower to reach convergence. MOGA II is an improved version of MOGA by Poloni [29]. Further details are presented in [30], while the logic scheme of the proposed methodology is summarized in Fig. 2.

However, as in many engineering design problems, some input quantities may only be known to some tolerance or may change during the plant's life. For this reason, optimizing a CHP plant for a specific energetic, economic or market scenario does not guarantee good performance when these scenarios change. Moreover, a calculated technical solution (i.e., CHP gas engine size and related nominal energetic performances) may not be matched by a corresponding product in the market. Therefore, the multi-objective approach has also been used to estimate the sensitivity of the results to a probable mismatch between numerical and marketed solutions, then also considering eventual changes in the reference energetic and economic scenarios.

To this aim, a robust design approach was adopted and the problem (2) was solved to evaluate the robustness of the calculated results. Some key decision variables or economic and energetic parameters of the developed calculation algorithm were redefined using a probability distribution before the related multi-objective optimization problems were solved. Therefore, with reference to the decision variable X_n in Fig. 2, a probabilistic characterization was assigned to that quantities.

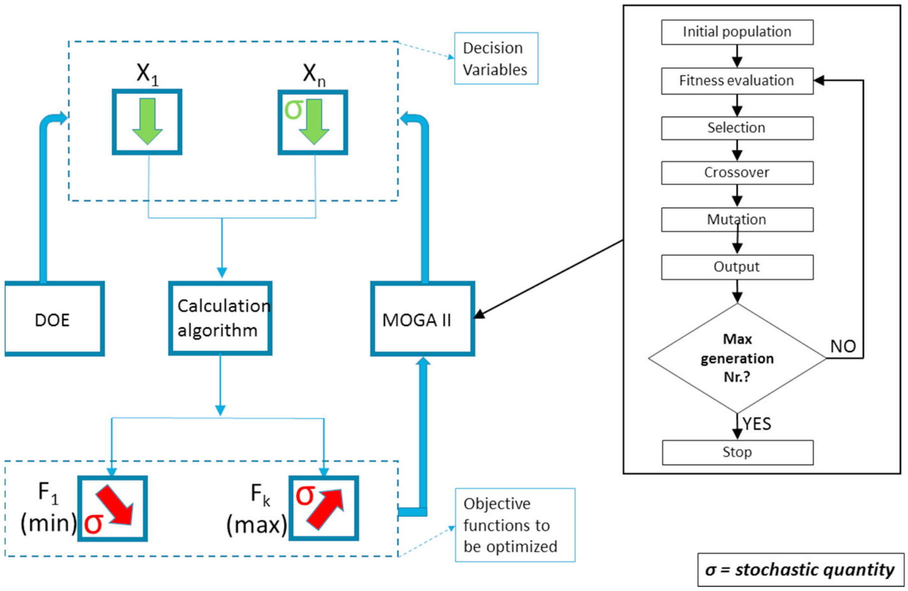

Fig. 2 – Workflow of the multi-objective optimization process.

When a robust design optimization is performed, the search of the most stable region is pursued by defining two different objectives for each function to optimize: both the mean value and the variance of each function are involved in the optimization process. Obviously, using probabilistic models for the input variables, the objective functions obtained as outputs of the optimization problem will also become stochastic. A stable solution is less dependent as possible on the unknown input parameters or, equivalently, it is less sensitive to fluctuations of that parameters. Therefore, dominant solutions such as those calculated by solving the optimization problem expressed by equation (1) may not include the most stable solution. It is thus possible that the most stable solutions are not characterized by the best performance. The mathematical formulation of the robust design optimization problem, considering a discrete formulation for the mean value and variance, as usually occurs in the engineering field, can be generally formalized as follows [31]:

$$\begin{aligned}
&min F(x,\sigma)\\
&p(x_j):\ P(x_j) = \textstyle\sum_{j=1}^{j} p(x_j) \in [0,1] \\
&max\ \ F_{mean},\ where\ F_{mean} = \bar{F} = \textstyle\sum_{j=1}^{q} {}^{F_j}/_{q} \\
&min\ \ \sigma_F^2,\ where\!: \sigma_F^2 = \textstyle\sum_{j=1}^{q} \frac{(F_j - F_{mean})^2}{q-1};\quad x_j \in R \quad \text{and} \qquad F\!: R \rightarrow R
\end{aligned} \tag{2}$$

In problem (2), σ is the fluctuation of the variable x, $p(x_j)$ is the probability density function and $P(x_j)$ is the cumulative distribution function. Further details addressing the reference calculation algorithm and the probability density functions adopted in this study are discussed in [21].

3. Case study: CROB Hospital

The reference user analyzed is the Oncological Reference Center of Basilicata (CROB), whose load profiles are shown in Fig. 1. Fig. 3a shows the optimal CHP plant configurations obtained. The overall energy savings reaches 18.2% , achieving an SPB of just over three years using three CHP engines of approximately 440 kW.

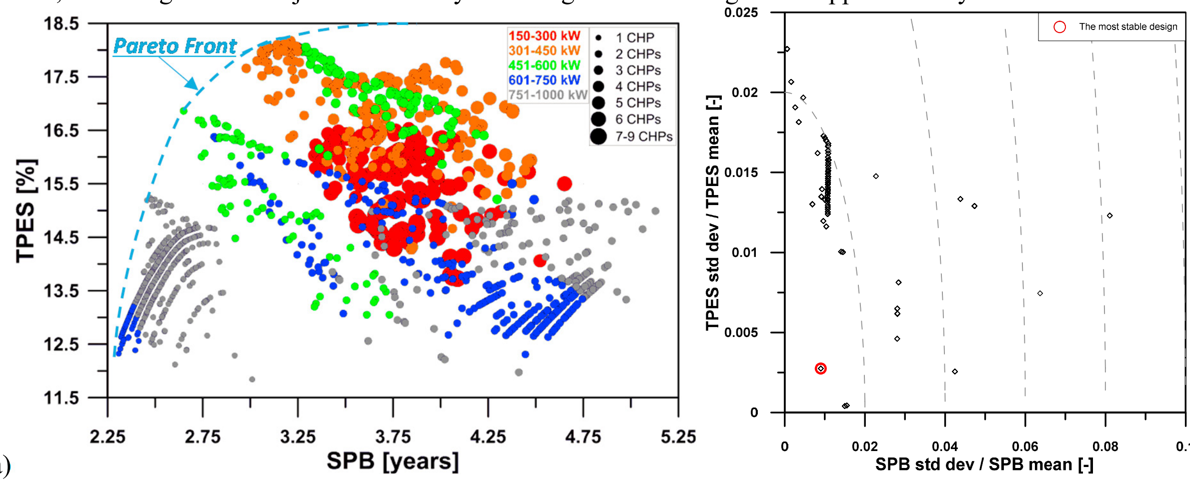

Fig. 3 – (a) Bubble chart representing engine size and number and (b) the Pareto optimal solutions.

Searching for stable economic and energetic solutions, the goal of the analysis was to minimize the mean values of the SPB and maximize the mean values of the TPES while obtaining low standard deviation values (referred to as *std-dev* in the subsequent graphs) for these quantities. Actually, searching for the most robust energetic and economic results, the authors were searching for solutions that minimize the ratio $\sigma_F/\bar{F}$ *(std-dev*/mean-value) for both the TPES and SPB. This ratio ($\sigma_F/\bar{F}$), accounts for the relative weight of the standard deviation of the considered objective functions over their mean value. Referencing the objective functions TPES and SPB, a multi-objective optimization problem was solved to estimate the sensitivity of the expected results, taking into account possible difficulties in finding commercially available CHP gas engines with sizes reasonably close to the optimal numerical solutions. For this purpose, the CHP engine size was turned into a statistical decision variable of the optimization problem and described through a uniform distribution. In particular, CHP engine sizes were defined through a set of 25 sample designs distributed over a range of 60 kW and centered around the mean value currently analyzed by the genetic algorithm MOGA II. Fig. 3b shows, in the $\sigma_F/\bar{F}\ (SPB) - \sigma_F/\bar{F}\ (TPES)$ plane, the Pareto optimal solutions obtained from the multi-objective robust design optimization. Most of the optimal solutions are characterized by high energetic stability (the ratio of $\sigma_F/\bar{F}$ for the TPES is mostly under 2%). The most stable plant design for the CROB is shown in red, and its main characteristics are summarized in Table 2.

CROB - The most stable plant design							
CHP number	Electrical power (mean value)	TPES min	TPES mean	TPES max	SPB min	SPB mean	SPB max
[-]	[kW]	[%]	[%]	[%]	[years]	[years]	[years]
1	**969.7**	**15.14**	**15.22**	**15.27**	**2.45**	**2.49**	**2.54**

Table 2 – Main characteristics of the most stable solution for the CROB.

Fig. 4-(a) shows how the expected results obtained through a deterministic definition of the input decision variables within the multi-objective optimization can overestimate the objective functions compared to the robust design approach.

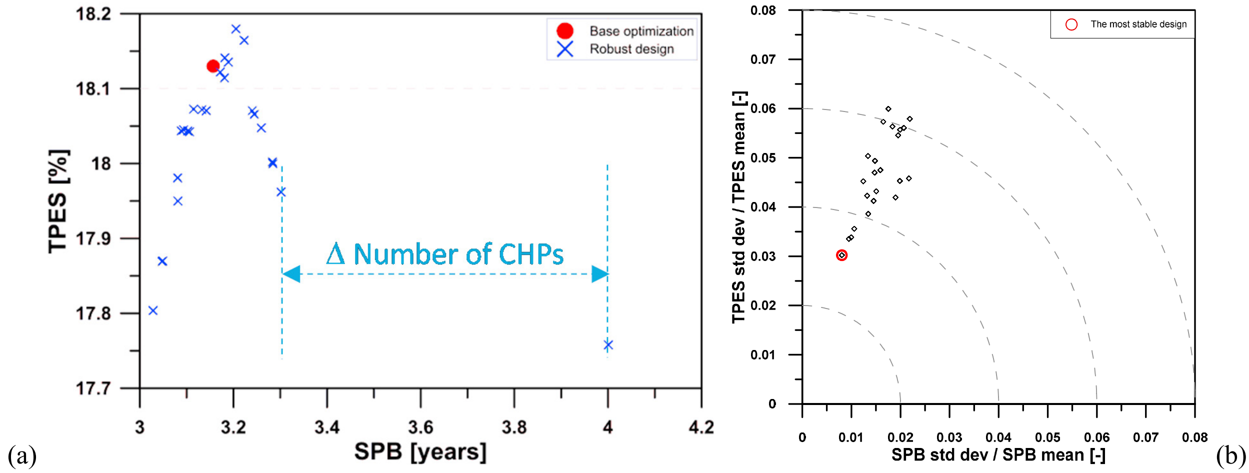

Fig. 4 – (a) Comparison between deterministic and stochastic approaches to multi-objective optimization. – (b) Pareto optimal solutions from the multi-objective robust design analysis.

Specifically, the red circles represent the maximum TPES solutions obtained for the studied hospital facility. The blue crosses represent the 25 sample designs belonging to the same robust design solution and therefore to the same statistical distribution for the engine size. In particular, the mean value of this distribution is equal to the engine size of the red solution. Fig. 4-(a) shows similar energetic and economic variations for the objective functions. The significantly higher value of the SPB for the solution on the right hand of Fig. 4-(a) is due to having one CHP engine more than the other solutions, according to the current values of the CHP engine size and the value of decision variable that determines the number of CHP adopted. To estimate the fluctuations induced in the expected results due to possible changes in the reference energetic and economic scenarios, a second multi-objective robust design optimization was performed with reference to TPES and SPB as objective functions. In this optimization problem, the selling price of the electricity in different time bands, the reference efficiency of the Italian thermoelectric generation and the selling price of the energy efficiency certificates recognized by the Italian legislation to cogeneration plants were set as stochastic variables and were described by normal probability distributions (Table 3). The gas engine size and number were the two decision variables of the problem.

Input decision variable	Range	Unit	Distribution	Std. deviation
Selling price in time band F1	0.10–0.14	€/kWh	Normal	0.003
Selling price in time band F2	0.076–0.116	€/kWh	Normal	0.003
Selling price in time band F3	0.045–0.085	€/kWh	Normal	0.003
Thermo-electric generation, reference efficiency	43.5–48.5	%	Normal	1
Selling price of the energy efficiency certificates	90–110	€/certificate	Normal	3

Table 3 – Stochastic decision variables used in robust design optimization.

The energetic and economic stability of the dominant solutions for the CROB is shown in Fig. 4-(b) in the $\sigma_F/\overline{F}$ $(SPB) - \sigma_F/\overline{F}$ $(TPES)$ plane. The standard deviation for the SPB is always under 2.5% of its mean value. This percentage increases to 6% for the TPES. The most stable plant design is shown inside a red circle, and its characteristics are reported in Table 4.

CROB - The most stable plant design							
CHP number	Electrical power (mean value)	TPES Min	TPES mean	TPES max	SPB min	SPB mean	SPB max
[-]	[kW]	[%]	[%]	[%]	[years]	[years]	[years]
1	**682**	**11.93**	**12.37**	**13.22**	**2.26**	**2.31**	**2.33**

Table 4 – Main characteristics of the most stable energetic and economic solution for the CROB.

4. Conclusions

The increasingly stringent requirements for carbon dioxide reduction led to a more widespread adoption of distributed energy systems. One of the most effective technique to face the energy saving challenges is the use of cogeneration systems. However, the adoption of distributed energy systems do not ensure the achievement of this mandatory aim without a proper sizing and operation of the plant. Therefore, advanced mathematical methods such as vector optimization algorithms could play a key role to identify optimal solutions even when conflicting goals are pursued. This paper addresses a specific application for the study of CHP systems, highlighting the potential of the proposed methods and the main results achieved. The proposed research activity is based on a specific calculation algorithm developed by the authors coupled to the evolutionary genetic algorithm MOGA II. Optimization analyses have been conducted on the basis of the load profiles of a reference hospital facility considering reciprocating internal combustion engines fueled by natural gas as cogeneration systems. Moreover, this study proposes an effective approach to identify the most stable plant configurations through a multi-objective robust design optimization. A first optimization problem was solved to estimate the sensitivity of the expected results to possible difficulties in finding commercially available CHP gas engines with sizes reasonably close to the optimal numerical solutions. Then, a second multi-objective robust design optimization has been performed to estimate the fluctuations of the expected results due to possible changes in the reference energetic and economic scenarios. Definitely, the proposed methodology provides a useful and flexible tool that can be focused on several innovative aspects within field of the energy systems. In particular, this study proposes an uncommon and effective approach to identify the most stable plant configurations through a multi-objective robust design optimization. Future improvements of the proposed methodology will address part load efficiency integration needed to obtain optimal operation strategies for the energy system. Moreover, the possibility to integrate energy storage technologies or ORC systems into the main CHP plant will be analyzed.

References

[1] Gimelli A, Muccillo M., Optimization Criteria for Cogeneration Systems: Multi-Objective Approach and Application in a Hospital Facility, Applied Energy 2013;104:910-923. http://dx.doi.org/10.1016/j.apenergy.2012.11.076.

[2] International Energy Agency, Key World Energy Statistics, 2016.

[3] Cameretti MC et al., Combined MGT – ORC solar – hybrid system. PART A: plant optimization. Energy Procedia 2015;81:368–78.

[4] Cameretti MC et al., Combined MGT – ORC solar – hybrid system. PART B: component analysis and prime mover selection. Energy Procedia 2015;81:379–89.

[5] Gimelli A. et al., The Study of a New Mechanical VVA System. Part I: Valve Train Design and Friction Modeling, International Journal of Research Engines, SEP 2015, Volume: 16 Issue: 6 Pages: 750-761. DOI: 10.1177/1468087414548773.

[6] Gimelli A. et al., The Study of a New Mechanical VVA System. Part II: Estimation of the Actual Fuel Consumption Improvement through 1D Fluid Dynamic Analysis and Valve Train Friction Estimation, International Journal of Engine Research, SEP 2015, Volume: 16, Issue: 6, Pages: 762-772. DOI: 10.1177/1468087414548773.

[7] Gimelli A. et al., Performance and Emissions of a Natural Gas Fueled Two-Stroke SI Engine. SAE 2008 World Congress & Exhibition. April 2008. Detroit, MI, USA. SAE paper 2008-01-0318.

[8] Bozza F. et al., 1D-3D Analysis of the Scavenging and Combustion Process in a Gasoline and Natural-Gas Fuelled Two-Stroke Engine. SAE 2008 World Congress & Exhibition. April 2008. Detroit, MI, USA. SAE paper 2008-01-1087.

[9] Bozza F. et al., Numerical and Experimental Investigation of Fuel Effects on Knock Occurrence and Combustion Noise in a 2-Stroke Engine. SAE International Journal of Fuels and Lubricants, ISSN: 1946-3952, May 2012 vol. 5 no. 2 674-695. doi:10.4271/2012-01-0827.

[10] De Simio L. et al., Experimental Analysis of a Natural Gas Fueled Engine and 1-D Simulation of VVT and VVA Strategies, SAE Technical Paper 2013-24-0111, 2013, doi:10.4271/2013-24-0111. ICE2013 - 11th International Conference on Engines & Vehicles, Capri, 15-19 Sept. 2013, Capri, Naples (Italy).

[11] Gimelli A., Muccillo M., Regulation Problems of Combined Cycle Gas-Steam Turbine Power Plant in a Liberalized Market: Part I - Experimental Investigation and Energetic Analysis, International Review on Modelling and Simulations (I.RE.MO.S.), Vol. 9, N. 4, August 2016. ISSN 1974-9821. DOI: 10.15866/iremos.v9i4.10755.

[12] Gimelli A., Muccillo M., Regulation Problems of Combined Cycle Gas-Steam Turbine Power Plant in a Liberalized Market: Part II - Thermodynamic Analysis, International Review on Modelling and Simulations (I.RE.MO.S.), Vol. 9, N. 5, October 2016, pp. 348-354. ISSN 1974-9821. DOI: 10.15866/iremos.v9i5.10756.

[13] Iodice P., Senatore A., Influence of Ethanol-Gasoline Blended Fuels on Cold Start Emissions of a Four-Stroke Motorcycle. Methodology and Results, SAE Technical Paper 2013-24-0117.

[14] Dentice d'Accadia M, Sasso M, Sibilio S, Vanoli L. Micro-combined heat and power in residential and light commercial applications. Applied Thermal Engineering 2003(10);23:1247-1259.

[15] Monteiro E, Moreira NA, Ferreira S. Planning of micro-combined heat and power systems in the Portuguese scenario. Applied Energy 2009;86:290–298.

[16] Kyung Tae Yun, Heejin Cho, Rogelio Luck, Pedro J Mago. Modeling of reciprocating internal combustion engines for power generation and heat recovery. Applied Energy 2013;102:327–335.

[17] Muccillo M, Gimelli A. Experimental Development, 1D CFD Simulation and Energetic Analysis of a 15 kW Micro-CHP Unit based on Reciprocating Internal Combustion Engine. Applied Thermal Engineering 2014; 71(2): 760-770. DOI: 10.1016/j.applthermaleng.2013.11.025.

[18] Akbari K, Nasiri MM, Jolai F, Ghaderi SF, Optimal investment and unit sizing of distributed energy systems under uncertainty: a robust optimization approach. Energy Build 2014;85:275–86. http://dx.doi.org/10.1016/j.enbuild.2014.09.009.

[19] Dagoberto Cedillos Alvarado, Salvador Acha, Nilay Shah, Christos N. Markides, A Technology Selection and Operation (TSO) optimisation model for distributed energy systems: Mathematical formulation and case study. Applied Energy, Volume 180, 15 October 2016, Pages 491–503. http://dx.doi.org/10.1016/j.apenergy.2016.08.013.

[20] Muccillo M., Gimelli A., Sannino R. Multi-objective optimization and sensitivity analysis of a cogeneration system for a hospital facility. Energy Procedia 2015; Volume 81, December 2015, Pages 585–596. doi:10.1016/j.egypro.2015.12.043.

[21] Gimelli A., Muccillo M., Sannino R., Optimal design of modular cogeneration plants for hospital facilities and robustness evaluation of the results, Energy Conversion and Management 134 (2017) 20–31, http://dx.doi.org/10.1016/j.enconman.2016.12.027.

[22] Das I, Dennis J. Normal boundary intersection, Alternate method for generating Pareto optimal points in multicriteria optimization problems. NASA Contractor Report 201616, ICASE Report No. 96-62, November 1996.

[23] Coello CA, Van Veldhuizen DA, Lamont GB. Evolutionary algorithms for solving multi-objective problems. Springer US; 2007. http://dx.doi.org/10.1007/978-0-387-36797-2.

[24] Lotov AV, Bushenkov VA, Kamenev GK. Interactive decision maps: approximation and visualization of Pareto Frontier. Boston: Kluwer Academic Publishers; 2004.

[25] Bozza F. et al., Strategies for Improving Fuel Consumption at Part-Load in a Downsized Turbocharged SI Engine: a Comparative Study, SAE Int. J. Engines 7(1):2014, doi:10.4271/2014-01-1064.

[26] Gimelli A., Luongo A., Muccillo M., *Efficiency and Cost Optimization of a Regenerative Organic Rankine Cycle Power Plant through the Multi-Objective Approach*, Applied Thermal Engineering, Volume 114, 5 March 2017, Pages 601–610. DOI: 10.1016/j.applthermaleng.2016.12.009. ISSN: 1359-4311.

[27] Ngatchou P, Zarei A, El-Sharkawi MA. Pareto multi objective optimization. Intelligent Systems Application to Power Systems, 2005. Proceedings of the 13th International Conference on:84–91. http://dx.doi.org/10.1109/ISAP.2005.1599245.

[28] Branke J, Deb K, Miettinen K., Slowinski R., Multiobjective Optimization. Interactive and Evolutionary Approaches, 2008. Springer. ISBN 978-3-540-88908-3. DOI: 10.1007/978-3-540-88908-3.

[29] Carlo Poloni, Andrea Giurgevich, Luka Onesti, Valentino Pediroda. Hybridization of a multi-objective genetic algorithm, a neural network and a classical optimizer for a complex design problem in fluid dynamics. Comput. Methods Appl. Mech. Engrg. 186 (2000) 403-420.

[30] C. Poloni, V. Pediroda. GA coupled with computationally expensive simulations: tools to improve efficiency. Genetic Algorithms and Evolution Strategies in Engineering and Computer Science, pages 267-288, John Wiley and Sons, England, 1997.

[31] L. Padovan, V.Pediroda, C. Poloni, MULTI OBJECTIVE ROBUST DESIGN OPTIMIZATION OF AIRFOILS IN TRANSONIC FIELD (M.O.R.D.O.), International Congress on Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems EUROGEN 2003, Barcelona,2003.