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COMPLEX ENERGY NETWORKS OPTIMIZATION: PART I – DEVELOPMENT AND VALIDATION OF A SOFTWARE FOR OPTIMAL LOAD ALLOCATION

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ABSTRACT

The growing diffusion of the distributed generation systems, due to the European and national legislations which impose the fossil fuel and greenhouse gas emissions reduction and the renewable sources exploitation, have led to an increase in the complexity of the existing energy networks.

The main issue of the complex energy grids is their management, which consists in the resolution and optimization of the load allocation problem by minimizing the primary energy consumption and, thus, improving the overall efficiency.

In this context, the aim of this paper is to develop and validate a non-linear algorithm suitable for the resolution of the load allocation problem. In detail, the software COMBO, which has been developed by the University of Bologna, is based on a non-heuristic algorithm and allows to optimize a complex energy network – characterized by electrical, thermal, cooling and fuel fluxes – by evaluating all the possible combinations of solutions. The objective function of the software consists in the minimization of the total cost of energy production, including not only the variable costs, but also the costs related to the environmental impact of the energy systems. In this paper the mathematical model of the algorithm at the basis of the software COMBO is presented and described in detail.

Furthermore, the software has been validated by its application to a case study and comparing the results with the ones obtained with a previously developed software based on a genetic algorithm (heuristic non-linear method).

Keywords: scheduling optimization, non-heuristic algorithm, complex energy network management, software development.

NOMENCLATURE

C	cost [€]
COP	coefficient of performance [-]
EER	energy efficiency ratio [-]
ITER	iteration [-]
l	load [-]
L	load limit [-]
NC	number of combinations for each iteration [-]
NS	number of generation systems [-]
OF	fitness function [€]
SC	number of combinations for each system [-]
TOL	tolerance value [-]

Acronyms

A	load matrix
CHP	combined heat and power
EGO	Energy Grid Optimizer
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non Linear Programming

Greek symbols

α	matrix creation parameter [-]
β	system combination parameter [-]
φ	corrective factor [-]
λ	fuel [-]

Subscripts and Superscripts

E	electricity
F	fictitious
high	higher
i	system number
j	combination number
k	iteration progressive number
low	lower
M	maintenance
max	maximum
min	minimum
opt	optimal
step	upper limit

INTRODUCTION

The last years have been characterized by a growing attention to the energy conversion efficiency improvement, mainly due to the increasing diffusion of distributed energy systems in most of the European countries as well as worldwide [1-5]. The main reason stands in the need to integrate the renewable resource generators with the traditional energy systems, in order to reduce the fossil fuel consumption and, thus, the greenhouse gas emissions [6-9]. On this purpose, in fact, many countries have forced strict constraints in order to reach these goals by stepped the existing legislations [10, 11].

As a consequence, the existing grids are becoming more complex both from the energy distribution and network management viewpoints [12, 13].

The main challenge for these complex energy grids – characterized by the electrical, thermal, cooling and fuel fluxes – is the definition of optimal management criteria (i.e. the optimization of the energy systems scheduling during the whole year of operation) [14-16]. Generally, this problem has been addressed by the researchers through the development and implementation of algorithms based on approximate methods or exact mathematical methods [17-20]. As it concerns the approximate methods, they face the nonlinearities of some constraints and of the objective function by implementing random search techniques [21, 22]. This allows to find a good approximate solution of the problem with acceptable computational time. The approximate techniques include the heuristic methods [23, 24] – such as the constructive and the local search algorithms – and the metaheuristic methods [25] – such as the trajectory and the population-based algorithms. In the framework of complex energy network optimization, a widely used approximate technique among the heuristic methods is represented by the genetic algorithms which are based on the genetic rules of the population evolution and allow to solve nonlinear problems with a good-quality solution [26, 27]. Moreover, firefly algorithms – also belonging to this type of methods but more recently developed – represent a population-based technique aimed to find the optimal solution by using a swarm intelligence approach [28].

With regard to the exact resolution methods, instead, they are able to provide the optimal solution of the problem but, in the case of highly complex problems, the computational time increases. Some exact methods are represented by enumerative algorithms, branch and bound [29] and linear programming (LP) [30]. Furthermore, the Mixed Integer Linear Programming (MILP) and Mixed Integer Non Linear Programming (MINLP) problems are exact resolution methods which are used for energy grid management and design [31]. In particular, the MILP problems are most widely used for the scheduling optimization of complex networks since, even if the nonlinearities of the problem are lost (being characterized by linear functions and discrete variables), they allow to find the exact solution [32-36]. On the other hand, the MINLP problems overcome the linearity of the MILP but the complexity of the problem and the high computational time needs to be improved [37-39].

The aim of this paper is the development of a novel software based on a non-heuristic algorithm, able to solve the non-linear problem of systems load allocation. In particular, the realized software, named COMBO, allows to create all the combinations of the energy systems loads and to evaluate each one of them with the main aim to find out the optimal solution, represented by the scheduling configuration which minimizes the fitness function. The latter – as will be better discussed in the following section – consists in the total energy production cost, taking into account also the so-called fictitious costs in order to consider the environmental aspects.

Furthermore, in this paper, the validation of the developed software is presented. To this respect, a network at the service of a residential neighborhood has been considered and implemented within the COMBO software. Finally, the results of the simulations have been compared with the results obtained with the application to the same case study of a genetic algorithm.

This paper represents the Part I of a wider study, representing the mathematical model of the developed software along with its validation. It will follow a Part II in which a case study concerning a residential neighborhood will be presented and analyzed with the software COMBO.

COMPLEX ENERGY GRID OPTIMIZATION WITH THE SOFTWARE COMBO: MATHEMATICAL MODEL

With the main purpose of evaluating the optimal scheduling of the production systems composing a complex energy network (characterized by electrical, thermal, cooling energy and fuel distribution), a new software, named COMBO, has been realized by the University of Bologna.

In particular, the developed software is able to simulate an energy grid by defining the optimal load of each system – such as prime movers (Combined Heat and Power application or electrical engines), thermal generators (auxiliary boilers and heat pumps), cooling systems (compression and absorption chillers) and non-programmable renewable sources generators – by minimizing the total cost of the produced energy. In order to fulfill the electrical, thermal and cooling demand of the users of the network, a connection to both the electric grid and the gas distribution network is included.

With reference to the algorithm operation, in Figure 1 the schematic flow chart of the software COMBO is presented.

As can be seen from Figure 1, the software calculation core is based on a non-heuristic algorithm that consists in an iterative process aimed at creating and at evaluating all the possible load combinations to find out the optimal solution, namely the load allocation among the energy systems which minimizes the objective function.

In detail, the input section consists in the definition of:

- users' energy demand (electrical, thermal, cooling and mechanical power required by the users connected to the network);
- prime movers (number, typology, size and main characteristics, such as the electrical and thermal design power output, off-design behavior, design efficiency, etc.);
- heating and cooling systems (number, typology, size, efficiency, etc.);
- renewable source generators (performances, peak power, etc.);
- tariff scenario (cost of the fuel, cost of purchased and sold electricity, etc.);
- internal parameters of the algorithm (number of iterations, tolerance value, etc.).

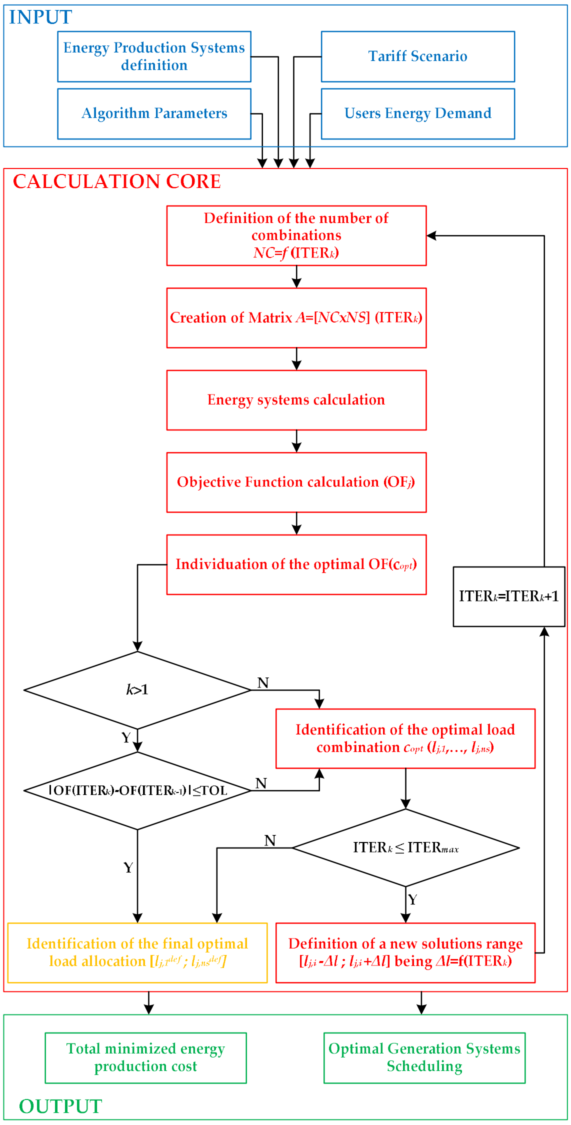


Figure 1 – Schematic flow chart of the software.

The output is the optimal load of each non-renewable generation system connected to the network, along with the minimized total cost of energy production.

As it regards the core of the calculation, a detailed description is given in the following paragraphs.

Creation of the combinations

The optimization method underlying the COMBO software consists in an iterative process aimed at creating and at exploring all the possible load combinations of the energy systems composing a certain network, in order to find out the optimal solution in terms of optimal systems load allocation and energy production cost minimization.

As a starting point, at each k^{th} iteration (ITER$_k$), the total number of combinations NC (j=1,…,NC) to be evaluated is defined with the following equation:

$$NC_k = SC^{NS} \tag{1}$$

in which NS (I=1,…,NS) indicates the total energy systems number and the term SC refers to the total number of combinations for a single energy system, defined as:

$$SC_{i,k} = \left\lfloor 1 + \frac{\left(L_{high\,i,k} - L_{low\,i,k}\right)}{L_{step}} \right\rfloor \tag{2}$$

being L_{high} and L_{low} the higher and lower parameter limits for the load range definition and L_{step} the step for the range solution investigation. All these parameters are defined at the beginning as input.

Therefore, according to the flow chart of Figure 1 and the previous equations, the developed algorithm generates the loads matrix $A = [NC \times NS]$ in which all the combinations are listed:

$$A_k = \begin{bmatrix} l_{1,1} & l_{1,2} & \cdots & l_{1,NS} \\ \vdots & \ddots & l_{j,i} & \vdots \\ \vdots & \cdots & \ddots & \vdots \\ l_{NC,1} & l_{NC,2} & \cdots & l_{NC,NS} \end{bmatrix} \Bigg|_k$$

where the general element $l_{j,i}$ is defined at each k^{th} iteration according to the following equation:

$$l_{j,i_k} = l_{i,min} + \left[\left(l_{i,max} + l_{i,min}\right) \cdot \frac{\left\{1 + \left\lfloor\left\lfloor \alpha - \left(\beta \cdot \left\lfloor\frac{\alpha}{\beta}\right\rfloor\right)\right\rfloor\right\rfloor\right\} \cdot \varphi_1 \cdot \varphi_2}{l_{step}} \right] \tag{3}$$

where $l_{i,min}$ and $l_{i,max}$ indicate respectively the minimum and maximum load values of the i^{th} system and l_{step} is the step for the load solutions investigation. The parameter β corresponds to the combinations that can be created for a single system (as well as SC of Eq.2), while α can be expressed as:

$$\alpha = \left\lfloor \frac{j-1}{SC^{i-1}} \right\rfloor \tag{4}$$

with j and i that refer respectively to the considered j^{th} combination and i^{th} system.

Furthermore, the terms φ_1, φ_2 of Eq.3 correspond to the corrective factors for the matrix loads definition which can be defined as:

$$\varphi_1 = \frac{\left(L_{high\,i,k} - L_{low\,i,k}\right)}{NC-1} \tag{5}$$

$$\varphi_2 = L_{low\,i,k} - \varphi_1 \tag{6}$$

After the matrix has been defined, the software analyzes all the combinations in order to point out the optimal one $c_{opt_k}(l_{i,opt_k})$. Then, with the aim to find a more accurate solution, at the k^{th}+1 iteration, for each system, a new load range is defined around the optimal one of the k^{th} iteration by creating the load matrix A_{k+1}. To this respect, the software calculates a new range of solutions by redefining the higher and lower limits of the ITER$_{k+1}$ according to the following equations:

$$l_{i,up_{k+1}} = l_{i,opt_k} + \Delta l \quad (7)$$

$$l_{i,down_{k+1}} = l_{i,opt_k} - \Delta l \quad (8)$$

where the term Δl allows to define the upper and lower loads limits in order to refine the optimal solution at the k^{th}+1 iteration. To this respect, the interval Δl decreases at each iteration. In fact, as can be observed from the previous equations, this range is defined each time as a function of the considered iteration, making the optimal combination more accurate.

Therefore, by considering the ITER$_k$, after the definition of the new load solution range, the algorithm elaborates the matrix and analyzes all the combinations on the basis of an objective function OF_{opt}^{k} (see Figure 1) that will be described in the following of the paper.

The iterative procedure of the developed algorithm ends if all the iterations (ITER$_{max}$), defined at the beginning of the calculation, have been processed and analyzed or if the absolute value of the difference between the optimal objective functions of the k^{th} iteration and of the k-1 iteration is lower than a given tolerance value (TOL):

$$\left|OF_{opt}^{k} - OF_{opt}^{k-1}\right| \leq TOL \quad (9)$$

Energy systems modelling

The energy systems calculation (see Figure 1) consists in the evaluation of the power generated by each energy system.

To this purpose, with the developed algorithm all the energy systems can be modeled with nonlinear efficiency curves (as a function of the load) which can be defined in the input section. An example of non-dimensional electrical and thermal efficiency curves of a CHP unit and of non-dimensional thermal efficiency trend of an auxiliary boiler are shown respectively in Figure 2 and in Figure 3 as function of the system's load [40]. On the basis of the performance curves, the produced electrical, thermal and cooling power and the fuel introduced into the prime movers and/or auxiliary boilers are calculated in order to determine the total produced power.

Therefore, the resulting total produced power is compared with the users demand, to point out (if there is) the non-produced power – which means the non-fulfillment of the users demand – or, conversely, if a surplus of power occurs – which means that the users demand is satisfied but with energy dissipations. On this regard, as it will be seen in the objective function definition, the developed algorithm elaborates the optimal solution by minimizing and/or nullifying the total dispersed and the non-produced energies.

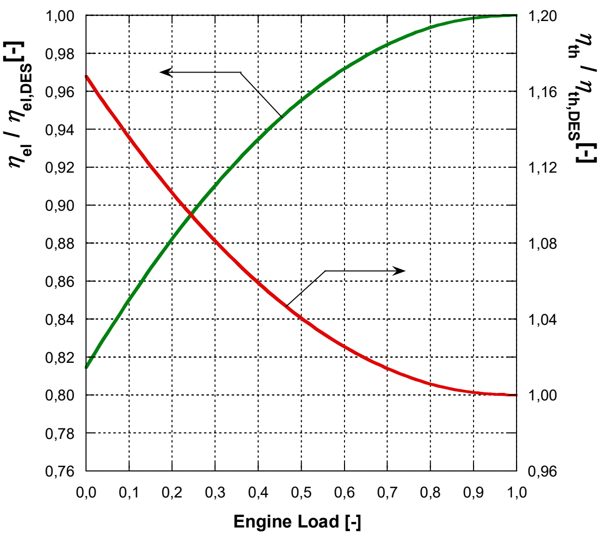


Figure 2 – Electrical and thermal efficiency of the internal combustion engine as function of the load.

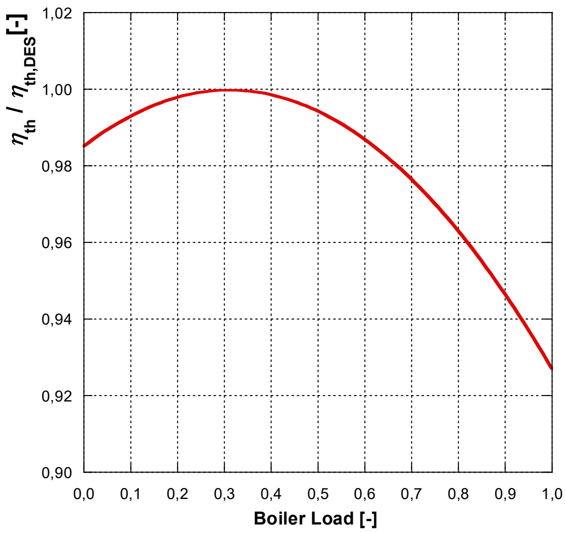


Figure 3 – Thermal efficiency of the auxiliary boiler as function of the load.

Moreover, since the developed software operates the systems calculation by maintaining the non-linearity of the problem constrains and since it potentially explores all the possible loads combinations, COMBO can find out the exact solution of the problem. Obviously, it requires a longer computational time for example with respect of the genetic algorithms.

Objective Function definition

In order to find out the optimal solution, once all the combinations have been listed in the matrix A, for each iteration (ITER$_k$), the algorithm analyzes all the possible combinations, on the basis of a defined objective function (OF). In particular, the OF consists in the total cost of the energy production and can be defined with the following expression:

$$OF = C_\lambda + C_M + C_E + C_F \tag{9}$$

where the term C_λ indicates the total cost of the fuel introduced into the prime movers and/or into the auxiliary boilers, C_M denotes the total cost of maintenance for the considered systems, C_E refers to the total cost of the purchased electricity and C_F represents the so called fictitious costs which are used in order to consider in addition to the economic ones. The so-defined objective function takes into account the same contributes of the software EGO (previously developed by the Authors to solve the scheduling optimization problem and based on genetic algorithms [40, 41]), namely the maintenance, fuel, electricity purchase ad fictitious costs, but differs for the definition of the fictitious costs. Indeed, while in the software EGO the fictitious costs include the heat dissipations through the chimney and the electricity introduction into the grid, in the software COMBO the fictitious costs have been defined with the main purpose of avoiding the electrical, thermal, cooling and, if present, mechanical energy non-production in order to ensure the fulfilment of the users energy needs.

As a consequence, the *fictitious costs* do not take into account the surplus of energy that can characterize some solutions, due to the combinatorial nature of the developed algorithm. In fact, depending on the nature of the energy surplus – which may be due to the employment of the prime movers, auxiliary boilers, etc. – it is accounted within the terms C_λ or C_E and the term C_M of Eq.9. In more detail, if the energy surplus is due to the prime movers and/or to the auxiliary boiler operations, it will results in an increase of the fuel introduced into the energy systems and, thus, in an increase in the fuel costs C_λ. Otherwise, if the energy surplus is due, to the heat pump or compression chiller employment, it will be accounted as an increase in the costs of the electricity purchase for its operation by means within the term C_E. Obviously, the use of an energy system involves some maintenance costs which are evaluated within the objective function (Eq.9) with the term C_M.

With respect to the *fictitious costs*, therefore, they are evaluated in the software COMBO as follows:

$$C_F = C_{th,NP} + C_{c,NP} + C_{mec,NP} \tag{10}$$

where the terms $C_{th,NP}$, $C_{c,NP}$ and $C_{mec,NP}$ stand respectively for the non-produced thermal, cooling and mechanical energy.

Furthermore, three virtual machines – which do not concur for the energy demand fulfilment – have been defined with the main purpose of quantify the non-produced energy by converting it in the equivalent amount of electricity purchase from the national grid beyond the energy systems size and the energy loads of each one. In particular, an electric engine, a heat pump and a compressor chiller have been defined and assumed to be fed by the purchase of electricity from the national grid.

More in detail, being $\xi_{E,pur}$ the specific costs of the electrical energy purchased from the national grid to feed the virtual machines, each term of the *fictitious costs* expression can be further explicated. To this respect, the costs associated to the thermal energy non-production $C_{th,NP}$ can be expressed as:

$$C_{th,NP} = \frac{Q_{th,NP}}{COP^*} \cdot \xi_{E,pur} \tag{11}$$

where $Q_{th,NP}$ is the non-produced thermal power and the term COP^* represents the Coefficient of Performance of the virtual heat pump.

The cooling non-production cost, instead, is calculated as follows:

$$C_{c,NP} = \frac{P_{c,NP}}{EER^*} \cdot \xi_{E,pur} \tag{12}$$

in which the term $P_{c,NP}$ defines the non-produced cooling power while EER^* represent the virtual compressor chiller Energy Efficiency Ratio.

The cost due to the non-production of mechanical power, which is represented by the term $C_{mec,NP}$ in Eq.10, is calculated with the following equation:

$$C_{mec,NP} = \frac{P_{mec,NP}}{\eta^*_{EM}} \cdot \xi_{E,pur} \tag{13}$$

being $P_{mec,NP}$ the mechanical power non-produced and η^*_{EM} the electromechanical efficiency of the virtual electric engine.

Finally, with respect to the non-production of electrical energy, it has to be underlined that it is evaluated, within the objective function of Eq.9, as an increase in the total cost of the purchased electricity (namely the term C_E). In more detail, taking into account the specific cost of the electricity purchase – represented with the $\xi_{E,pur}$, according to the previously equations – the total cost of the electricity purchased from the grid is defined as follows:

$$C_E = P_{EL,NP} \cdot \xi_{E,pur} \tag{14}$$

where the term $P_{EL,NP}$ represents the non-produced electrical energy.

As aforementioned, once the fitness functions have been evaluated, the software points out the combination with the minimum value and use this for the successive iteration.

TEST AND VALIDATION OF THE SOFTWARE COMBO

With the main purpose of validating the developed software presented in this paper, a neighborhood network has been considered as case study. In order to evaluate a year of operation of the network, three typical days have been individuated – representative of wintertime, summertime and mid-season – for the network simulations. In addition, the same grid has been implemented and analyzed with EGO, a software based on genetic algorithms, in order to compare the results obtained from the two software. In the following section the case study is presented along with the main input for the calculation. Furthermore, the software EGO, which has been used for the comparison, is briefly described and the results of the validation are presented.

Case study: a residential neighborhood network

The energy grid considered for the validation of the developed software is a small-medium neighborhood network consisting of 13 residential buildings – which includes 960 households – and 4 tertiary users – two schools, 1 day-hospital structure and a supermarket – for a total of 17 users to be fulfilled [42]. With respect to the analysis of the network, three typical days have been identified. In detail, summertime, wintertime and mid-season typical behavior has been considered by taking into account the typical weather conditions in the North of Italy. In particular, in Figure 4, Figure 5 and Figure 6 the electrical, thermal and cooling profiles, namely the energy required from all the users, of each considered typical day have been respectively shown [42].

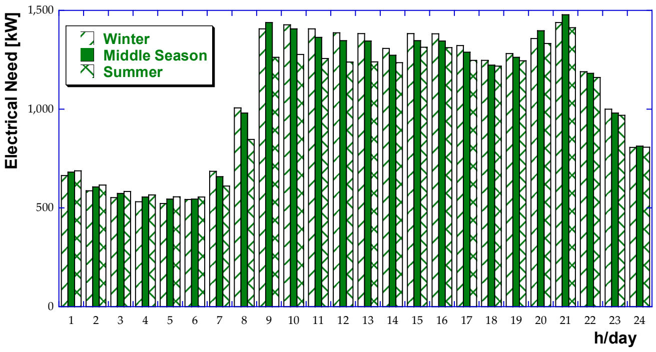


Figure 4 – Hourly electrical needs of the network for the three typical days.

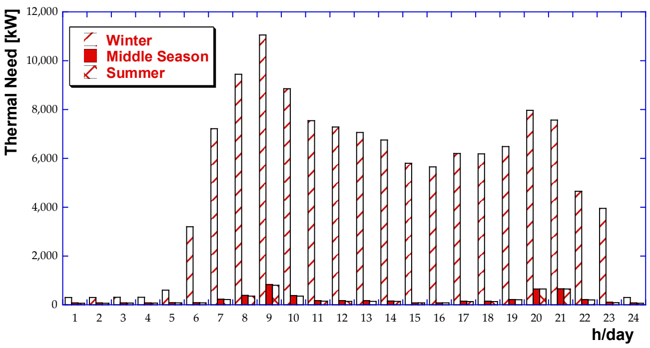


Figure 5 – Hourly thermal needs of the network for the three typical days.

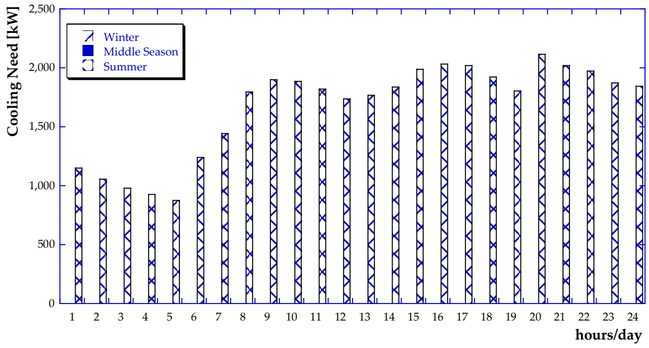


Figure 6 – Hourly cooling needs of the network for the three typical days.

The energy network set as case study is equipped with two identical internal combustion engines (working as CHP units), characterized by a rated electrical power equal to 730 kW each. Furthermore, natural gas auxiliary boilers and a heat pump are included for the thermal power production and compression and absorption chillers for the cooling power production. The main characteristics of the aforementioned energy systems are listed in Table 1.

Table 1: Main parameters of the energy production systems.

Internal Combustion Engine (each)		
Fuel Type		Natural Gas
Design Electric Power	[kW]	730
Design Thermal Power	[kW]	778
Design Electrical Efficiency	[-]	0.4161
Design Thermal Efficiency	[-]	0.4425
Auxiliary Boilers		
Design Thermal Power	[kW]	11´600
Design Thermal Efficiency	[-]	0.80
Heat Pump		
Design Thermal Power	[kW]	20´000
COP	[-]	4
Compression Chillers		
Design Cooling Power	[kW]	2´200
EER	[-]	4
Absorption Chillers		
Design Cooling Power	[kW]	2´000
EER	[-]	0.67

The software EGO

The software EGO has been previously developed by the Authors with the purpose to define the optimal load allocation of the energy systems of a given energy distribution network. The calculation core of this software is based on a genetic algorithm, which follows the rules of evolution by creating a population of individuals in order to find a good solution of the problem. As aforementioned, the software EGO is based on the minimization of a fitness function (based on the total cost of energy production) with a general expression equal to the one presented in Eq.9, but with a different definition of the fictitious costs term.

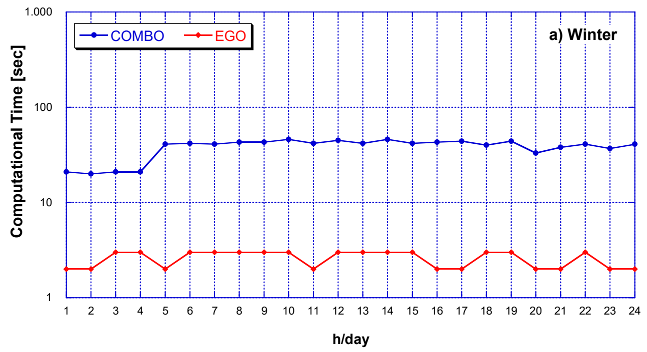
This is due to the strategy at the basis of the software, which already allows to avoid the non-fulfillment of the users' needs by the employment of the back-up systems (auxiliary boilers, electrical grid and compression chillers). Further detail concerning the mathematical model of software EGO can be find in [40, 41]. In order to validate the software presented in this paper, the selected case study has been implemented both with COMBO and with EGO. The results of the simulations obtained with the two software have been then compared as will be shown in the following.

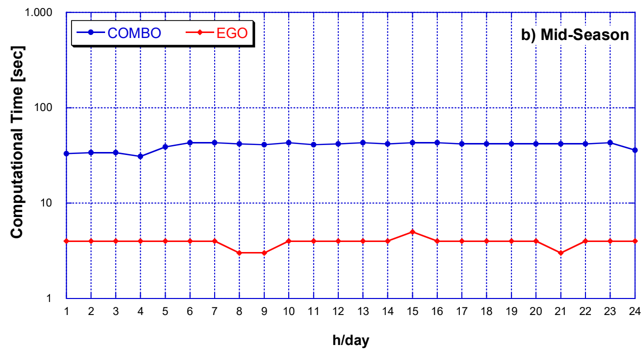
Results and discussion

In this section the results of the software validation are presented considering the three typical days. In particular, the comparison between COMBO and EGO, in terms of computational time and number of solutions evaluated by each software, are shown respectively in Figure 7 and Figure 8.

On one hand, with reference to the computational time of Figure 7, it can be noted that COMBO takes longer time for the problem resolution if compared to EGO. Overall, the calculation time required by EGO is in the order of few seconds (ranges from 2 to 5 seconds for a single simulated hour) while for COMBO it varies from a few tens of seconds (ranges from 20 to 46 seconds for each simulated hour).

On the other hand, however, the number of solutions analyzed by COMBO is much higher than the one evaluated by EGO, as can be seen in Figure 8. In particular, the number of solutions analyzed by COMBO for the single case (namely a single hour) is in the order of the million (and more precisely a value equal to 1˙176˙490 for each hour) against the 21˙000 solutions evaluated each hour by EGO. As a consequence, from the combined analysis of the results shown in Figure 7 and in Figure 8 it appears that COMBO evaluates from 25.5 to about 58.8 thousand solutions per second while EGO investigates a number of solutions per second ranging between 4.2 and 10.5 thousand. On the basis of these results, and in particular on the computational time (in Figure 7), it can be derived that COMBO is probably more suitable for the network design and/or forecasted scheduling, while for the real-time management of the grid is more appropriate the software EGO.





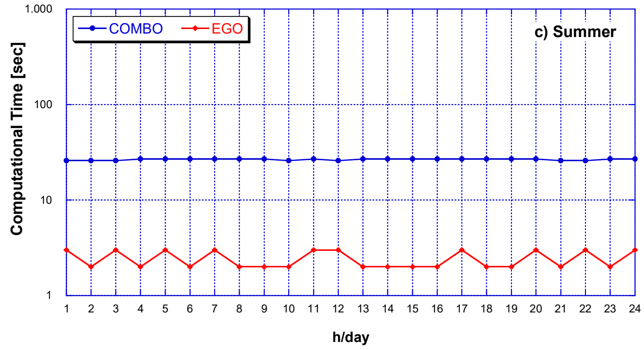
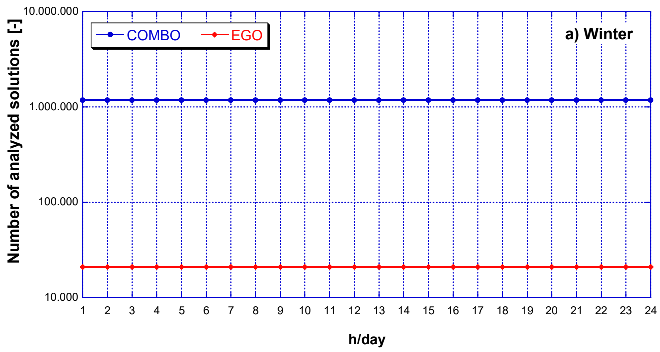
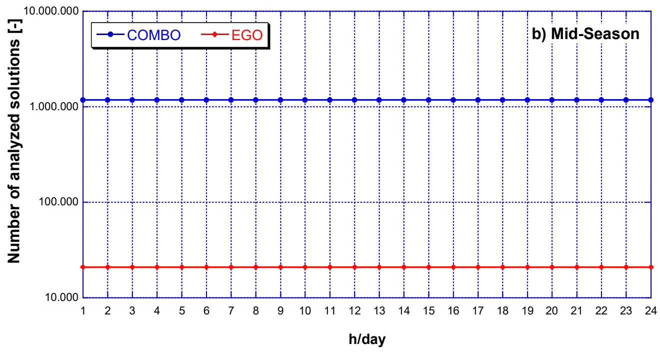


Figure 7 – Computational time of COMBO and EGO.





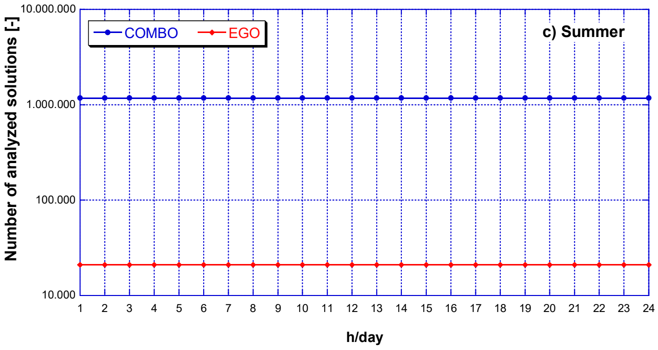


Figure 8 – Number of solutions analyzed by COMBO and EGO as a function of the typical day.

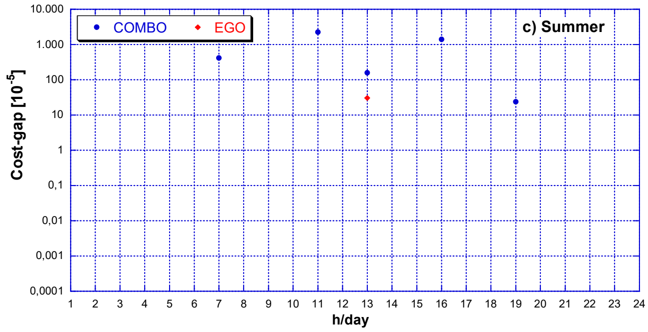
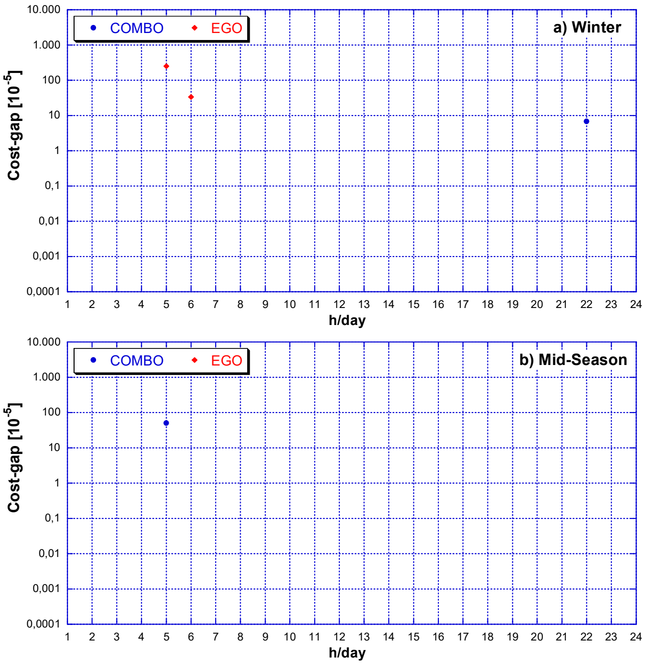
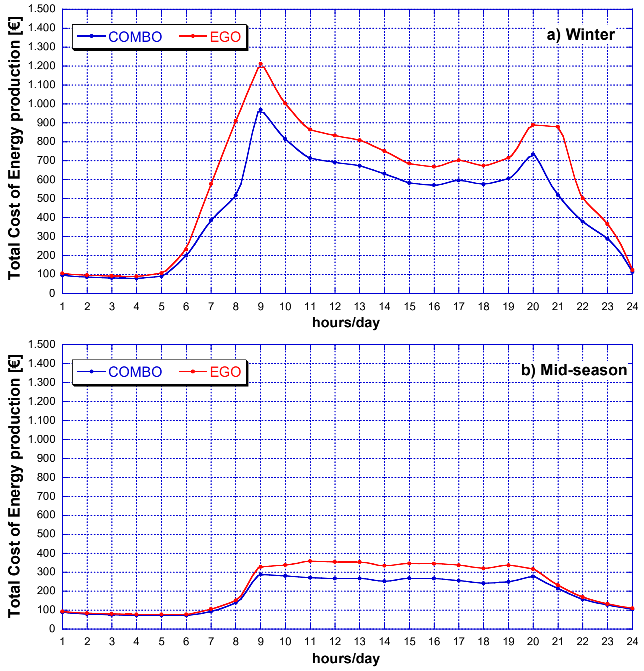


Figure 9 – Costs gap for the software COMBO and EGO, as a function of the typical day.

In Figure 9, the absolute value of the difference between the objective function (including fictitious costs) and the cost of energy production is presented. This parameter – which has been named *cost-gap* – takes into account the reliability of COMBO (or EGO). In fact, it denotes how the load allocation performed by the software differs from the constrains of the desired strategy, which is defined by means of the fictitious costs. It follows that, if the software respects all the constraints, the corresponding value of the cost-gap is equal to zero. The cost-gap values are presented in Figure 9 with reference to each typical day. These values suggest a strong agreement for both COMBO and EGO between the objective function value and the effective cost of energy generation.



Finally, in Figure 10, the hourly cost of energy production for each typical day is shown. As it can be seen, different results have been obtained, depending on the typical day. In particular, while during wintertime and middle season the solutions obtained from the software EGO entail a higher total cost of energy production with respect to COMBO, a different behavior can be seen for summertime where the total cost of energy production resulting from EGO almost coincides with the one resulting from COMBO.



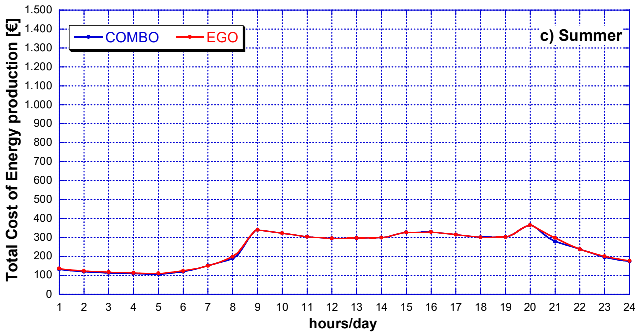


Figure 10 – Hourly profile of the energy production costs, as a function of the typical day and for the two analyzed software.

This evidence can be explained considering the different construction of the objective function of the two algorithms and, in particular, the different definition of the *fictitious costs*. In fact, as is described in the previous section, the *fictitious costs* of the software EGO are defined by taking into account both the energy surplus and the energy non-production. On the other hand, the *fictitious costs* of the software COMBO consider the only non-produced energy since the energy surplus is accounted as an increase in the other terms of the objective function (see Eq.9). As a consequence, the difference in terms of costs, resulting from EGO and from COMBO (see Figure 10) is due to the virtuous behavior from the environmental and/or electricity grid stability viewpoints. This is a consequence of the different way in which the two software asses both the thermal energy dissipation (from the prime movers and not recovered) and the electricity fed into the grid.

According to the tariff scenario chosen for this analysis, the approach at the basis of the software COMBO results more convenient from an economic point of view, as strongly evident from Figure 10a.

Furthermore, it can be deduced that, on the basis of the boundary conditions and the tariff scenario, the different approaches of the two software may lead to a lower total cost of energy production considering the load allocation proposed by COMBO or EGO, depending in particular on the ratio between the purchased electricity and fuel cost. According to these results, further analysis will be carried out in order to reach a higher flexibility in the management of the energy systems with both the software. As a consequence, the same flexibility (i.e. a higher robustness of the algorithm) could be achieved for both forecast and real time control decision problems.

CONCLUSIONS

This paper represents the Part I of a wider study on complex energy networks optimization. In particular, in this first part, the mathematical model of an in-house developed software is presented along with its validation. The software, called COMBO, has been realized with the main purpose of evaluating the optimal load allocation between the energy systems connected to a complex electrical, thermal, cooling energy and fuel distribution network. In more detail, COMBO is based on a non-linear algorithm which allows to potentially analyze all the possible loads combinations, among the considered energy systems, to guarantee the fulfillment of the users' energy needs. At the basis of the developed optimization algorithm stands an iterative procedure, leading to the minimization of the total costs of energy production accounting the economic aspects. The software has been tested and validated by its application to a case study, represented by a residential neighborhood, and comparing the obtained results (in terms of performance parameters) with the results of the software EGO, previously developed by the Authors and based on genetic algorithms. The comparison has been carried out considering a whole year of operation of the network, divided into three typical days representative of wintertime, mid-season and summertime. The results show that the software COMBO allows to investigate a greater number of solutions with respect to EGO, but with longer computational time. However, considering the number of solutions evaluated for the unit of time step, it must be highlighted that COMBO evaluates from 25.5 to 58.8 thousand solutions per second, while EGO investigates a number of solutions per second ranging between 4.2 and 10 thousand. As a consequence, COMBO is probably more suitable for the network design and/or forecasted scheduling, while for the real-time management of the grid is more appropriate the software EGO. Furthermore, considering the results in term of total cost of energy production, it can be noted that the different approach of the software COMBO (with respect to the software EGO) affects these results. In more detail, the difference between the results obtained with the two software is mainly due to the definition of the *fictitious costs* of the objective function.

Starting from the obtained results, further investigation will be made in the future to evaluate the more suitable strategy.

REFERENCES

[1] Ackermann, T., Göran, A., Lennart, S. Distributed generation: a definition. *Electric power systems research*, 57(3) (2001) 195-204.

[2] Pepermans, G., Driesen, J., Haeseldonckx, D., Belmans, R., D'haeseleer, W. Distributed generation: definition, benefits and issues. *Energy Policy*, 33(6) (2005) 787-798.

[3] Pepermans, G. et al. Distributed generation: definition, benefits and issues. *Energy Policy*, 33(6) (2005) 787-798.

[4] Flores, R.J., Shaffer, B.P., Brouwer, J. Dynamic distributed generation dispatch strategy for lowering the cost of building energy. *Applied Energy*, 123 (2014) 196-208.

[5] Picciariello, A., et al. Distributed generation and distribution pricing: Why do we need new tariff design methodologies. *Electric Power Systems Research*, 119 (2015) 370-376.

[6] Wang, C., Song, G., Li, P., Ji, H., Zhao, J., Wu, J. Optimal siting and sizing of soft open points in active electrical distribution networks. Applied Energy, 189 (2017) 301-309.

[7] Anaya, K.L., Pollitt, M.G. Integrating distributed generation: Regulation and trends in three leading countries. *Energy Policy*, 85 (2015) 475-486.

[8] Popp, D., Hascic, I., Medhi, N. Technology and the diffusion of renewable energy. *Energy Economics*, 33(4) (2011) 648-662.

[9] Jäger-Waldau, A., Huld, T., Bódis, K., Szabo, S. Photovoltaics in Europe after the Paris Agreement. In: 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC), 2018, June, pp. 3835-3837

[10] Adil, A.M., Ko, Y. Socio-technical evolution of Decentralized Energy Systems: A critical review and implications for urban planning and policy. *Renewable and Sustainable Energy Reviews*, 57 (2016) 1025-1037.

[11] Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. *Official Journal of the European Union*, 5 (2009).

[12] Hao, X., An, H., Qi, H., Gao, X. Evolution of the exergy flow network embodied in the global fossil energy trade: Based on complex network. *Applied Energy*, 162 (2016) 1515-1522.

[13] Considine, T., Principal, T.C., Cox, W.T. Smart Loads and Smart Grids-Creating the Smart Grid Business Case. Presented at GridInterop, 1 (2009).

[14] HA, M.P., Huy, P.D., Ramachandaramurthy, V.K. A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms. Renewable and Sustainable *Energy Reviews*, 75 (2017) 293-312.

[15] Luo, P., Wang, X., Jin, H., Li, Y., Yang, X. Load Management for Multiple Datacenters towards Demand Response in the Smart Grid Integrating Renewable Energy. In: Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence. 2018, December, pp. 140-144.

[16] Marah, R., El Hibaoui, A. Algorithms for smart grid management. *Sustainable cities and society*, 38 (2018) 627-635.

[17] Festa, P. (2014, July). A brief introduction to exact, approximation, and heuristic algorithms for solving hard combinatorial optimization problems. In 2014 16th International Conference on Transparent Optical Networks (ICTON) (pp. 1-20). IEEE.

[18] Attiya, G., Hamam, Y. (2004, February). Two phase algorithm for load balancing in heterogeneous distributed systems. In 12th Euromicro Conference on Parallel, Distributed and Network-Based Processing, 2004. Proceedings. (pp. 434-439).

[19] Mellouk, L., Aaroud, A., Benhaddou, D., Zine-Dine, K., Boulmalf, M. Overview of mathematical methods for energy management optimization in smart grids. In 2015 3rd International Renewable and Sustainable Energy Conference (IRSEC), 2015, December, pp. 1-5.

[20] Melhem, F.Y. (2018). Optimization methods and energy management in" smart grids" (Doctoral dissertation).

[21] Chen, Y.K., Wu, Y.C., Song, C.C., Chen, Y.S. Design and implementation of energy management system with fuzzy control for DC microgrid systems. *IEEE Transactions on Power Electronics*, 28(4) (2012) 1563-1570.

[22] Lin, M.H., Tsai, J.F., Yu, C.S. A review of deterministic optimization methods in engineering and management. *Mathematical Problems in Engineering*, 2012.

[23] Cooper, L. Heuristic methods for location-allocation problems. *SIAM review*, 6(1) (1964) 37-53.

[24] Javaid, N., Javaid, S., Abdul, W., Ahmed, I., Almogren, A., Alamri, A., Niaz, I. A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid. *Energies*, 10(3) (2017) 319.

[25] Blum, C., Roli, A. Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM computing surveys (CSUR)*, 35(3) (2003) 268-308.

[26] Sivanandam, S.N., Deepa, S.N. Genetic algorithms. In Introduction to genetic algorithms. Springer, Berlin, Heidelberg (2008), 15-37.

[27] Song, Y.H. Modern optimisation techniques in power systems. Springer Science & Business Media, Vol. 20, 2013.

[28] Chaurasia, G.S., Singh, A.K., Agrawal, S., Sharma, N.K. A meta-heuristic firefly algorithm based smart control strategy and analysis of a grid connected hybrid photovoltaic/wind distributed generation system. *Solar Energy*, 150 (2017) 265-274.

[29] Mitten, L.G. Branch-and-bound methods: General formulation and properties. *Operations Research*, 18(1) (1970) 24-34.

[30] Murty, K.G. (1983). Linear programming. Chichester.

[31] Lee, J., Leyffer, S. Mixed integer nonlinear programming. Springer Science & Business Media, Vol. 154, 2011.

[32] Omu, A., Choudhary, R., Boies, A. Distributed energy resource system optimisation using mixed integer linear programming. *Energy Policy*, 61 (2013) 249-266.

[33] Arcuri, P., Florio, G., Fragiacomo, P. A mixed integer programming model for optimal design of trigeneration in a hospital complex. *Energy*, 32(8) (2007) 1430-1447.

[34] Lyzwa, W., Wierzbowski, M., Olek, B. MILP formulation for energy mix optimization. *IEEE Transactions on Industrial Informatics*, 11(5) (2015) 1166-1178.

[35] Polat, U., Gürtuna, F. A Review of Applications of Linear Programming and Mixed Integer Linear Programming in Energy Management: From Policy Makers/Producers to Consumers. *European Journal of Engineering and Applied Sciences*, 1(2) (2018) 84-89.

[36] Yang, Y., Zhang, S., Xiao, Y. An MILP (mixed integer linear programming) model for optimal design of district-scale distributed energy resource systems. *Energy*, 90 (2015) 1901-1915.

[37] Marzband, M., Sumper, A., Domínguez-García, J. L., Gumara-Ferret, R. Experimental validation of a real time energy management system for microgrids in islanded mode using a local day-ahead electricity market and MINLP. *Energy Conversion and Management*, 76 (2013) 314-322.

[38] Alipour, M., Zare, K., Abapour, M. MINLP probabilistic scheduling model for demand response programs integrated energy hubs. *IEEE Transactions on Industrial Informatics*, 14(1) (2017) 79-88.

[39] Elsido, C., Bischi, A., Silva, P., & Martelli, E. Two-stage MINLP algorithm for the optimal synthesis and design of networks of CHP units. *Energy*, 121 (2017) 403-426.

[40] Ancona, M.A., Baldi, .F, Bianchi, M., Branchini, L., Melino, F., Peretto, A., Rosati, J. Efficiency Improvement On a Cruise Ship: Load Allocation Optimization. *Energy Conversion and Management*, 164 (2018) 42-58.

[41] Ancona, M.A., Bianchi, M., Branchini, L., De Pascale, A., Melino, F., Peretto, A. Generation Side Management In Smart Grid. *Proceedings of the International Conference ASME-ATI-UIT 2015*, 17-20 May 2015, Naples, Italy.

[42] Ancona, M.A., Branchini, L., De Pascale, A., Di Pietra, B., Melino, F., Puglisi, G., Zanghirella, F. Complex Energy Networks Optimization for Renewables Exploitation and Efficiency Increase. AIP Conference Proceedings 2191, 020007 (2019).