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Research paper

Unit commitment optimization of a micro-grid with a MILP algorithm: Role of the emissions, bio-fuels and power generation technology

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ABSTRACT

Management strategies of complex energy systems composed by different technologies is mandatory to exploit optimally the characteristics of each power generator, to reduce the cost of energy, the impact of greenhouse gases emissions and to increase the penetration of mini- and micro-grids into energy systems. To this purpose, optimization methods and algorithms have to be developed to assess the unit commitment of generators and to suggest decision variables in the definition of the emission costs. In this paper, a novel Mixed Integer Linear Programming (MILP) optimization algorithm has been developed to compute the optimal management of a micro-energy grid composed either by four Internal Combustion Generators (ICGs), or three ICGs and a Micro Gas Turbine (MGT). The algorithm optimizes a multi objective function that takes in consideration the total cost, the NO_x and the CO_2 emissions of the system, while setting some technological constraints, like start-ups and transients that are typically neglected. Moreover, different fuelling of the devices is evaluated. The model proved the importance of including an accurate model of the greenhouse gases emissions as they can significantly affect the optimization results. Furthermore, it proved to be very flexible and to be a proper basis to be adopted in more complex systems embedding energy storage devices and renewable energy systems.

1. Introduction

Small power grids like micro and mini grids can be defined as electrical distributed systems composed by energy resources and loads of different nature. They can either operate in island mode or they can be connected to a main electrical grid and their development constitutes the foundation of distributed generation energy systems (Gharehpetian and Mohammad-Mousavi-Agah, 2017). Nowadays, the deployment of such a systems and their techno-economic feasibility (Singh and Baredar, 2016) became fundamental in a scenario where the effects of climate change are no longer negligible. In such a context, the development of management and control techniques of the various energy resources is a key aspect for an efficient and sustainable deployment of distributed power systems. Many examples are already available in the literature. For instance, a detailed review of management strategies applied to microgrids is presented by the authors of Zia et al. (2018). In such a context, to increase the systems performance, optimization techniques and energy management algorithms have to be employed during both the design and the operation phase. For example, the authors of Alberizzi et al. (2019) investigated the sizing of an off-grid hybrid renewable energy system using a MILP algorithm to define the optimal number of solar panels and wind turbines required to meet a defined load. In Malik others (2020), the optimization of distributed network parameters has been analysed through a multi-objective particle swarm optimization procedure to increase the penetration of intermittent power generators into the power system. In Chakir others (2020), the authors proposed an energy management algorithm for grid connected PV–battery systems. In Twaha and Ramli (2018), a review of various optimization approaches to design and operate both off-grid and grid connected distributed energy systems has been realized. Regarding the energy systems operation phase, one of the biggest issues that raises during this step is the choice of the unit commitment (UC) strategy of the generators composing the system (Abujarad et al., 2017); i.e. the so-called UC problem. The UC problem is thus an optimization problem to determine the optimal schedule of the generators considering the constraints that define the problem boundary conditions and the different targets over a delimited time period. The UC problem has been addressed by many authors and belongs to various aspects of energy systems. For example, in Sankar et al. (2018) an islanded urban micro grid constituted by PV systems, diesel generators (DG) and micro gas turbines has been considered and the UC of MGTs and DGs has been investigated. In Saleh (2019), the authors developed a Lagrangian relaxation unit commitment (LRUC) method to modulate the electric power

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Nomenclature

Abbreviations

GHG	Greenhouse gas
GA	Genetic algorithm
ICG	Internal combustion generator
i:	Time interval index [−]
j:	Machine index [−]
M	Machine (ICG, or MGT)
MGT	Micro gas turbine
MILP	Mixed integer linear programming
N:	Total number of time discretization steps [−]
PSO	Particle swarm optimization algorithm
UC	Unit commitment

Internal Combustion Generators and Micro Gas Turbine parameters

D_f:	Bio-diesel fraction in the fuel mixture [−]
$D_{t_{min}}^{ICG}$:	ICG minimum down-time [h]
$D_{t_{min}}^{MGT}$:	MGT minimum down-time [h]
E_M:	Energy delivered by the machine (ICG or MGT)
E_{el}:	Load fraction [kW]
F_c^M:	ICGs and MGT fuel cost [€/kWh]
LHV:	Lower Heating Value [MJ/kg]
$N_{s.up}^M$:	Number of start-ups of the machine [−]
O_c^M: :	ICGs and MGT operating cost [€/h]
P_{max}^{ICG}:	ICG rated power [kW]
P_{max}^{MGT}:	MGT rated power [kW]
P_{min}^{ICG}:	ICG minimum output power [kW]
P_{min}^{MGT}:	MGT minimum output power [kW]
P_{ICG}:	Power delivered by the ICG [kW]
P_{MGT}:	Power delivered by the MGT [kW]
P_{rup}^{ICG}:	ICG ramp-up power limit [kW]
P_{down}^{ICG}:	ICG ramp-down power [kW]
P_{rup}^{MGT}:	MGT ramp-up power limit [kW]
P_{down}^{MGT}:	MGT ramp-down power [kW]
Sup_c^M:	ICGs and MGT start-up cost [€/s.up]
$U_{t_{min}}^{ICG}$:	ICG minimum up-time [h]
$U_{t_{min}}^{MGT}$:	MGT minimum up-time [h]
U_t^M:	Operating time of the machine [h]
w_{CO_2}:	CO_2 emissions cost [€/ppm]
w_{NO_x}:	NO_x emissions cost [€/ppm]
η_{el}:	Electrical efficiency [−]
ρ_f:	Fuel density [kg/m^3]

generated by the permanent magnet generator of a wind system in response to changes in the wind speed and/or power demand. The optimal UC of conventional generators is also fundamental in a deregulated market with an increasing share of renewables to enhance the grid capacity to absorb a higher share of renewable energy (Raja Nivedha et al., 2019). Various techniques are described in literature and they are mainly based either on mathematical programming methods or on meta-heuristic algorithms (Sedghi et al., 2016). The former group of methods, like Linear Programming (LP) or Mixed Integer Linear Programming (MILP), guarantees the identification of a global optimal solution during the optimization process and they are supported by high performance solvers (Brito et al., 2020). The latter group of methods, like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) Algorithms, optimizes a problem considering a set of candidate solutions that moves into a search space towards the problem solution; the drawback is that they do not always guarantee that the solution found is the global optimal one, they suffer from mathematical rigours and they lack of the formal model theory; on the other hand, they require less computational resources and can be applied to optimization problems with non-linear relations between optimization variables (Azamathulla et al., 2008). Considering some practical examples, in Kazemi et al. (2016) the authors developed an algorithm to compute the optimal scheduling of diesel, solar and wind generators to minimize the total production cost of an autonomous grid. They concluded that in presence of intermittent generators like the renewable ones, the time resolution choice significantly affects the results of the simulation. In Swarup and Yamashiro (2003), the authors applied a GA to handle systems with a large number of units and time discretization steps to develop a management strategy on a cost based optimization. In Yu et al. (2007), different PSO methods are used to solve the short-term hydro-thermal scheduling problem, i.e. the optimal schedule of hydro and thermal power plants that minimizes the operation costs. The authors of Logenthiran and Srinivasan (2010) applied three versions of PSO: (i) binary PSO, (ii) improved binary PSO and (iii) PSO with Lagrangian Relaxation to solve the UC problem of different sized power systems. They concluded that the best problem solution is obtained with the improved binary PSO method. In Wu et al. (2020), a multi-objective PSO algorithm has been developed to be applied to hydropower schemes, in particular it has been used to investigate the alternatives generating of hydropower planning environmental impact assessment. Other research works used MILP methods to solve the optimal scheduling problem of power system generators. For example, in kai Feng et al. (2019) a MILP algorithm has been developed to study the UC of thermal plants in the East China Power Grid that have to perform peak shaving regulation tasks. The authors demonstrated that the MILP model is able to effectively smooth the residual load curve by gathering power generation of thermal plants at peak periods. The authors of Simonetti et al. (2020) used a MILP algorithm to assess the optimal operating plan of three different solar assisted heat pumps on both an energetic and economic basis. They concluded that the highest energetic performance is achieved with a dual source heat pump system with the largest battery size, while from an economic point of view, a conventional air-to-water heat pump without electric storage guarantees the highest economic saving. Other critical aspects of the optimization problems based on MILP models are: (i) the definition of multi-objective functions that take into account the several aspects of power generation systems, like the cost of the electricity produced and the emissions, other than the sole energetic aspects; (ii) the non-linear nature of the performance figures of power generators, which is, as mentioned before, a critical drawback of LP models (Urbanucci, 2018; Hobbs et al., 2001). In multi-objective problems, a solution to identify an optimal strategy is to define more multi-objective functions and apply an algorithm that optimizes the both simultaneously (Elsoragaby others, 2020), or to embed into a single cost function all the different possible performance parameters of power generation systems. In order to do so, specific conversion factors are required to define the impact of, for example, emissions and energy costs on the final decision variable. Therefore, a critical sensitivity analysis is required to identify and to drive the final optimal management choices. As concerns the non-linear behaviour of power generation systems, in some cases, the assumption of linear boundary conditions is not sufficient to describe the problem accurately and it can lead to results that are not representatives. To deal with this issue, a solution is to adopt a piece-wise approximation of non-linear functions (Simonetti et al., 2020). In this research paper, a MILP algorithm has been developed to study the optimal UC of an energy system and it has been tested on two test cases. In the first test case, an energy system composed by four Internal Combustion Generators (ICGs) has been analysed with the goal of minimizing both the total cost of the system (fuel, operation and start-up costs) and the green-house gases emissions expressed as NO_x and CO_2, constituting thus a multi-objective optimization problem. These two polluting compounds are chosen as they represent the most critical ones for the environment when combustion systems are considered. In the second test case, an ICG has been substituted with a MGT in order to show the importance of the GHGs emission models on the simulation. A MILP algorithm has been preferred over others optimization methods due to the complex search space that usually characterizes optimal scheduling problems. This feature implies the presence of a large number of local minima that complicates the adoption of other techniques based on heuristic and meta-heuristic methods. For this reason, an algorithm that guarantees a global optimal solution has been chosen. The novelty of this investigation work is constituted by the accurate representation of the GHGs emission curves of the generators, which is a parameter that is usually considered proportional to the generated power through a constant or even neglected. The paper demonstrates how their modelling can strongly influence the optimal UC of the energy system units and therefore the importance of a correct representation of such parameters. In this case, the emission functions that describe the NO_x and the CO_2 emissions of the machines has been piece-wise linearized to allow using it in the algorithm still granting a highly realistic model; this should overcome the drawback of using non-linear correlations inside MILP algorithms. In addition, the optimization algorithm embeds special features that are often neglected in literature: the model is designed to be flexible and allows to introduce whatever source of power generation and it embeds peculiar operating conditions, like start-ups and shutdowns. The paper is organized as follows: in the first section, the case study along with the ICGs and the MGT models are presented; in the second section the MILP optimization algorithm is described; in the third section results are discussed and in the last section conclusions are drawn.

2. Research and methods

2.1. Case study

The case studies analysed in this paper represent a typical off-grid energy system that is constituted by four ICGs, comprising Internal Combustion Engines and a MGT fed with syngas, which supply energy to an electrical load, whose curve is depicted in Fig. 1. The generators are also tested with alternative fuel feed. The aim is to model a typical micro-grid that can be composed of several power generators and a set of electric appliances, that can be managed together to optimize the energy island. The load profile has a typical trend of a small rural mountain village, where a higher energy demand is concentrated during the central day hours. The load profile has been depicted considering the data of a measurement campaign performed on mountain huts located in the Penserjoch mountain pass of the Italian region of South Tyrol. A detailed description of the data acquisition campaign is reported in Alberizzi et al. (2019). The management optimization algorithm for the energy system has been realized using the PyCharm Integrated Development Environment provided by the

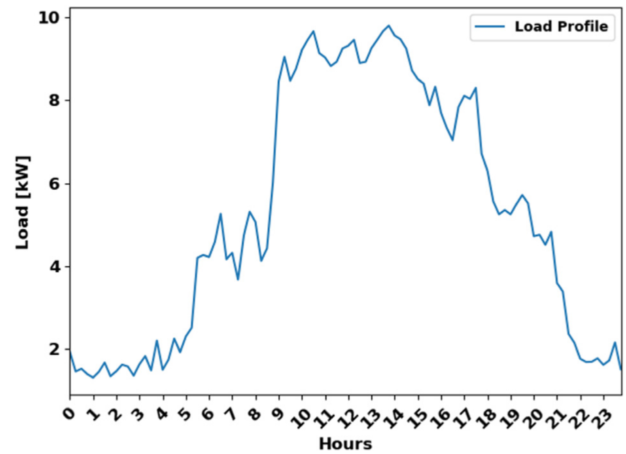

Fig. 1. Power absorbed by the load per day.

Python programming language (PyCharm, 2020). The simulation has been run on a time span of 24 hours with a discretization time step of 15 minutes. This choice has been made considering other research work present in the literature (Lamedica et al., 2018) and taking into account the trade-off between results accuracy and computational resources.

2.2. Internal Combustion Generators (ICGs) and Micro Gas Turbine (MGT)

The machines described in the paper are based on ICGs and a MGT, whose size fits the requirement of a typical mountain hut located in South Tyrol. These specific power generation units were selected as these devices are installed at the premises of the laboratories of the Free University of Bozen – Bolzano and a detailed measurement campaign was performed on these machines to assess their performance and emission figures. The MGT is based on a regenerative Brayton cycle in cogeneration mode. A detailed description of the machine is reported in Nicolosi and Renzi (2020). When fuelled with Natural Gas it generates a rated power of 3.2 kW_{el} with an electrical efficiency η_{el} of 16%. When fuelled with a low Lower Heating Value (LHV) fuel as Syngas, the η_{el} drops down due to the higher power required by the fuel compressor unit. The characteristics of the Syngas used to run the MGT are reported in Caligiuri et al. (2017), Caligiuri and Renzi (2017) and represent a good example of a bio-fuel that can be obtained from an air gasification process of biomass. Due to the lower LHV, the amount of fuel required to run the machine is almost ten times higher than with natural gas fuelling. However, the use of Syngas reduces significantly the GHGs emissions of the machine and the environmental impact of the carbon dioxide is further reduced because it proceeds from renewable sources. The ICGs and the MGT have been modelled considering features that characterize the main technological aspects of the machines in design and off-design operating conditions; the algorithm has to take them into account when running the simulation to find the optimal problem solution. The parameters used to model the ICGs and the MGT are listed in Table 1. They are related to: (i) the maximum and minimum power that each machine can deliver during each time discretization interval, (ii) the energy production and operation costs; (iii) the up- and down-ramp of the single asset as well as the minimum up- and down-time; (iv) the CO_2 and the NO_x emissions costs.

The optimization algorithm computes the electrical power that the ICGs and the MGT should deliver each time step to supply the electrical load while considering some constraints that will be

Table 1
Parameters characterizing ICGs.

ICGs and MGT models parameters			
P_{max} [kW]:	Rated power	F_c [€/kWh]:	Fuel cost
P_{min} [kW]:	Minimum output power	O_c [€/h]:	Operating cost
P_{rup} [kW/h]:	Ramp-up power limit	Sup_c [€/s.up]:	Start-up cost
P_{down} [kW/h]:	Ramp-down power limit	w_{CO_2} [€/ppm]:	CO_2 emissions cost
U_t [h]:	Minimum up-time	w_{NO_x} [€/ppm]:	NO_x emissions cost
D_t [h]:	Minimum down-time	η_{el} [−]:	Electrical efficiency

Table 2
ICGs power limits and electrical efficiency at full load.

Generator	P_{max} [kW]	P_{min} [kW]	η_{el} [−]
ICG_1	4	1.5	0.19
ICG_2	3.7	1.2	0.19
ICG_3	2.9	0.7	0.20
ICG_4	2.5	0.5	0.21
MGT	2.5	0.5	0.11

Table 3
ICGs type and biodiesel fraction in the fuel mixture.

Generator	Biodiesel fraction	LHV [MJ/kg]	ρ_f [kg/m^3]
ICG_1	25%	41.3	832.5
ICG_2	0%	42.6	827.7
ICG_3	50%	40.1	847.2
ICG_4	75%	38.8	859
MGT	Syngas	4.90	

Table 4
ICGs operational limits.

Generator	P_{rup} [kW/h]	P_{down} [kW/h]	U_t [−]	D_t [−]
ICG_1	1.2	2.4	1	0.75
ICG_2	2	1.6	0.75	0.25
ICG_3	2.9	2.9	0.5	1
ICG_4	2.5	2.5	0.25	0.25
MGT	2.5	2.5	0.25	0.25

described in the following sections. The electrical power delivered by the ICGs is related to the mechanical power through Eq. (1). As a first approximation, the electrical efficiency is considered as constant and reported in Table 2.

$$P_m = \frac{P_{el}}{\eta_{el}} \tag{1}$$

In this case, this assumption is possible because the constraints that have been defined for the analysed test cases tend to limit the machines operations at partial load. To correlate the CO_2 and the NO_x emissions to the power generated by the ICGs and the MGT, a diesel–biodiesel generator and a MGT with a nominal power output coherent with the analysed load has been selected (Nicolosi and Renzi, 2020; Caligiuri et al., 2019). In the case of the ICGs, the amount of CO_2 and NO_x emissions vary according to a semi-quadratic function described by Eq. (2) and Eq. (3), where E_{el} indicates the load fraction and D_f the biodiesel fraction present in the fuel mixture (Caligiuri et al., 2019).

$$CO_2^{ICG} = 0.7 + 2.7 \cdot E_{el} + 0.08 \cdot D_f + 0.005 \cdot E_{el} \cdot D_f + 2.2 \cdot 10^{-5} \cdot D_f^2 \tag{2}$$

$$NO_x = -0.25 + 181 \cdot E_{el} - 2.7 \cdot D_f - 2.9 \cdot E_{el} \cdot D_f + 0.0561 \cdot D_f^2 \tag{3}$$

While the CO_2 emissions curve of the MGT is expressed by Eq. (4), which describes the MGT CO_2 emissions expressed in mass fraction depending on the load fraction E_{el}. As far as this analysis is concerned, the NO_x emissions of the MGT can be considered as negligible if compared with the NO_x emissions of the ICG.

$$CO_2^{MGT} = -0.0024 \cdot E_{el}^2 + 0.0175 \cdot E_{el} \tag{4}$$

The GHGs emissions curves of the ICGs have been experimentally derived by laboratory tests and realized with different biodiesel fraction in the fuel mixture in the case of the ICG. As concerns the MGT, the performance data have been obtained through a simulation routine developed by some of the authors of this work; as concerns the emissions, they have been evaluated through CFD simulations on the MGT burner fed with syngas (Nicolosi and Renzi, 2020). In order to fit the curves into the MILP algorithm, they have been piecewise linearized as illustrated in Figs. 2 and 3 through the method described in Brunner (1980). In this investigation work, ICG_2 corresponds exactly to the generator described in Caligiuri et al. (2019) with a null biodiesel fraction in the fuel mixture. In order to test the algorithm simulating an optimization with different power generation systems, the size of ICG_1, ICG_3 and ICG_4 has been chosen to be similar to the one of ICG_2. On the other hand, due to the lack of experimental data on NO_x and CO_2 emissions of generators of similar size, the emission curves of the other ICGs have been assumed equal to the ones of ICG_2 but with varying shares of biodiesel fraction in the fuel mixture. Table 3 presents the ICGs and the MGT types, the fuel used to feed the MGT, the biodiesel fraction used in the fuel mixture that determines the emission curves of Figs. 2 and 3.

Table 4 lists the ICGs and the MGT characteristics. The values of ramp-up and ramp-down and the values of minimum down and up time, i.e. the minimum time intervals that an ICG and the MGT have to wait before turning on after a shut-down and turning off after a start-up respectively, are coherent with the selected technologies, being the size of these machines very small and, therefore, capable of granting a relatively quick response. In general, the choice of the ramp-up and ramp-down have been chosen in order to grant a smoother generation curve and to grant the assumed condition of working close to the best efficiency point, justifying thus the assumption of a constant efficiency. However, we have adopted a faster response for ICG3, ICG4 and the MGT, which is technically feasible for both ICGs and MGT technologies, to grant a sufficiently quick response to the sharp variations of the load.

2.3. Optimization problem

An optimization problem is constituted by three main elements: (i) an objective function that represents the target of the problem, (ii) a set of decision variables that will determine the final value of the objective function and (iii) a set of constraints that limits the values that can be assigned by the algorithm to the decision variables. The optimization algorithm is responsible to find the optimal value of the objective function, depending on the optimization target, assigning the values to the decision variables while respecting the constraints. In this case, a MILP algorithm has been realized to solve the optimization problem with the programming environment PyCharm of the Python programming language (PyCharm, 2020). MILP algorithms belong to the class of iterative optimization methods that, compared with other optimization algorithms like the ones based on heuristic methods, require more computational resources. However, these methods are based on solid solvers and mathematical foundations

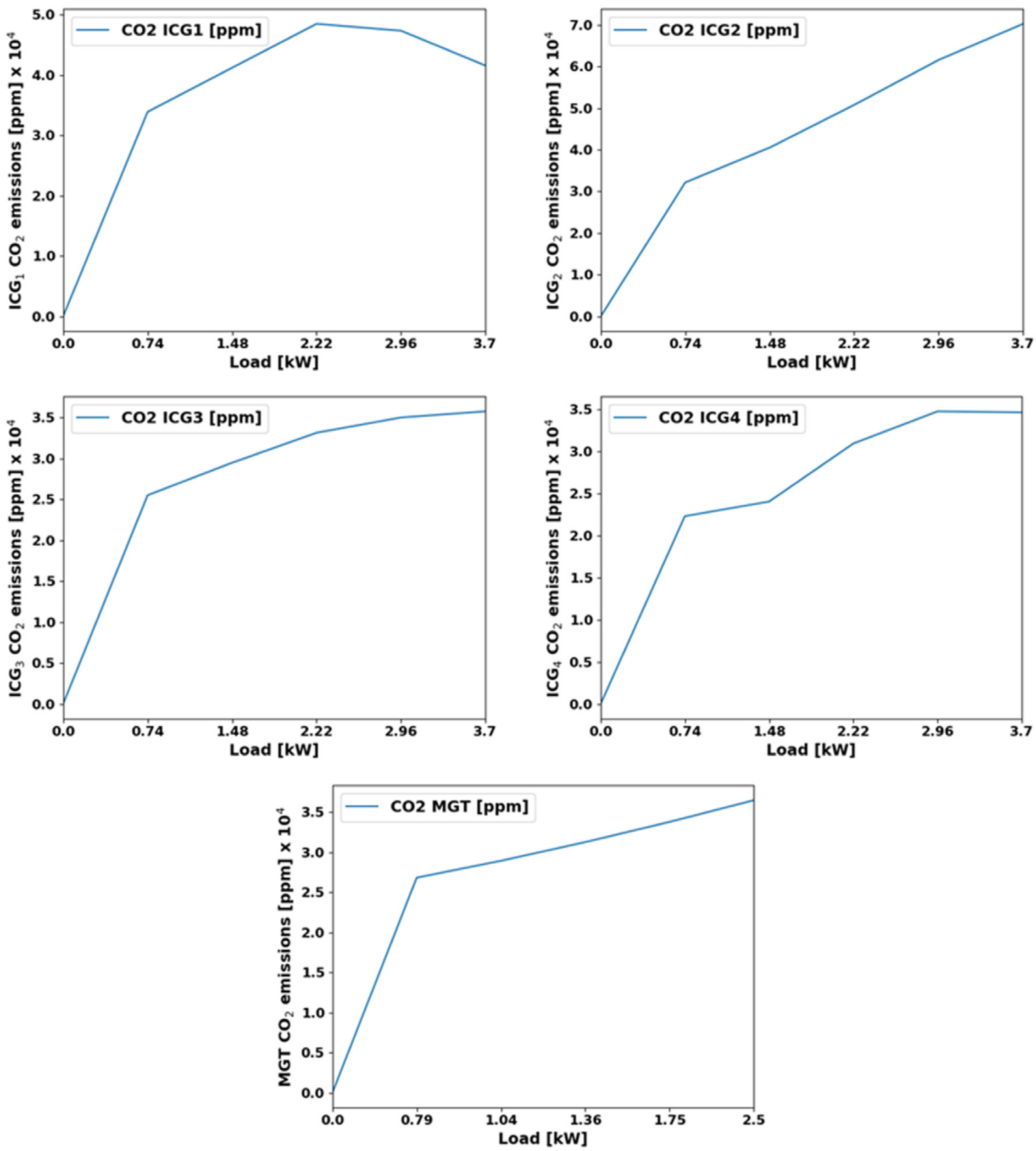

Fig. 2. Piecewise linearization of CO_2 emission function.

that guarantee the certainty of the solution with a well-known optimality level. In this case, the Gurobi solver has been used to find the problem optimal solution (GUROBI, 2020). A flow chart that shows the problem optimization steps is reported in Fig. 4. The problem is initially defined by the input performance parameters of the ICGs and the MGT, which represent the technologies features, the load characteristics, the total costs and GHGs emissions curves. Then, the objective of the optimization is specified, i.e. the minimization of the total costs of the system and the GHGs emissions. The optimization process starts afterwards and it consists in the assignment of the optimization variables to evaluate the objective function value iteratively until the optimal solution is obtained.

2.4. Objective function

The objective function of the problem is constituted by the sum the of total costs of the system and the total GHGs and harmful emissions expressed in terms of CO_2 and NO_x and it is defined by Eq. (5). It is thus a two-terms multi-objective function. In order to be able to compare the two terms at a software level during the optimal solution computation, a weight factor must be assigned to the term related with the total greenhouse gases emissions to convert it into a cost. The value of weight factors has been chosen to convert the emissions of the ICGs and the MGT into a cost that is relevant during the optimization process; too small weight factors would cause the MILP algorithm not to consider the emission terms in the optimization process.On the other hand, a too high weight factor would make the other terms negligible if compared with the emission terms. In the literature

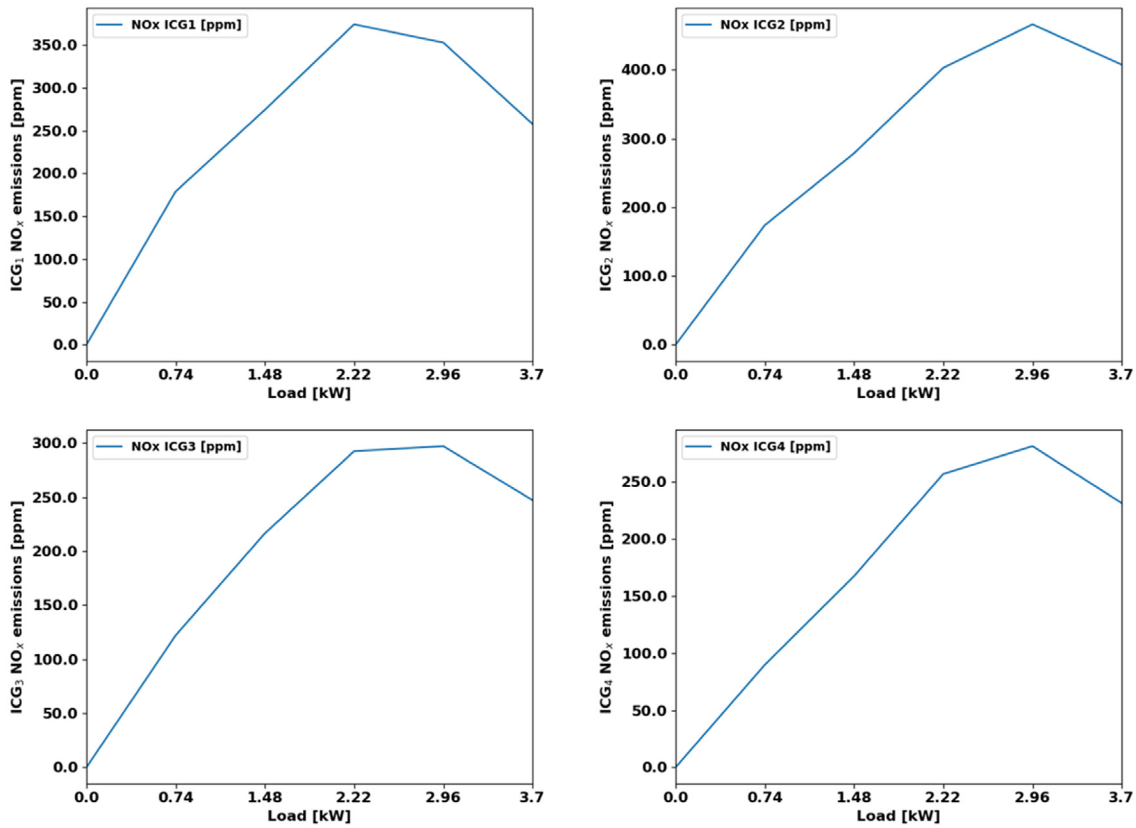

Fig. 3. Piecewise linearization of NO_x emission function.

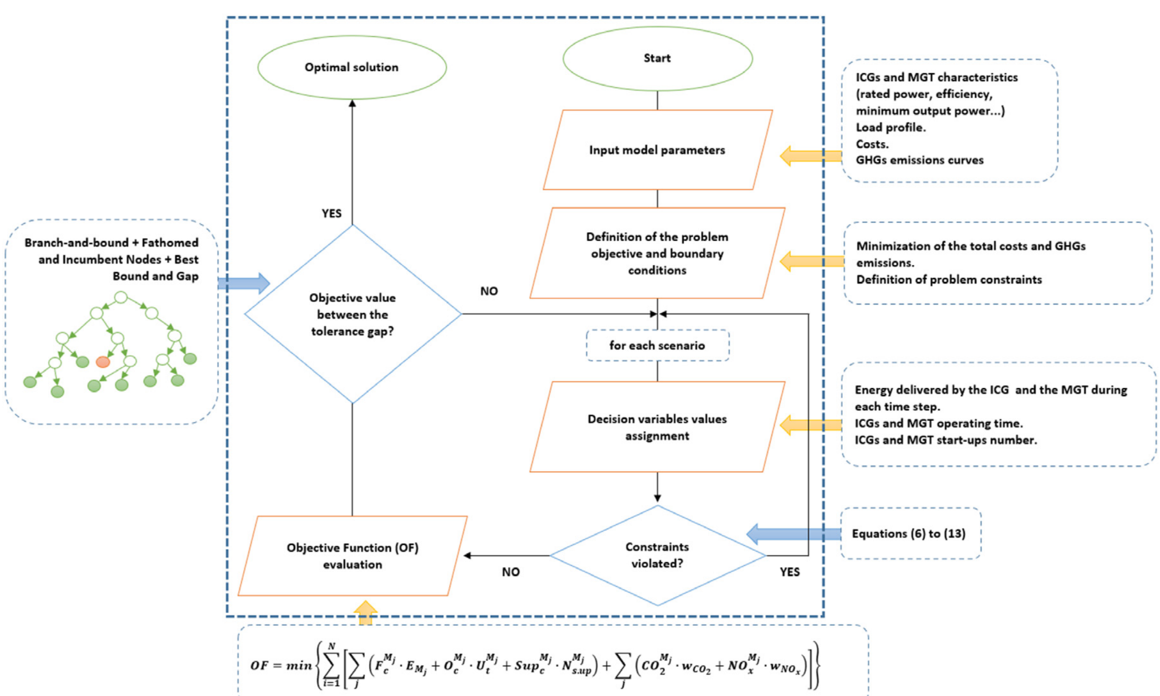

Fig. 4. Flow chart of the MILP optimization algorithm.

there are no unique references to the costs to apply to the CO_2 and the NO_x emissions. The carbon taxes across the world applied to the electricity sector can vary significantly according to the policy of a specific country, ranging from less than 1 to 127 €/ton as reported in Stevens and Carrol (2020) while to consider the effects of other GHGs emissions costs on the electrical energy sector such as the NO_x, different scenarios are usually evaluated (Moradones and Cabello, 2019) and compared. In this case, the GHGs emissions weight factors have been assessed through a sensitivity analysis of their values. They have thus been chosen such as the effects of the emissions terms are not considered either negligible or too relevant when compared to the other costs. A sensitivity analysis has been considered also regarding the syngas cost used to feed the MGT due to the price variability of this type of fuel. In this research work, two scenarios have been evaluated.

$$min\left\{\sum_{i=1}^{N}\left[\sum_{j}\left(F_c^{M_j}\cdot E_{M_j}+O_c^{M_j}\cdot U_t^{M_j}+Sup_c^{M_j}\cdot N_{s.up}^{M_j}\right)\right.\right.$$
$$\left.\left.+\sum_{j}\left(CO_2^{M_j}\cdot w_{CO_2}+NO_x^{M_j}\cdot w_{NO_x}\right)\right]\right\} \tag{5}$$

where:
i: ith time interval.
N: Total number of time discretization intervals.
j: ICG and MGT number.
$F_c^{M_j}$ [€/kWh]: Fuel cost associated to the jth machine M that can be an ICG or the MGT.
E_{M_j} [kWh]: Energy delivered by the jth machine during the ith time step.
$O_c^{M_j}$ [€/h]: Operating cost of the jth machine.
$U_t^{M_j}$ [h]: Operating or up-time of the jth machine.
$Sup_c^{M_j}$ [€/s.up]: Start-up cost of the jth machine.
$N_{s.\,up}^{M_j}$ *[-]:*Number of start-ups of the jth machine.
$CO_2^{M_j}$ [ppm]: CO_2 emissions of the jth machine.
w_{CO_2} [€/ppm]: weight factor associated to the CO_2 emissions or CO_2 emissions cost
$NO_x^{M_j}$ [ppm]:NO_x emissions of the jth machine.
w_{NO_x} [€/ppm]: weight factor associated to the NO_x emissions or NO_x emissions cost

2.5. Optimization variables

The optimization variables determine the final value of the objective function and their value is computed by the algorithm to minimize the latter. In this case, the optimization variables are: (i) the energy that each ICG and the MGT deliver per time step; (ii) the ICGs and MGT operating time and (iii) the ICGs and MGT start-ups number. Since the time period has been discretized in 96 time steps, represented in the equations by N, and the energy system is composed by 4 ICGs or 3 ICGs and a MGT, the total number of optimization variables will thus depend on all those three elements.

2.6. Problem constraints

In optimization problems, optimization variables have usually to be subjected to constraints that set the so-called boundary conditions. Constraints objective is to limit the values assigned by the algorithm to the optimization variables in order to simulate the real system operations. In MILP problems, constraints that bound decision variables have to be expressed by linear equalities and inequalities. In this case, the major limitation raises when functions that represent a variable trend do not have a linear shape, as the relations that describe the polluting gases emissions. To solve this issue, the functions have been piece-wise linearized. The constraints for this optimization problem are defined during each time discretization interval i and they are related with:

Table 5
ICGs and MGT costs.

Generator	Fc [€/kWh]	O_c [€/h]	Sup_c [€/s.up]	w_{CO_2} [c€/ppm]	w_{NO_x} [c€/ppm]
ICG1	0,2	0,12	0,88	0.02, 0.04, 0.08, 0.12	4, 8, 12, 16
ICG2	0,16	0,08	0,76		
ICG3	0,24	0,16	0,84		
ICG4	0,28	0,2	0,8		
MGT	0.16, 0.12	0,2	0,8		

- The power that during each time step can be delivered to the load expressed by Eq. (6), where $P_{ICG_j}(i)$ and $P_{MGT}(i)$ represent the power delivered by the jth ICG and by the MGT during the ith time interval, while $P_l(i)$ is the power required by the load during the ith time interval. N is the total number of time discretization intervals.
- The maximum and minimum power delivered to the load by the ICGs and the MGT in each time step: Eq. (7) where $P_{min}^{ICG_j}$, $P_{max}^{ICG_j}$, P_{min}^{MGT} and P_{max}^{MGT} are the upper and lower power limits of the ICGs and the MGT.
- The ramp-up and the ramp-down power limits of the ICGs and the MGT: Eqs. (8) and (9), where $P_{rup}^{ICG_j}$, P_{rup}^{MGT}, $P_{down}^{ICG_j}$ and P_{down}^{MGT} are the rump-up and the ramp-down power limits of the ICGs and the MGT. $\Delta P_{ICG_j}(i)$ and $\Delta P_{MGT}(i)$ represent the power increase and the power decrease during two consecutive time steps.
- The minimum ICGs and MGT up- and down-time, that is the minimum time interval where the ICGs and the MGT have to operate or have to remain turned off when they are turned on or shut down respectively: Eqs. (10) and (11).
- The GHGs emissions that are a function of the delivered power of each ICG and the MGT during each time interval i represented by $P_{ICG_j}(i)$ and $P_{MGT}(i)$: Eqs. (12) and (13).

$$\sum_{i=1}^{N}\left(\sum_{j}P_{ICG_j}(i)+P_{MGT}(i)\right)=\sum_{i=1}^{N}P_l(i) \tag{6}$$

$$\begin{aligned}P_{min}^{ICG_j}&\leq \textstyle\sum_{i:1}^{N}P_{ICG_j}(i)\leq P_{max}^{ICG_j}\\ P_{min}^{MGT}&\leq \textstyle\sum_{i:1}^{N}P_{MGT}(i)\leq P_{max}^{MGT}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta P_{ICG_j}(i)&\leq P_{rup}^{ICG_j}\\ \Delta P_{MGT}(i)&\leq P_{rup}^{MGT}\end{aligned} \tag{8}$$

$$\begin{aligned}-\Delta P_{ICG_j}(i)&\leq P_{down}^{ICG_j}\\ -\Delta P_{MGT}(i)&\leq P_{down}^{MGT}\end{aligned} \tag{9}$$

$$\begin{aligned}U_{t_{min}}^{ICG_j}&\leq U_t^{ICG_j}\\ U_{t_{min}}^{MGT}&\leq U_t^{MGT}\end{aligned} \tag{10}$$

$$\begin{aligned}D_{t_{min}}^{ICG_j}&\leq D_t^{ICG_j}\\ D_{t_{min}}^{MGT}&\leq D_t^{MGT}\end{aligned} \tag{11}$$

$$NO_x^{ICG_j}(i)=f(P_{ICG_j}(i)) \tag{12}$$

$$\begin{aligned}O_2^{ICG_j}(i)&=f\left(P_{ICGj}(i)\right)\\ CO_2^{MGT}(i)&=f\left(P_{MGT}(i)\right)\end{aligned} \tag{13}$$

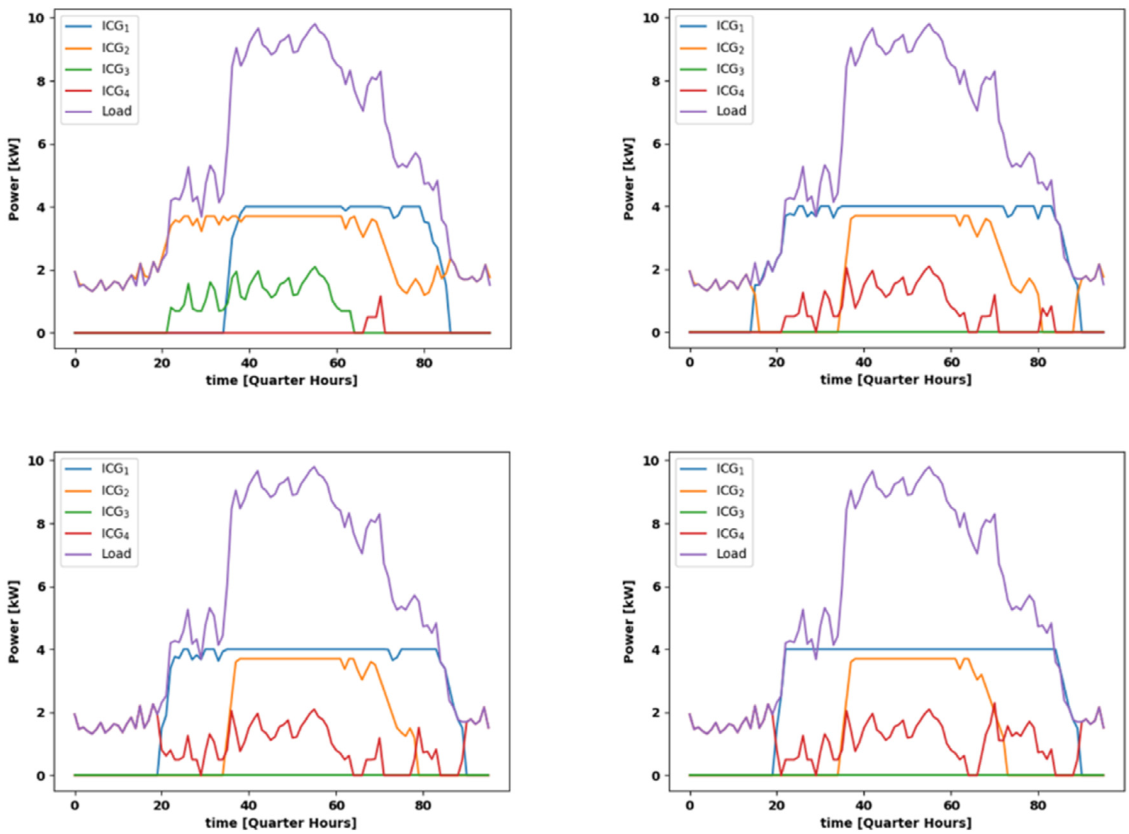

Fig. 5. ICGs UC with different weight factors for the GHGs. T. left (w_{CO_2}: 0.02, w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12). B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

3. Results and comments

The algorithm has been tested on two case studies, which simulate: (i) an energy system constituted by four ICGs and (ii) an energy system constituted by three ICGs and an MGT. The simulation has been run on a daily time interval discretized per quarter hours, i.e., the optimization problem is constituted by 96 time discretization intervals, and with four different values of CO_2 and NO_x weight factors. The values of the biodiesel fraction used in the fuel mixture are reported in Table 2, while the ICGs and the MGT characteristics are indicated in Tables 3 and 4. Table 5 shows the costs associated to the ICGs and the MGT, namely the fuel (IRENA, 2013), the operation and the start-up costs, along with the NO_x and CO_2 weight factors used to run the different simulations and to perform the sensitivity analysis. The results of the simulation are shown in Figs. 5, 6 and 7. The curves depicted in the three figures represent the optimal scheduling of the ICGs and the MGT during the daily operation. In particular, the graphs depict the scheduling solutions that minimize the total cost of the energy system while considering the GHGs emissions in four different scenarios considering the test cases. It can be noticed how the introduction of an increasing weight factor for the NO_x and the CO_2 emission costs significantly affects the problem solution. ICG_1 and ICG_2 are the machine with the highest rated powers, therefore the algorithm relies mainly on them to supply the base load and limiting the number of starts-up and shuts-down. Their activities increase or decrease with the growth of the GHGs emissions weight factors. ICG_1 is characterized by a reduction of the CO_2 and NO_x concentration when it works at full power. On the other hand, ICG_2, if compared with ICG_1, is characterized by CO_2 emission levels that do not decrease significantly at full load. Therefore, increasing the GHGs emission costs, ICG_1 gains progressively ICG_2 energy shares becoming the predominant machine in the UC problem. The algorithm exploits it when the load needs are higher and reduces its use during low load periods decreasing its activity levels at higher weight factors. ICG_3, ICG_4 and the MGT are used as complements during high peaks load periods being characterized by a lower rated power. Their roles change significantly depending on the weight factors used to consider the GHGs emissions. Considering the test case shown in Fig. 5, at low values of CO_2 and NO_x weight factor, ICG_3 is preferred to ICG_4 due to slightly lower values of fuel and operation costs. On the contrary, at high values of GHGs weight factors, ICG_4 substitutes ICG_3 presenting a CO_2 and a NO_x emission curves that guarantee a lower emission level. The test case depicted in Fig. 6, shows how the UC of the energy system changes when the MGT substitutes ICG_4. At lowest weight factor level, the UC of the system matches exactly with the one described in the previous case. The MGT is do characterized by lower GHGs emissions but also by a lower efficiency. On the other hand, increasing the GHGs emissions costs, the MGT activity increases. The trends of ICG_1 and ICG_2 reflects the ones described for the previous test case, with an ICG_1 activity directly proportional to the GHGs emissions weight factors and an ICG_2 inversely proportional to the GHGs emissions weight factors. On the other hand, if compared with the test case of Fig. 5, the energy share delivered by the MGT is higher than the energy share delivered by ICG_4 as Table 6 and Table 7 show. Considering the test case of Fig. 7, the MGT is much more exploited than the ICG_4 reported in the previous test cases. This is due to the significantly lower GHGs emissions and

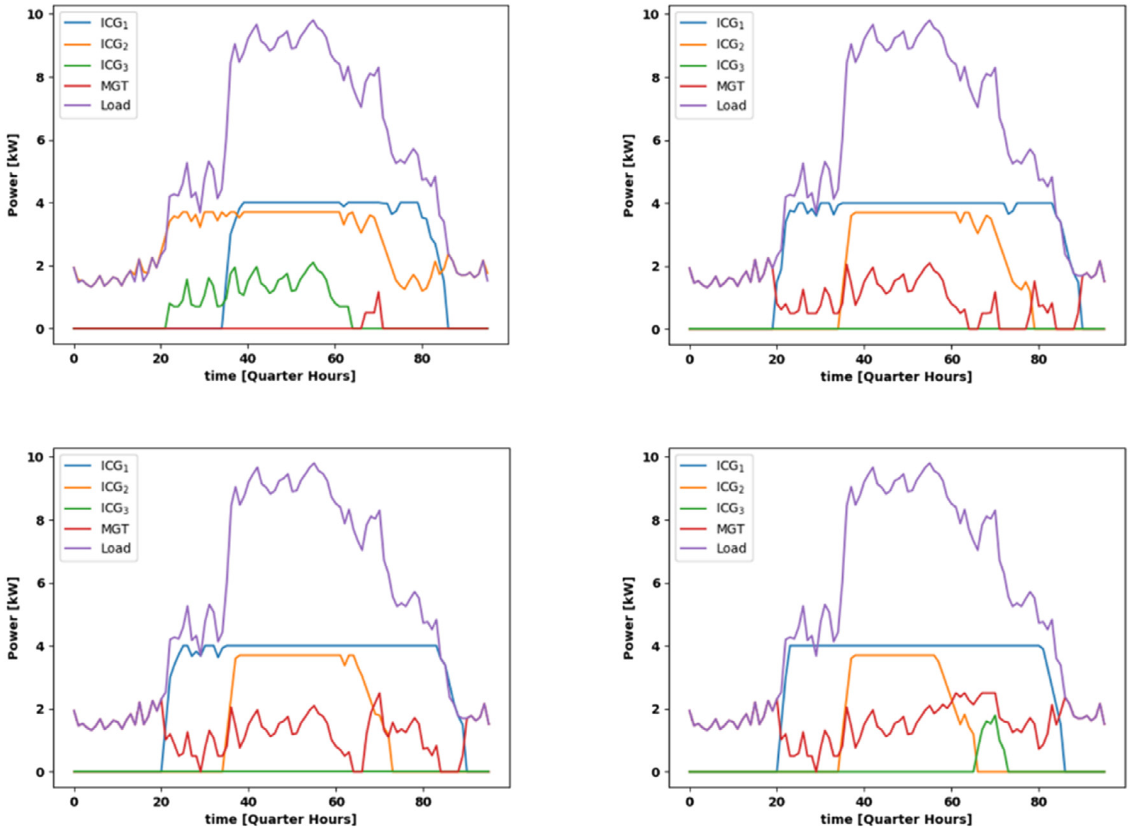

Fig. 6. ICGs and MGT UC with different weight factors for the GHGs emissions and a MGT fuel cost of 0.16 €/kWh. T. left w_{CO_2}: 0.02w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12). B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

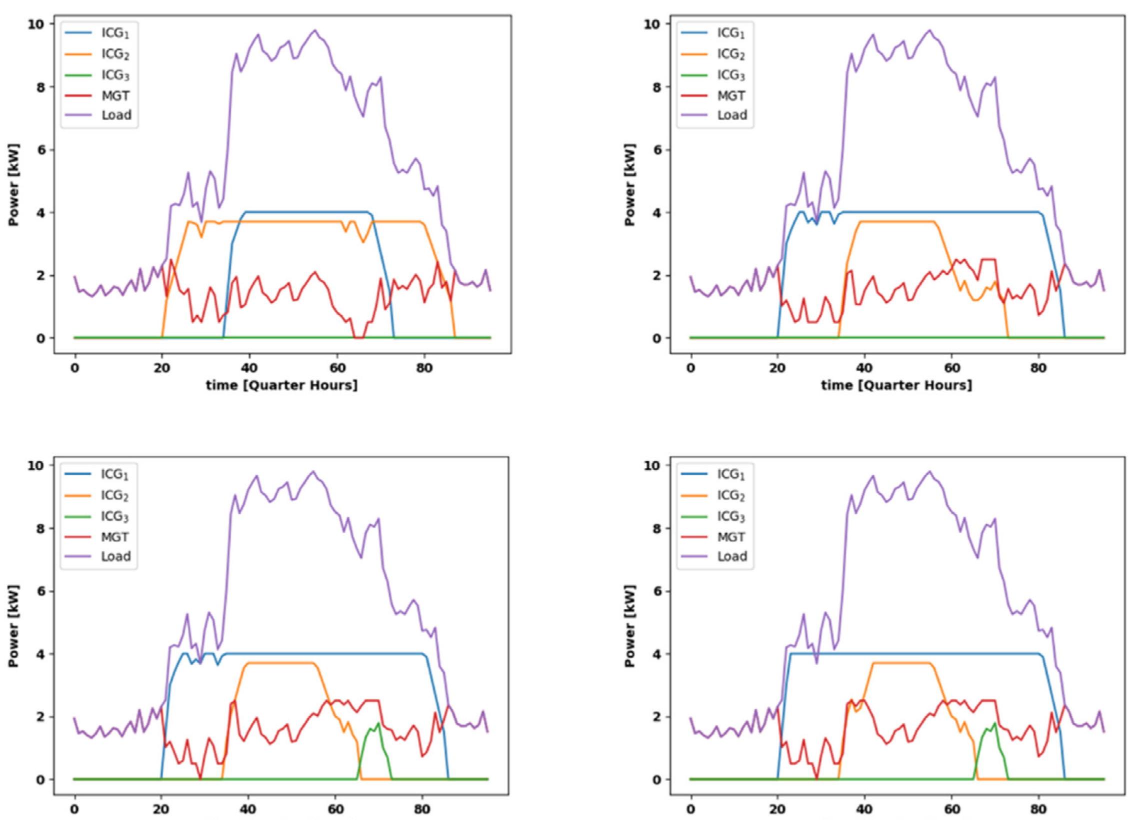

Fig. 7. ICGs and MGT UC with different weight factors for the GHGs emissions and a MGT fuel cost of 0.12 €/kWh. T. left w_{CO_2}: 0.02w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12). B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

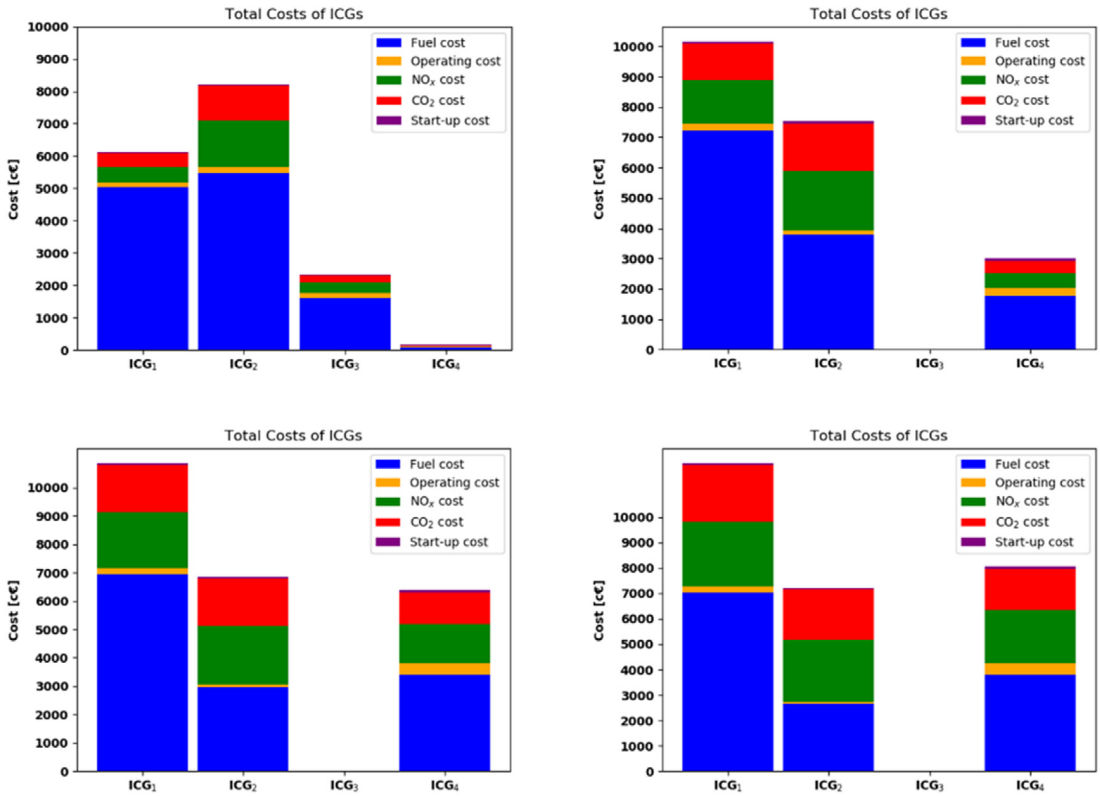

Fig. 8. ICGs costs with different weight factors for the GHGs emissions. T. left w_{CO_2}: 0.02w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12), B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

fuel cost characterizing the machine, the algorithm operates the MGT instead of ICG_3 also at low GHGs weight factors. Increasing the GHGs emissions weight factors, the MGT increases its activity replacing progressively a portion of the energy delivered by ICG_2. In this test case, the algorithm starts to operate ICG_3 only with the highest GHGs weight factors values at the expense of ICG_2. The figures and tables in the Appendix section show the distribution of the total cost for each machine and quantify them furtherly demonstrating the outcomes. In particular, the bars in Figs. 8–10 show the total cost of each machine divided in fuel, operating and GHGs costs, while in Tables 9–11 these costs are quantified. It can be noticed that the start-up cost is barely present because, in the cases analysed, it resulted negligible with respect to the others as well as the operating cost that present a reduced share if compared with fuel and GHGs emissions cost. The share of GHGs cost increases with the increasing trend of the weight factors used in the simulation thus affecting the machines operating strategy and favouring the ones characterized by lower emissions curves. It can be seen in Tables 9 and 10 the growth of the fuel and GHGs costs of ICG_1, ICG_4 and the MGT with the weight factor rise and the reduction of ICG_2 and ICG_3 activities demonstrated by the fuel and GHGs costs downturn. Tables 6, 7, 8 show the energy fraction that each ICG and the MGT deliver to the load in the two test cases analysed varying the GHGs emissions weight factors. It is evident the increase of the use of ICG_4 and the MGT activity in the three cases with the growth of the GHGs weight factors and the switch between ICG_1 and ICG_2 with the first weight factors increase. In all cases, the CO_2 and the NO_x emissions of the system start to be significant in the optimization process and the algorithm operates the energy system assets to limit them. In particular, the ICG_4 and the MGT are more exploited due to their lower GHGs emissions characteristics, while ICG_1 increases its activity since its CO_2 and NO_x emission curves are characterized by a decreasing trend when it operates at full load. It can be noticed that the graphs and the tables reflect the trends described by Figs. 5–7. In particular, the significant role that the CO_2 and the NO_x emissions and their accurate modelling can play when assessing the energy system optimal management.

4. Conclusion

In this research paper, a MILP algorithm has been developed to study the optimal scheduling of an energy system composed by four ICGs and an energy system composed by three ICGs and a MGT. The optimization problem has been set up in the form of a multi-objective optimization where both the total costs of the energy systems and the GHGs emissions of the generators constitute the problem optimization targets expressed in terms of CO_2 and NO_x. The total costs have been considered as the sum of fuel costs, operating costs and start-up costs. In order to include the GHGs into the objective function, a weight factor has been assigned to the CO_2 and the NO_x emissions to convert them into a cost. The optimization variables have been constrained considering some typical features of ICGs and MGTs like maximum and minimum power limits, power rump-up and down constraints during the considered time discretization steps and maximum up and down time constraints. Moreover, in order to overcome the drawback of MILP algorithms related with the presence of non-linear relations between optimization variables, the semi-quadratic GHGs emission curves of the ICGs and the MGT have been piece wise linearized. Furthermore, simulations have been run considering four different NO_x and CO_2 emissions weight factors and two different syngas costs to show the sensibility of these parameters on the outcomes of the simulations. Considering the first test case, i.e. an energy system constituted by four ICGs, results show that the optimal management tends to favour the adoption of traditional diesel fuelled generators over the ones run with some shares of biodiesel due to the lower cost of operation.

However, the energy share assigned to the diesel–biodiesel fuelled ICGs increases with higher weight factors. Considering the second test case, i.e. an energy system constituted by three ICGs and a MGT, the low CO_2 emissions that characterize the MGT strongly influence the simulation results, also when lower GHGs emissions weight factors are considered especially in the case of a lower syngas cost. This paper demonstrates that the modelling phase of GHGs emissions and their impact on the energy systems optimization process have to be accurately evaluated in order to supply correct management data of off-grid system based on multiple power generation devices. Also, the definition of the emission costs plays a crucial role that have to be accurately evaluated by the policy makers to push the introduction of renewable fuels and more clean power production devices, like MGTs. The results of this investigation work demonstrate the importance to develop optimization tools to manage energy systems when more technologies are involved in order to increase the global efficiency of the micro-grid. The optimization algorithm that has been described in this paper represents a first step towards a more detailed and integrated tool, which can help engineers and designers during the management phase of more complex power systems. Moreover, the results obtained can delineate guidelines for policy makers to help them to define emission costs to apply to energy systems. A further development of this investigation work will take in consideration how the efficiency variability of the considered machines at partial load can affect the simulation results and the integration of renewable energy technologies and storage systems.

CRediT authorship contribution statement

Francesco F. Nicolosi: Methodology, Formal analysis, Data curation, Formal analysis, Writing - review & editing. **Jacopo C. Alberizzi:** Methodology, Investigation, Writing - original draft, Writing - review & editing, Software. **Carlo Caligiuri:** Investigation, Resources, Data curation. **Massimiliano Renzi:** Conceptualization, Methodology, Formal analysis, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Figs. 8–10 and Tables 6–11.

Table 6
ICGs energy fractions delivered to the load with varying GHGs emissions weight factors.

w_{CO_2}, w_{NO_x}	ICG_1	ICG_2	ICG_3	ICG_4
0.02–4	37.72%	51.26%	10.50%	0.53%
0.04–8	54.02%	35.49%	0.00%	10.49%
0.08–12	52.15%	27.78%	0.00%	20.08%
0.12–16	52.68%	24.87%	0.00%	22.45%

Table 7
ICGs and MGT energy fractions delivered to the load with varying GHGs emissions weight factors with a MGT fuel cost of 0.16 €/kWh.

w_{CO_2}, w_{NO_x}	ICG_1	ICG_2	ICG_3	MGT
0.02–4	37.72%	51.26%	10.50%	0.53%
0.04–8	52.09%	27.75%	0.00%	20.16%
0.08–12	51.74%	24.57%	0.00%	23.69%
0.12–16	49.35%	19.14%	1.71%	29.80%

Table 8
ICGs and MGT energy fractions delivered to the load with varying GHGs emissions weight factors with a MGT fuel cost of 0.12 €/kWh.

w_{CO_2}, w_{NO_x}	ICG_1	ICG_2	ICG_3	MGT
0.02–4	27.97%	44.60%	0.00%	27.43%
0.04–8	49.04%	20.98%	0.00%	29.98%
0.08–12	49.10%	18.46%	1.71%	30.73%
0.12–16	49.35%	17.67%	1.71%	31.27%

Table 9
Total ICGs costs.

Generator	w_{CO_2}, w_{NO_x}	Fc [€]	O_c [€]	Sup_c [€]	CO_2 [€]	NO_x [€]	Total [€]
ICG1	0.02, 4	50.28	1.53	0.44	4.12	4.87	61.24
	0.04, 8	72.11	2.25	0.44	12.17	14.55	101.52
	0.08, 12	69.38	21	0.44	22.48	19.76	114.16
	0.12, 16	70.44	2.1	0.66	33.43	25.7	132.33
ICG2	0.02, 4	54.67	1.92	0.19	10.98	14.25	82
	0.04, 8	37.9	1.38	0.95	15.41	19.74	75.37
	0.08, 12	29.56	0.88	0.57	22.4	20.69	74.1
	0.12, 16	26.6	0.76	0.57	29.82	24.35	82.1
ICG3	0.02, 4	15.96	1.68	0.21	2.36	3.13	23.34
	0.04, 8	0	0	0	0	0	0
	0.08, 12	0	0	0	0	0	0
	0.12, 16	0	0	0	0	0	0
ICG4	0.02, 4	0.89	0.2	0.3	0.14	0.13	1.65
	0.04, 8	17.74	2.4	1.2	4.21	4.94	30.49
	0.08, 12	33.83	4	1.5	14.81	15.05	68.19
	0.12, 16	38.02	4.3	1.5	24.38	20.99	89.19

Table 10
Total ICGs and MGT costs with a MGT fuel cost of 0.16 €/kWh.

Generator	w_{CO_2}, w_{NO_x}	Fc [€]	O_c [€]	Sup_c [€]	CO_2 [€]	NO_x [€]	Total [€]
ICG1	0.02, 4	50.28	1.53	0.44	4.12	4.87	61.24
	0.04, 8	67.36	2.1	0.44	11.24	13.18	96.32
	0.08, 12	69.94	2.07	0.44	22.12	19.38	113.95
	0.12, 16	65.79	1.95	0.66	31.01	23.79	123.2
ICG2	0.02, 4	54.67	1.92	0.19	10.97	14.25	81.99
	0.04, 8	29.56	0.88	0.57	9.89	13.79	56.01
	0.08, 12	26.15	0.76	0.57	19.55	18.02	65.15
	0.12, 16	20.41	0.62	0.57	22.89	19.24	64.17
ICG3	0.02, 4	15.86	1.68	1.21	2.36	3.13	23.33
	0.04, 8	0	0	0	0	0	0
	0.08, 12	0	0	0	0	0	0
	0.12, 16	2.6	0.28	0.21	2.34	2.05	7.47
MGT	0.02, 4	0.97	0.2	0.3	0.16	0	1.63
	0.04, 8	37.09	4.05	1.2	9.29	0	51.63
	0.08, 12	43.55	4.35	1.2	21.03	0	70.13
	0.12, 16	54.91	4.75	0.6	36.42	0	96.67

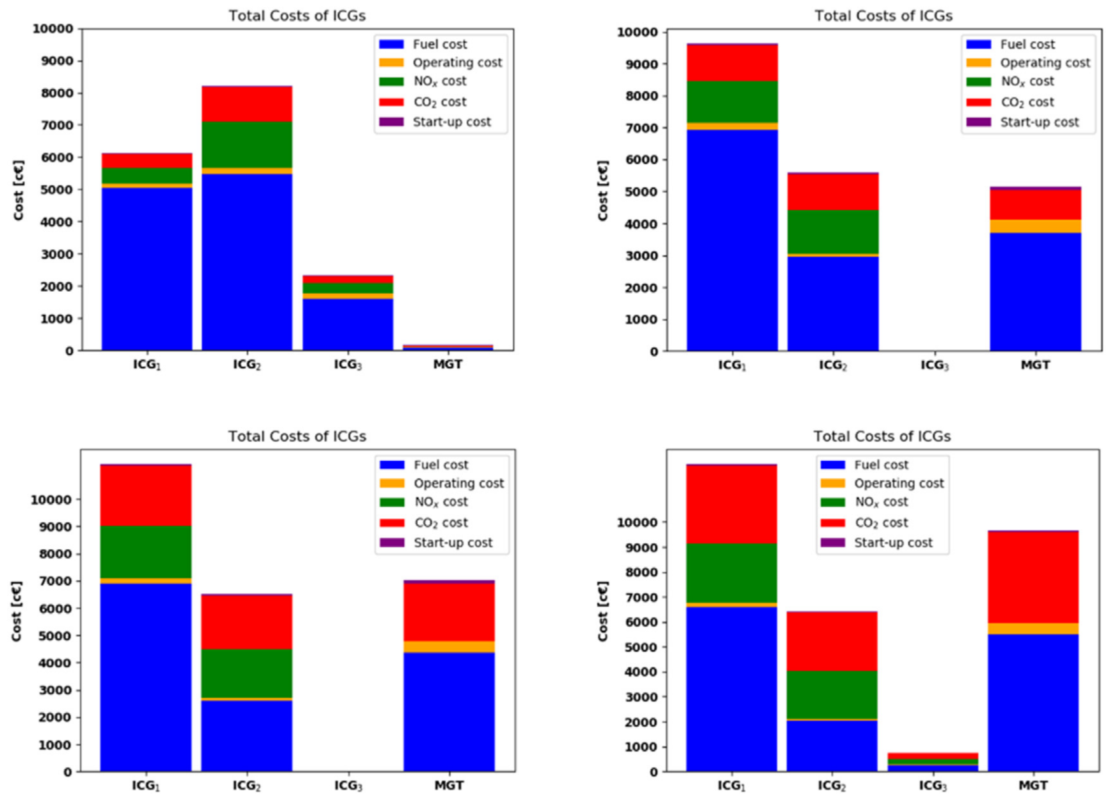

Fig. 9. ICGs costs with different weight factors for the GHGs emissions. And a MGT fuel cost of 0.16 €/kWh. T. left w_{CO_2}: 0.02w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12), B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

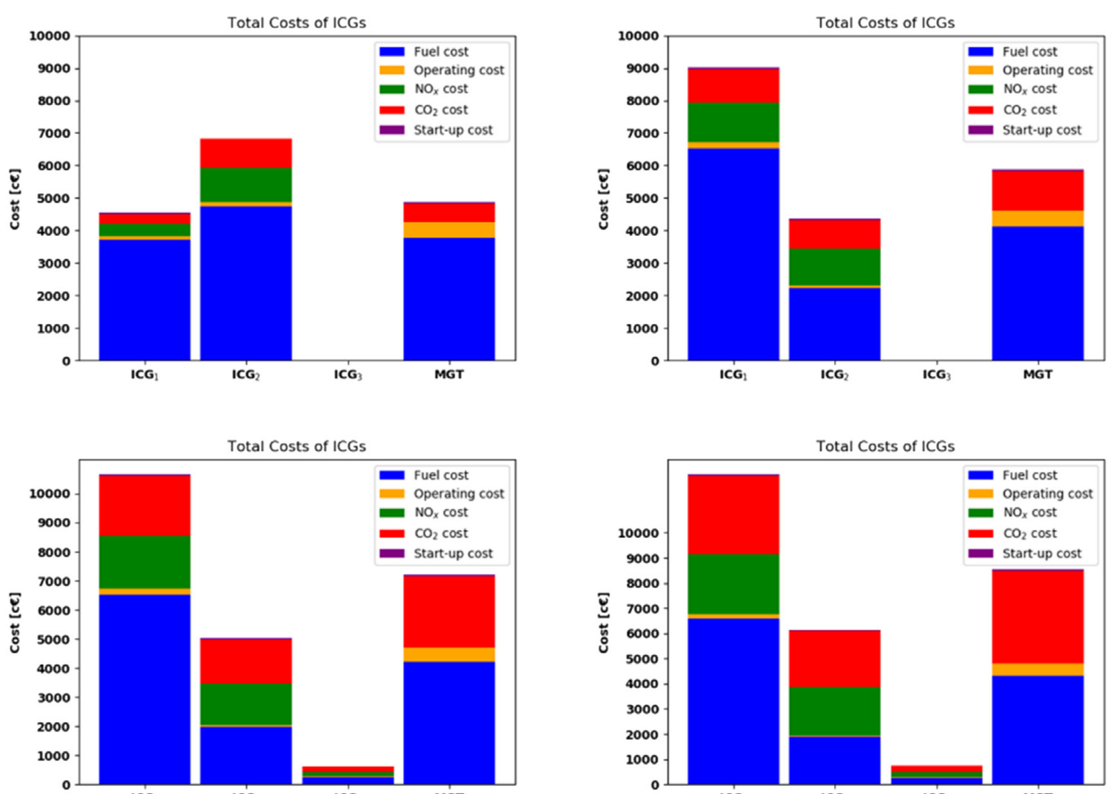

Fig. 10. ICGs costs with different weight factors for the GHGs emissions. And a MGT fuel cost of 0.12 €/kWh. T. left w_{CO_2}: 0.02w_{NO_x}: 4). T. right (w_{CO_2}: 0.04, w_{NO_x}: 8). B. left (w_{CO_2}: 0.08, w_{NO_x}: 12), B. right (w_{CO_2}: 0.12, w_{NO_x}: 16).

Table 11
Total ICGs and MGT costs with a MGT fuel cost of 0.12 €/kWh.

Generator	w_{CO_2}, w_{NO_x}	Fc [€]	O_c [€]	Sup_c [€]	CO_2 [€]	NO_x [€]	Total [€]
ICG1	0.02, 4	37.16	1.14	0.44	3.06	3.02	45.42
	0.04, 8	65.2	1.95	0.48	10.41	12.12	90.16
	0.08, 12	65.22	1.95	0.44	20.81	18.17	10.659
	0.12, 16	65.79	1.95	0.66	31.01	23.79	123.2
ICG2	0.02, 4	47.4	1.42	0.19	8.78	10.67	68.37
	0.04, 8	22.32	0.76	0.38	8.86	11.21	43.52
	0.08, 12	19.62	0.62	0.38	15.17	14.42	50.21
	0.12, 16	18.85	0.62	0.38	22.18	19.22	61.24
ICG3	0.02, 4	0	0	0	0	0	0
	0.04, 8	0	0	0	0	0	0
	0.08, 12	2.6	0.28	0.21	1.56	1.54	6.18
	0.12, 16	2.6	0.28	0.21	2.34	2.05	7.47
MGT	0.02, 4	37.76	4.65	0.6	5.82	0	48.83
	0.04, 8	41.31	4.8	0.3	12.24	0	58.65
	0.08, 12	42.3	4.75	0.6	24.55	0	72.21
	0.12, 16	43.21	4.75	0.6	36.97	0	85.52

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