OPTIMAL OPERATION OF A 30kW NATURAL GAS MICROTURBINE CLUSTER

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Această lucrare pune în discuție diferite strategii pentru optimizarea regimului de funcționare a unui grup de microturbine pe gaz natural având o putere nominală de 30kW, în cazul unor aplicații de tip" load-following".Operarea microturbinelor în grup asigură o bună flexibilitate însă ridică şi problema funcționării la nivele intermediare de încărcare. Aceasta presupune emisii foarte mari de NOx şi CO. În aceste condiții, a fost folosit Algoritmul Evolutiv pentru a optimiza operarea acestui grup din punct de vedere al emisiilor poluante şi al consumul de combustibil.

This paper discusses optimal operation strategies of a 30 kW natural gas microturbine (MT) cluster for electrical load-following applications. The cluster operation assures a good operational flexibility, but, at the same time, also the aspect of the partial-load MT characteristics, in terms of energy efficiency and pollutant emissions has to be taken into consideration. In particular, the experimental results show that the NOx and CO emissions are higher when the MT is operated below its rated capacity. Under these circumstances, the Evolutionary Algorithm has been employed in order to optimize the operation of this cluster from the point of view of the pollutant emissions and fuel consumption.

Keywords: natural gas microturbine, distributed generation, evolutionary algorithms, multi-objective optimization, environmental impact

1. Introduction

Natural gas microturbines (MTs) have been employed more and more in the last few years, especially in urban areas, where severe local air quality requirements impose serious constraints not only to the machine operation but also to the technology selection [1]. On the other hand, experimental results show that at full load, MTs show relatively low emissions of hazardous pollutants like NO_x and CO [2,3] but these tend to worsen consistently at partial load (see for

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example [4,5]), and even to exhibit non-monotonic variations with respect to the loading level. An important aspect related to the MTs, is the possibility to be operated in clusters. This permits the setup of optimal dispatch strategies of the different units with the goal of minimizing specified objective functions [18]. In case of load-following applications, the development of different control strategies could prove effective to limit not only the emissions from the MT cluster but also the fuel consumption.

This paper discusses the formulation and solution of an optimization problem with the aim of minimizing the NOx and CO emissions and also the fuel consumption for a cluster of 4 natural gas MTs of 30 kW each (this is important, for instance, in microgrid applications) [17, 18]. In other words, this optimization procedure takes into account at the same time the optimization of CO2 emissions, energy efficiency and fuel costs (which are closely related to the minimization of the fuel consumption objective), the local environmental impact from the MT cluster being minimized with respect to NOx and CO emissions.

2. Microturbine energy and emission performance

Generally, the energy performance of a MT unit is expressed by the ratio of its electrical energy output W [kWhe] to its fuel energy input F [kWht], $\eta_W = W/F$ [17, 18]. Another key aspect is the fact that MTs can cogenerate heat with high overall efficiency [11]; however, this work concentrates only on electrical applications, namely, under the electrical load-following operation mode, implicitly assuming that the heat production covers part of the thermal load, with backup boilers available to supply the remaining heating load.

Another important fact is that the electrical efficiency decreases at partial loads due to the changes in the thermodynamic cycle. In addition, the incomplete combustion process which occurs at partial loads causes also an increase in pollutant emissions [12, 17, 18]. That is why, in some cases, when the MTs are operated below 50% of their rated output, the emissions become so high that the manufacturers themselves advice to switch the units off [18].

On the other hand, the emission performance is characterized through an emission factor model [2]. According to this, the mass of a given pollutant p emitted while producing the electrical energy output W is expressed as $m^p = \mu^p \cdot W$, with μ^p representing the emission factor (specific emissions) of the same pollutant p, in [mg/kWhe]). The emission factor depends on the technology, size of the unit and also on the operating conditions [2-4,13, 18].

3. Multi-objective operational optimization of the emissions and energy efficiency for a cluster of 4 MTs

Let us consider a given hourly electrical load energy W_{TOT} [kWhe] to be supplied by a cluster of 4 MT units operating in electrical load-following mode. In this respect, the objectives which have to be minimized are:

- NOx emissions, the most dangerous pollutant in case of equipments fed by natural gas [13, 18], especially in urban areas which are often subject to severe regulatory air quality constraints.
- CO emissions, usually very low at full load, but severely increasing at partial loads due to the incomplete combustion process which occurs in such conditions, due to the aging of the components or inaccurate maintenance.
- Fuel consumption which represents the energy efficiency goal. This practically corresponds in economic terms to the minimization of the costs to purchase the fuel. Apart from this, assuming that all MT units will adopt the same fuel (in our case, natural gas), the fuel consumption minimization coincides approximately to the CO2 emission minimization, according to the concepts discussed in [1,12, 18].

The constraints of this optimization problem refer to the energy balance between the power generated by the MT cluster and the total load which has to be covered, as well as the operational limits of each MT in the cluster. The parametric analyses effectuated in this work are associated to the useful electrical output from the MTs. Thus, the reference power of each MT unit is obtained by subtracting from the rated power the power needed to serve the auxiliary services of the unit (the gas compressor, in particular).

In mathematical terms, we shall consider a cluster of i = 1,…, N MTs, each of which has a reference power $P_i^{(r)}$ [kWe]. The loading level α_i of the i-th MT unit, for i = 1,…, N, is expressed in relative values with respect to the reference power and varies in the range [0;1]. Considering the minimum power $P_i^{(\min)}$ of the i-th unit, the constraint on the minimum loading of the MT unit is reflected on limiting the loading level within the range [$\alpha_i^{(\min)}$;1], where $\alpha_i^{(\min)} = P_i^{(\min)} / P_i^{(r)}$ [17, 18].

When is operated at the loading level α_i, each unit i in the cluster is characterized by its electrical efficiency η_i, specific NOx emissions $\mu_i^{NO_x}$ [mg/kWhe], and specific CO emissions μ_i^{CO} [mg/kWhe], for i = 1,…, N.

Considering a period τ = 1 hour and a given hourly energy W_{TOT} supplied by the cluster of MTs to the load (which is valued at 120 kWhe), the optimizations of the individual objectives are expressed as [6,18]:

a) minimization of the overall NOx emissions:

$$\min\ \hat{f}^{NO_x}\left(W_{TOT}\right)=\sum_{i=1}^{N}\mu_i^{NO_x}\ \alpha_i\ P_i^{(r)}\tau \tag{1}$$

b) minimization of the overall CO emissions:

$$\min \hat{f}^{CO}\left(W_{TOT}\right)=\sum_{i=1}^{N}\mu_i^{CO}\ \alpha_i\ P_i^{(r)}\tau \tag{2}$$

c) minimization of the fuel consumption:

$$\min \hat{f}^{F}\left(W_{TOT}\right)=\sum_{i=1}^{N}\frac{\alpha_i\ P_i^{(r)}\tau}{\eta_i} \tag{3}$$

The constraints are given by the energy balance

$$\sum_{i=1}^{N}\alpha_i\ P_i^{(r)}\tau-W_{TOT}\ =0 \tag{4}$$

and by the loading level limits, for i = 1,…, N [8,18]:

$$\alpha_i\in\left\{0\cup\left[\alpha_i^{(\min)};1\right]\right\} \tag{5}$$

For each objective $Z=\left\{NO_x,F,CO\right\}$, the above formulation is transformed into a penalized objective function, by considering the penalty factor γ applied to the energy balance constraint [7,8,9,10]:

$$f^{Z}\left(W_{TOT}\right)=\hat{f}^{Z}\left(W_{TOT}\right)-\gamma\cdot\left|\sum_{i=1}^{N}\left(\alpha_i\ P_i^{(r)}\tau\right)-W_{TOT}\ \right| \tag{6}$$

s.t. (5).

The variables to be optimized are the loading levels α_i, for i = 1,…, N.

The main challenges which appear when computing the optimal solution depend not only on the non-linearity of the energy efficiency, but also on the emission characteristics, in the latter case with possible non-monotonic emission profiles at variable MT loading. These non-monotonic emission characteristics generate a non-convex search space.

The optimization of the objective functions formulated above is carried out in this paper by using an Evolutionary Algorithm (EA) [14, 17, 18]. The MT unit data (power, efficiency and emissions) are coded by using a discrete number of points, representing the switch-off condition and at the same time a predefined number of discrete loading levels in the range [$\alpha_i^{(\min)}$;1]. As an example of EA convergence, Fig. 1 shows the reduction of the objective function (1) for two sampled values of total hourly energy, namely, W_{TOT} = 70 and 100 kWhe. More details on the EA formulation and application are provided in Section 4.

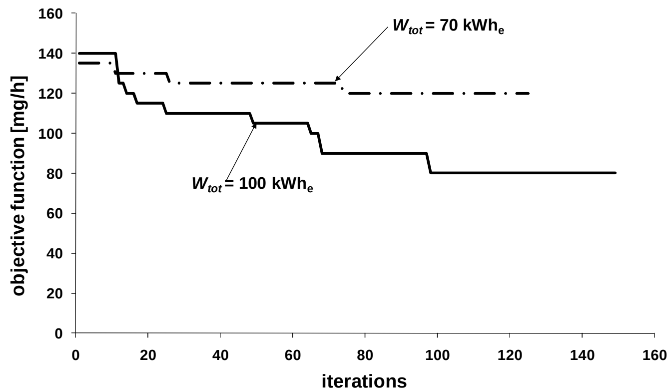

Fig. 1. Convergence of the evolutionary algorithm for a cluster of 4 units.

4. Problem solution through the Evolutionary Algorithm

The multi-objective optimization problem introduced in the previous section has been solved through specific EA programming tools.
The input data at partial load are the NO_x and CO emission characteristics and the MT efficiencies. Both emission characteristics and efficiencies are coded as matrices [17,18]. As far as the algorithm implementation regards, the chromosome structure is formed by a number N of genes equal to the number of MTs. Each of these genes is defined by D discrete states, representing a specific operating level. The level #1 is synonym with the switch-off condition. The other D-1 levels are defined in the range $\left[\alpha_i^{(\min)};1\right]$, for i = 1,…, N. To form the initial population of K chromosomes, the authors have assigned random levels to the genes.

All the objective functions are positive-valued. Due to the fact that the EA solves a maximization problem while here the objectives have to be minimized, each chromosome is associated to a fitness (to be maximized) defined by using the inverse of the objective function; considering the m-th chromosome for the objective Z, its fitness can be formulated as [17, 18]:

$$\psi_m^Z = \frac{1/f_m^Z\left(W_{TOT}\right)}{\sum_{v=1}^{M} 1/f_v^Z\left(W_{TOT}\right)} \tag{7}$$

Then, the classical genetic operators (selection, crossover and mutation) are applied in order to form a new population. The chromosome *selection* is carried out by using the mechanism of the biased roulette wheel, in which the chromosomes of the new population are randomly selected taking into account the value of their fitness. Crossover is applied to pairs of chromosomes of the population, if a randomly extracted number from a uniform probability distribution in the range [0;1] is lower than the user-defined crossover probability p_C. For the pairs of chromosomes satisfying the condition $r < p_C$, crossover is performed in a single position which is randomly chosen. Finally, the *mutation* is performed on a single gene, but the decision whether the mutation has to be performed or not is taken using a two-step mechanism [17, 18]. This mechanism is based on a user-defined mutation probability p_M referred to a chromosome. Given a random number r' extracted from a uniform probability distribution in the range [0;1], if for a chromosome the condition $r' < p_M$ is satisfied, then a randomly chosen gene inside the chromosome becomes subject to mutation [17, 18]. In such conditions, the discrete loading level in this gene is changed into a different loading level randomly chosen within the domain of definition of the D loading levels. The mutation and the crossover alike have the role of improving the diversity of the chromosome population and thus to avoid a situation when the algorithm remains blocked in a local minimum of the search space.

The *elitist* variant of the EA has been adopted in this implementation, meaning that one copy of the chromosome corresponding to the best fitness is reproduced in the successive population without being modified by the selection, crossover and mutation operators. The stop criterion will be satisfied when no improvement of the best fitness over a predefined threshold $\varepsilon > 0$ is obtained a certain number I of successive iterations [17, 18].

5. Case study applications and parametrical analysis

The optimizations illustrated in this section are carried out on a cluster of 4 equal MTs. The MTs used have 30 kWe of rated capacity. The emission characteristics for the NOx and CO pollutants are indicated in Fig. 2, based on a sampled number of points elaborated from [4], for discrete steps of 1 kWe. The efficiency values for a 30 kW and 60 kW unit (for comparison purposes), on the other hand, are indicated in Fig. 3.

Individual optimizations have been run for the NOx, CO emissions and also for the fuel consumption, considering different values of the total hourly energy W_{TOT} delivered to the electrical load [16, 17, 18].

In the EA implementation, the values of the basic parameters related not only to the crossover and mutation probability but also to the initial population have been chosen after a number of preliminary tests, in order to find a compromise between the solution effectiveness and the computation time. The initial population contains K = 100 chromosomes, the crossover probability is pC = 0.6, and the mutation probability pM = 0.1 [15, 17, 18]. This mutation probability has been chosen relatively high compared to common values used in other similar applications. This will allow more frequent replacements of the discrete levels in the genes. The other parameters are the threshold ε = 0.1 (in order to test the effective fitness improvement) and the limit I = 20 used in the stop criterion [17, 18]. Another important aspect is that the EA was not run for cases in which the loading level was clearly represented by a well-determined and intuitive combination of MT loading levels (like for a total load which is lower than the minimum loading level of a single MT or close to the sum of the reference powers of all MTs).

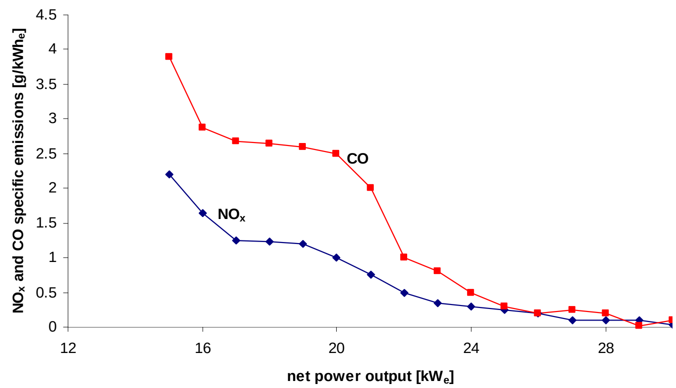

Fig. 2. NOx and CO emission characteristics of the 30 kWe MT

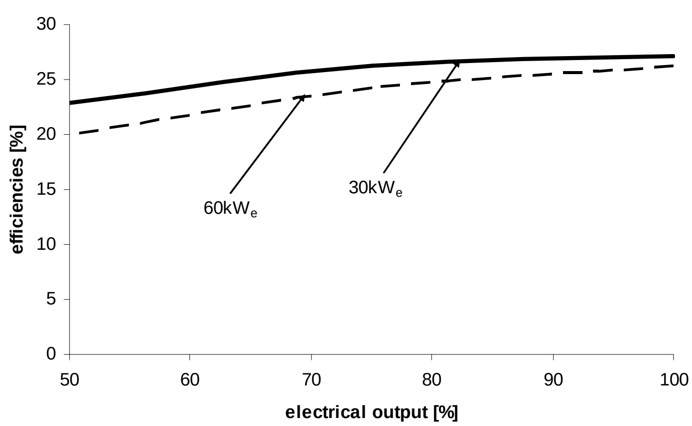

Fig. 3. Electrical efficiency for a 30kWe and a 60 kWe MT

In the formation of the initial population, an additional criterion has been introduced in this specific case with limited number of MTs, with the objective of increasing the number of initial chromosomes subject to null or small penalties in the penalized objective function (6). In this respect, one half of the initial chromosomes chosen at random are accepted only if the corresponding total hourly energy does not differ with more than 1% (in deficit or excess) compared to W_{TOT} [17, 18].

Fig. 4 through Fig. 6 show the NOx emissions, CO emissions and fuel consumption results, respectively, obtained with the three optimization objectives for the microturbine cluster of 30 kWe. The bounces in the emission and fuel consumption trends observed at multiples of the reference power practically correspond to the moments in which the second, third and fourth MT begin to function. Comparing the optimal with the non-optimal results, the significant differences due to the conflicting nature of the NOx and CO emissions in the intermediate partial-load operation region are obvious. Fig. 6, instead, shows no significant change in the fuel consumption from the different optimization strategies [18].

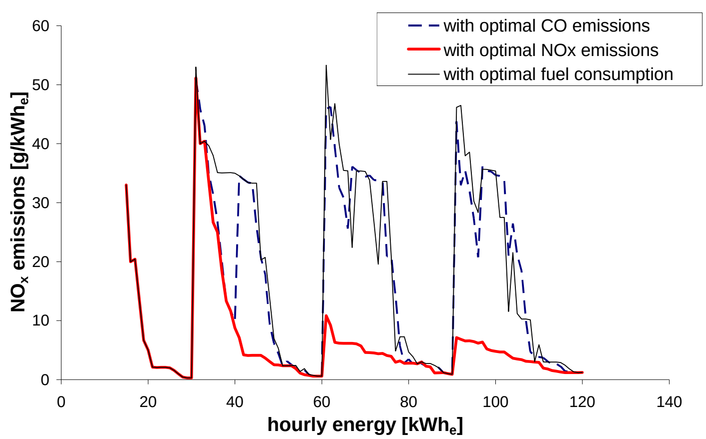

Fig. 4. NOx emissions with different optimization objectives

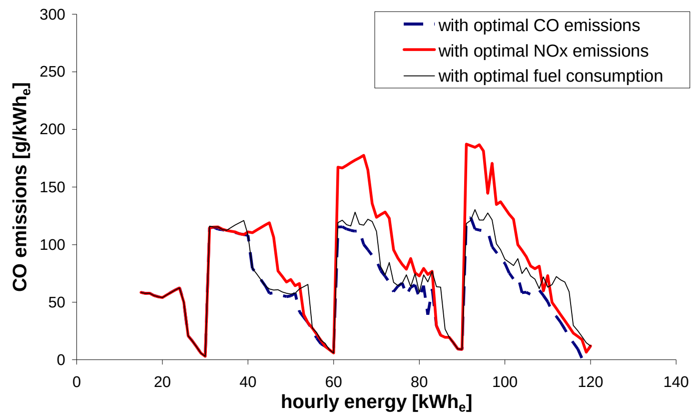

Fig. 5. CO emissions with different optimization objectives

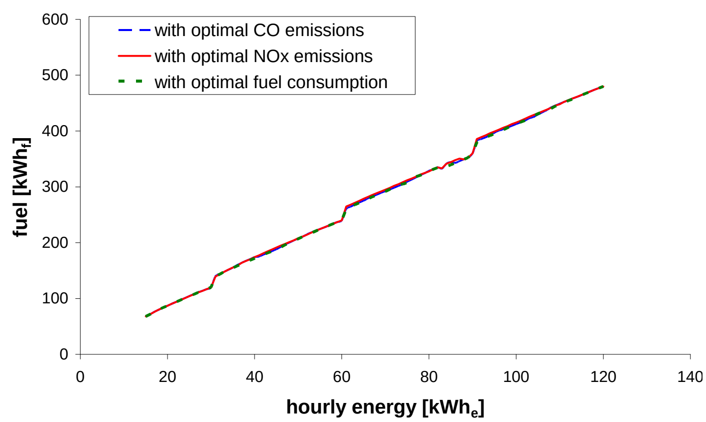

Fig. 6. Fuel consumption with different optimization objectives

The usage of the MT units at the various hourly energy values is shown in Fig. 7 for minimum NOx emissions, in Fig. 8 for the minimum CO emissions and in Fig. 9 for the minimum fuel consumption.

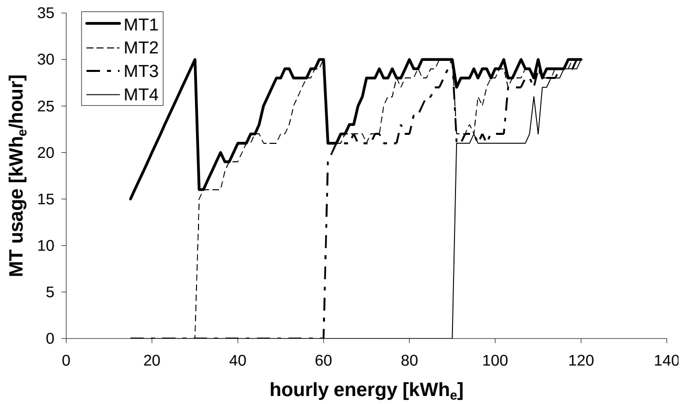

Fig. 7. MT usage with optimal NOx emissions.

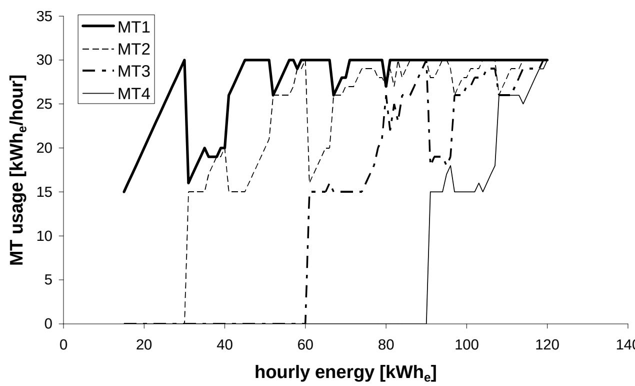

Fig. 8. MT usage with optimal CO emissions.

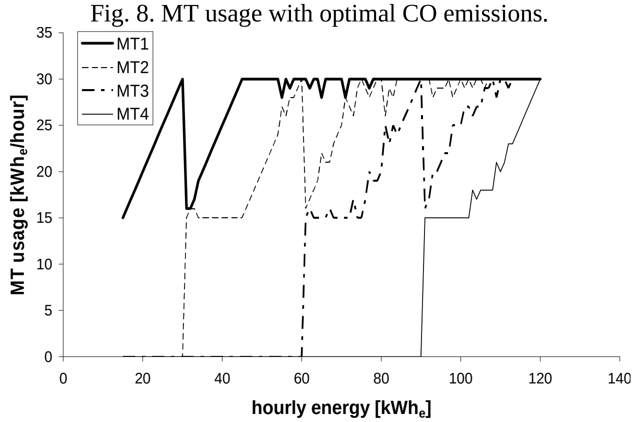

Fig. 9. MT usage with optimal fuel consumption

Since the MTs are identical, the attribution of the loading levels to each unit can be made arbitrarily. In order to obtain a better representation, for each hourly energy, the loading levels in the optimal cases have been sorted in descending order, assigning the highest loading level to the unit MT1, the successive value in descending order to the unit MT2, and so forth. In reality, the unit schedule has to be analysed by considering specific load patterns in the time domain and taking also into consideration further operational constraints (for example, the number of switch on/off operations during one day, to avoid maintenance problems) [18].

6. Conclusions

At present, the energy systems are more and more facing a plurality of objectives to be optimized, calling for adequate multi-objective optimization techniques. This paper has addressed the issues which appear when considering the minimization of different objectives (in our case NO_x, CO emissions and fuel consumption) of a cluster of identical MTs functioning in load-following mode.

In particular, the MT usage patterns show that the operation in nearly optimal conditions is possible without requiring an excessive number of switch on/switch off operations during one day [18]. At the same time, this algorithm is more efficient in the case of minimizing the pollutant emissions, while it impacts less on the fuel consumption. All the concepts illustrated can be applied in a straightforward manner also to cases with higher number of MTs or different MT characteristics. In this respect, work in progress is aimed at generalizing this kind of application in order to discuss not only the emission impact, energy efficiency and economic assessment of the combined local generation systems but also their influence on the central energy networks.

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