# Assessing the robustness of solutions to a multi-objective model of an energy management system aggregator


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***Abstract*—An approach for robustness analysis of non-dominated solutions to a multi-objective optimization model of an energy management system aggregator (EMSA) in face of uncertainty is presented. The EMSA is an intermediary entity between households and the System Operator (SO), capable of contributing to balance load and supply, and therefore coping with the intermittency of renewable energy sources (RES) and facilitating a load follows supply strategy in a Smart Grid environment. Household clusters provide load flexibility to satisfy system services requested by the SO, involving decreasing or increasing load in specific time slots. The EMSA multi-objective optimization model considers the maximization of profits and the minimization of the imbalance between the amounts of load flexibility provided by the end-user clusters to satisfy SO requests, taking into account revenues from the SO and payments to the clusters. A hybrid evolutionary approach combining Genetic Algorithms (GA) with Differential Evolution (DE) has been designed to deal with this model, and its behaviour subject to different scenarios of uncertainty is evaluated. The robustness analysis of non-dominated solutions produced by the hybrid evolutionary approach is based on the degree of robustness concept, taking into account the changes in the performance of the objective functions when small perturbations of the model nominal coefficients occur.**



***Keywords— multi-objective optimization, evolutionary algorithms, energy management systems, aggregator, uncertainty, robustness;***


## I. Introduction

In a smart grid environment, in which the electricity delivery system is integrated with Information and Communication Technologies (ICT), it is expected that the end-user will become a prosumer (i.e., simultaneously producer and consumer of electricity) and dynamic (time-differentiated) electricity tariffs will be applicable. In order to engage end-users into Demand Response (DR) programs, i.e. adjusting consumption patterns by reacting to price signals, households need to have home energy management systems (HEMS) based on ICT and endowed with intelligence to optimize the usage of loads without compromising comfort requirements, also allowing the two-way communication with the System Operator (SO) [1].

In this context, DR programs can contribute to delivery ancillary services, i.e., services provided by the SO to ensure reliable system operations, by exploiting the load flexibility displayed by end-users [2]. This role can be performed by an energy management system aggregator (EMSA), which an intermediary entity operating between household clusters and the SO, enabling the optimization and coordination of a large-scale dissemination of HEMS. The EMSA uses the demand-side flexibility offered by end-user clusters to provide system services requests, involving decreasing or increasing the power required in each time slot of a planning horizon.

The EMSA multi-objective optimization model considers the maximization of profits and the minimization of the imbalance between the amounts of load flexibility provided by the end-user clusters to satisfy SO requests, taking into account revenues from the SO and payments to the clusters. However, several sources of uncertainty are at stake that should be incorporated into the EMSA decision-making process to obtain robust non-dominated solutions to the multi-objective model, i.e., solutions that are in some way "immune" to some degree of data uncertainty, having in mind their practical implementation.

The purpose of this paper is to present an approach that analyzes whether the non-dominated solutions computed by a hybrid genetic/differential evolution algorithm are robust based on a degree of robustness concept. The assessment of solution robustness is done considering perturbations in the nominal coefficients of the model within a prespecified range and evaluating the corresponding changes in the objective function space for a given solution structure.

This paper is structured as follows. Section II describes the methodological framework for the assessment of solution robustness in multi-objective optimization also presenting a brief literature review. Section III presents the EMSA multi-objective model and the robustness analysis approach, as well as the case study. Section IV presents some illustrative results and the main conclusions are drawn in section V.

## II. Robustness in Multiobjective Optimization

Mathematical models for decision support in complex real-world contexts should take into account multiple axes of evaluation of the merits of different courses of action (solutions), which are operationalized by conflicting and incommensurate objective functions instead of being combined in a single economic indicator. Multi-objective models allow exploring a larger set of diversified potential solutions and unveiling the trade-offs to identify satisfactory compromise solutions. A feasible solution is called non-dominated (also Pareto optimal, efficient or non-inferior) if no improvement in all objective functions is simultaneously possible, i.e. improving an objective function can be done only by deteriorating at least one of the other objective function values. These are the solutions that should be considered for selection and practical implementation according to the preferences of a decision maker (DM).

The data used in mathematical models are generally uncertain, often resulting from assumptions done based on the context of the problem, prediction and forecast of occurrences, measurements subject to errors, etc. Multi-objective optimization in face of uncertainties is very relevant in practice, since slight difference in environmental conditions or variations in the solution structure after implementation can be crucial to overall operational success or failure. Since the data to be supplied to the model is subject to several sources of uncertainty, solutions should be assessed for robustness, i.e., their performance in the multiple objective functions in face of data perturbations should be analysed. Therefore, it is necessary to identify non-dominated solutions displaying not just satisfactory values for the multiple objective functions but also being somehow insensitive to slight variations in the model data coefficients. That is, the algorithm to solve the multi-objective optimization model should strive for robust solutions.

The notion of robustness is not used uniformly in the literature, possibly due to the diversity of real-world problems in which uncertainty is an inherent feature. One of the first concepts of robustness in optimization problems was presented by Gupta and Rosenhead [3] and several meanings of robustness and ways to deal with uncertainty to derive robust solutions have been introduced by different authors. Hites et al. [4] distinguishes four different concepts of robustness: robust decision, robust solution, robust conclusion and robust method. Often robustness signifies that the solution is good in all or most scenarios, where a scenario is a group of possible values for the model data, and not bad in none. A common interpretation of robustness in the literature is that a solution is robust when it is immune to small perturbations; i.e., when exposed to different conditions comparatively to a nominal situation due to the uncertainty of some parameters (input data, decision variable value, DM's preferences, etc.) the solution still performs well enough in terms of the objective function values.

A survey of optimization in uncertain environments is presented in [5]. Studies focused on robustness in multi-objective optimization models and a comprehensive overview of multi-objective evolutionary algorithms (EA) in uncertain environments is provided in [6], including design issues, namely regarding changes to standard EA to produce robust solutions, and applications. An extension to Pareto dominance considering the uncertainty of the multi-objective functions within intervals is presented in [7], deriving a theory of "probabilistic dominance" able to orient the selection operators to obtain the Pareto set. The Robust Multi-Objective Genetic Algorithmic (RMOGA) is proposed in [8] to optimize two objectives: a fitness value and a robustness index enabling to analyse the trade-offs among performance and robustness of solutions using distance metrics. Two robust multi-objective optimization procedures are presented in [9] with the aim of finding a robust frontier composed by robust solutions instead of the global Pareto optimal front, by extending the techniques used in single objective robust optimization, assuming that the DM is not interested in finding "global best" solutions which may be too sensitive to small environmental changes. The concept of degree of robustness of non-dominated solutions is incorporated into an EA by [10], which is based on the behaviour of the solution in its neighbourhood when subject to perturbations in the decision variable space and the objective function coefficients. An approach based on the classification of robustness regions of the Pareto front is proposed in [11], distributing the solutions along the most robust regions according to parameter values and degree of robustness with the aim of finding the most robust Pareto front.

The next section presents an approach to evaluate non-dominated solutions based on the degree of robustness proposed in [10][12].

## III. A Multiobjective Optimization For An EMS Aggregator

This section presents a framework for the EMSA role and a multi-objective optimization model considering two objective functions (maximizing the EMSA profits and minimizing the imbalance between the amounts of load flexibility provided by the end-user clusters to satisfy SO requests), comprising the information exchange between HEMS, EMSA and SO, as displayed in Figure 1.

Fig. 1 – EMSA Global Architecture.


### A. Model

The multi-objective optimization model includes two objective functions (for details see [13]):

- F1 (economic function) - the aim is to maximize the EMSA profits, taking into account the remuneration for selling the load flexibility obtained from the end-user clusters to the SO, the rewards paid to each cluster, the penalties paid to the SO for not meeting the flexibility requests and the sanctions applied to each cluster for the amount of flexibility compromised with the cluster and not made available.

The load flexibility provided by each cluster is considered as uncertain since the end-user may use loads that were previously committed as available (that is, the cluster response is not entirely reliable). To take this uncertain behaviour into account a degree of reliability associated with each cluster is generated within a certain pre-defined range (e.g., 90% and 100%) for the entire planning period or a degree of reliability is associated with each cluster for each time slot.

- F2 (fairness function) – the aim is to minimize the inequity (imbalance) among clusters, i.e., minimizing the maximum relative difference between the load flexibility offered by the clusters and the one actually used by the EMSA, as a surrogate for fairness in the usage of end-user load flexibility.

The model is supplied with a representative sample of real data obtained through audits in 30 households, using the Cloogy device (www.cloogy.pt) during one year, January 2013 to January 2014, of continuous (24/7) electricity consumption measurements with a time resolution of 15 minutes.

The aim is to obtain non-dominated solutions displaying a good performance for various sets of plausible data, i.e. robust solutions for practical implementation.

### *B. Algorithmic Approach*

The algorithmic approach has been designed to deal with the main characteristics of the EMSA model, namely its combinatorial nature, conflicting objective functions and uncertainty of the load flexibility provided by end-users. EA are stochastic search and optimization methods that have proved very efficient and effective in dealing with multi-objective models of combinatorial nature. However, it cannot be assumed that EA are intrinsically robust to uncertainties and therefore specific analysis to identify robust solutions is necessary. An hybrid evolutionary approach has been developed combining GA (based on the non-dominated sorting genetic algorithm (NSGA-II) [14]) and differential evolution (DE) based on previous experience on solving problem with those characteristics and making the most of the advantages of both approaches to characterize the non-dominated front and explore the trade-offs among the conflicting objectives. NSGA-II ranks solutions in terms of non-dominance and assigns a crowding distance to each individual, which measures how much each individual contributes to diversity within a dominance rank [14]. A population of size $N$ gives origin to an offspring population of the same size through crossover and mutation operators. Both populations are combined and the population of size $2N$ is sorted into non-dominance levels. Individuals are selected to be introduced into the new generation population using the non-dominance level and their proximity in the objective function space. If additional individuals in the last rank front exist with respect to slots remnant in the new population of size $N$, a diversity preserving mechanisms is used. Individuals from this last front are placed in the new population based on how much they contribute to diversity in that front. The algorithm iterates until a termination condition is met, such as attaining a pre-specified maximum number of generations or when no evolution of population is achieved after a certain number of generations. Parents are selected for mating using a tournament selection operator, which uses the rank and crowding distance of individuals within the NSGA-II framework. The DE variant is used to generate $N$ offspring from the selected parents [15].

This hybrid GA/DE approach generally obtains non-dominated fronts displaying a good spread of solutions and expected convergence to the Pareto-optimal front (which is unknown).

### *C. Robusteness Analysis*

The aim of robustness analysis is to assess the quality of solutions for different plausible configurations of model data, changes in decision variable values and possibly also parameters controlling the algorithmic approach.

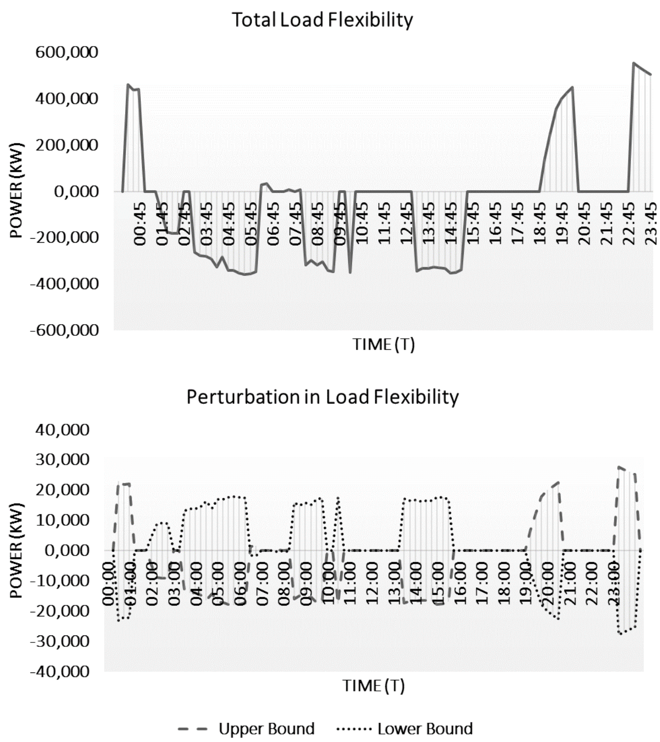
The degree of robustness, as proposed in [10] [12], is based on assessing the effects of perturbations ($\delta$) in the decision variables space and model coefficients regarding the objective function values. The parameter ($\delta$) is associated with the amplitude of the perturbation applied to the non-dominated solution $x$, which is assessed by inspecting successively expanding neighbourhoods of possible values. This perturbation may be assigned to each time slot ($\delta_t$) of the load flexibility aggregated from each cluster by the EMSA.

Figure 2 (bottom) displays the maximum deviation of consumption regarding the daily baseline consumption. This maximum deviation may have positive values, which correspond to load flexibility representing the amount of load available to decrease consumption, and negative values, which correspond to load flexibility representing the amount of load available to increase consumption, in each time slot. The maximum deviation considered was [-5%; +5%] as a condition of feasibility, since it is a conservative deviation of consumption mentioned in the literature related to energy savings due to behavioural change influence [16].

After the execution of the hybrid evolutionary approach and the identification of the non-dominated front, solutions $(x)$ dispersed along this front are randomly selected for robustness analysis in face of perturbations. These solutions are randomly perturbed in the range [-5%, +5%] in each time slot, thus originating neighbour (perturbed) solutions $(x^{\delta t})$.

The assessment of the degree of robustness of a solution is based on its behaviour around its nominal point, i.e., the position of the selected solution without perturbation and the perturbed solutions derived from the application of small perturbations in each time slot. The image of these solutions in the objective function space belong to a pre-specified $\eta$-neighbourhood degree surrounding $f(x)$, as can be seen in Figure 3 where η means the level of tolerance with respect to changes in the objective function values regarding to the nominal solution.

Fig. 2 - Representation of a non-dominated solution - Load Flexibility gathered and the maximum admissible deviation [$\boldsymbol{\delta_t}$ =-5%, $\boldsymbol{\delta_t}$ =+5%].




The displacement of the perturbed solutions is assessed according to the quadrant, which is centred on the selected solution. In the 1st quadrant (Q. I) and in the 3rd quadrant (Q. III) the solution presents better performance according to one objective function and worse performance for the other objective function; in the 2nd quadrant (Q. II) the solution presents worst performance for both objective functions; in the 4th quadrant (Q. IV) the perturbed solution presents better performance for both objective functions. The level of the perturbation is progressively enlarged, starting with a random rate bounded in *[$\delta_t$ =-1%; $\delta_t$ =+1%]* until *[$\delta_t$ =-5%; $\delta_t$ =+5%]*, with an increment of 1%.

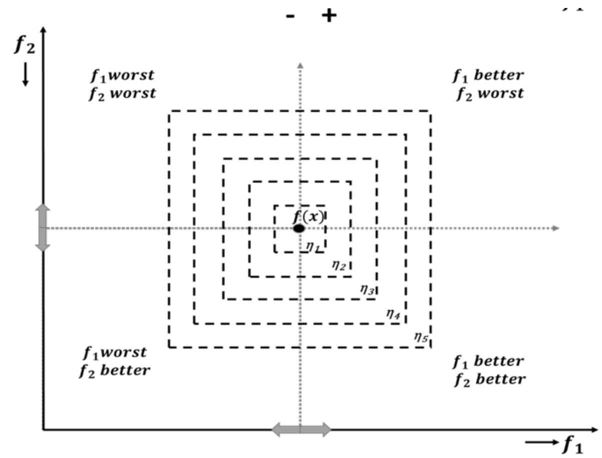
The degree of robustness of the selected solution *x* is a value *k, k*∈*{1, ..., 5}*, when at least 80% of the perturbed solutions belong to the $\eta_k$ neighbourhood around *f(x)*.

TABLE I. DEGREE OF ROBUSTNESS K

| *k* | *$\eta_k$ - neighbourhood around f(x)* |
|---|---|
| *1* | *$\eta_1 \in ]-0.05f(x); 0.05f(x)]$* |
| *2* | *$\eta_2 \in ]-0.10f(x); 0.10f(x)]$* |
| *3* | *$\eta_3 \in ]-0.15f(x); 0.15f(x)]$* |
| *4* | *$\eta_4 \in ]-0.20f(x); 0.20f(x)]$* |
| *5* | *$\eta_5 \in ]-0.25f(x); 0.25f(x)]$* |

The location of more robust solutions on the non-dominated front is a relevant insight to aid the selection of a compromise solution.

Fig. 3 - Representation of the selected solution *x*, *η*-neighborhood degree around the nominal solution *f(x)*.




## IV. RESULTS AND DISCUSSION

Illustrative results of the computational experiments are herein presented. The Pareto front is displayed in Figure 4 identifying 6 compromise solutions to be subject to perturbations and study their behavior in the objective function space to evaluate robustness.

Fig. 4 - Pareto front indicating the solutions that are subject to robustness analysis.

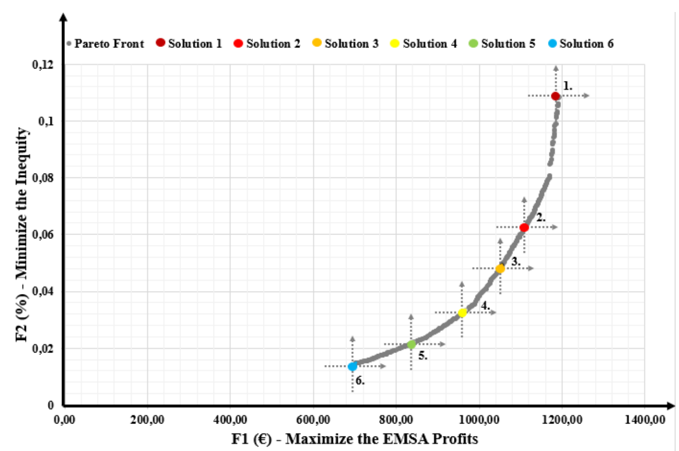



Table 2 displays the maximum deviations (%) of the objective functions for each selected solution when subject to small perturbations in all time slots with respect to the nominal values, i.e., the maximum deviation ($\boldsymbol{\eta}^{max}$) that will be possible to occur when the selected solution is subject to perturbations within the range [-5%, 5%] regarding the load flexibility indeed provided.

The cells in grey indicate that the perturbations applied to the selected solution lead the derived perturbed solution to an inadmissible region (since η>25%). The most common perturbation range that keeps solution robustness is [$\delta_t$ =-3%, $\delta_t$ =+3%].

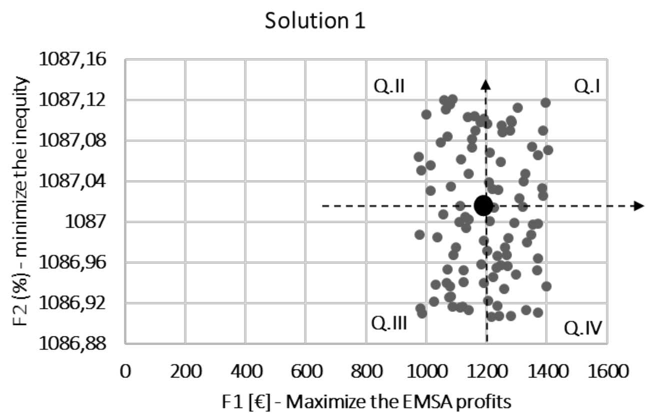
TABLE II. MAXIMUM DEVIATION $\eta^{MAX}$ IN THE OBJECTIVE FUNCTIONS W.R.T. THE NOMINAL SITUATION (%)

| | F1 | F2*$10^4$ (%) | F1 | F2*$10^4$ (%) | F1 | F2*$10^4$ (%) |
|---|---|---|---|---|---|---|
| | Solution 1 | | Solution 2 | | Solution 3 | |
| $\delta_t$ = -1% | -6,08% | -3,00E-05 | -6,49% | -4,26E-05 | -6,78% | -4,64E-05 |
| $\delta_t$ = 1% | 6,08% | 3,00E-05 | 6,49% | 4,26E-05 | 6,78% | 4,64E-05 |
| $\delta_t$ = -2% | -12,15% | -9,00E-05 | -12,99% | -1,28E-04 | -13,56% | -1,39E-04 |
| $\delta_t$ = 2% | 12,15% | 9,00E-05 | 12,99% | 1,28E-04 | 13,56% | 1,39E-04 |
| **$\delta_t$ = -3%** | -18,23% | -1,00E-04 | -19,48% | -1,42E-04 | -20,34% | -1,55E-04 |
| **$\delta_t$ = 3%** | 18,23% | 1,00E-04 | 19,48% | 1,42E-04 | 20,34% | 1,55E-04 |
| $\delta_t$ = -4% | -24,31% | -1,20E-04 | -25,98% | -1,71E-04 | -27,12% | -1,86E-04 |
| $\delta_t$ = 4% | 24,31% | 1,20E-04 | 25,98% | 1,71E-04 | 27,12% | 1,86E-04 |
| $\delta_t$ = -5% | -30,38% | -1,50E-04 | -32,47% | -2,13E-04 | -33,90% | -2,32E-04 |
| $\delta_t$ = 5% | 30,38% | 1,50E-04 | 32,47% | 2,13E-04 | 33,90% | 2,32E-04 |
| | Solution 4 | | Solution 5 | | Solution 6 | |
| $\delta_t$ = -1% | -7,23% | -5,08E-05 | -7,86% | -5,39E-05 | -8,27% | -5,59E-05 |
| $\delta_t$ = 1% | 7,23% | 5,08E-05 | 7,86% | 5,39E-05 | 8,27% | 5,59E-05 |
| $\delta_t$ = -2% | -14,45% | -1,52E-04 | -15,73% | -1,62E-04 | -16,54% | -1,68E-04 |
| $\delta_t$ = 2% | 14,45% | 1,52E-04 | 15,73% | 1,62E-04 | 16,54% | 1,68E-04 |
| **$\delta_t$ = -3%** | -21,68% | -1,69E-04 | -23,59% | -1,80E-04 | -24,81% | -1,86E-04 |
| **$\delta_t$ = 3%** | 21,68% | 1,69E-04 | 23,59% | 1,80E-04 | 24,81% | 1,86E-04 |
| $\delta_t$ = -4% | -28,90% | -2,03E-04 | -31,46% | -2,16E-04 | -33,08% | -2,24E-04 |
| $\delta_t$ = 4% | 28,90% | 2,03E-04 | 31,46% | 2,16E-04 | 33,08% | 2,24E-04 |
| $\delta_t$ = -5% | -36,13% | -2,54E-04 | -39,32% | -2,69E-04 | -41,34% | -2,79E-04 |
| $\delta_t$ = 5% | 36,13% | 2,54E-04 | 39,32% | 2,69E-04 | 41,34% | 2,79E-04 |

The (nominal) solution selected suffers a random perturbation bounded by [$\delta_t$ =-3%, $\delta_t$ =+3%] in the 96 time slots of the load flexibility diagram, in order to analyze the degree of robustness of each selected solution.

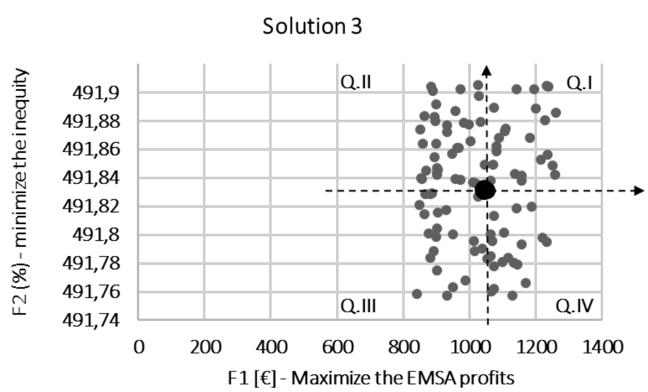
Figures 5, 6, 7 and 8 present the results of the analysis done for four solutions (1, 3, 4, and 6), i.e., two extreme solutions (the individual optima of each objective function) and two intermediary solutions. The position of randomly perturbed solutions within the admissible perturbation range is displayed for comparison with the nominal solution (at the centre). The dispersion of solutions in each quadrant and the amount of solutions in each $\eta_k$ neighbourhood around *f(x)*, which determine the degree of robustness, offer information about the expected behaviour of the solution when subject to changes.

Fig. 5 – Robustness information of solution 1.



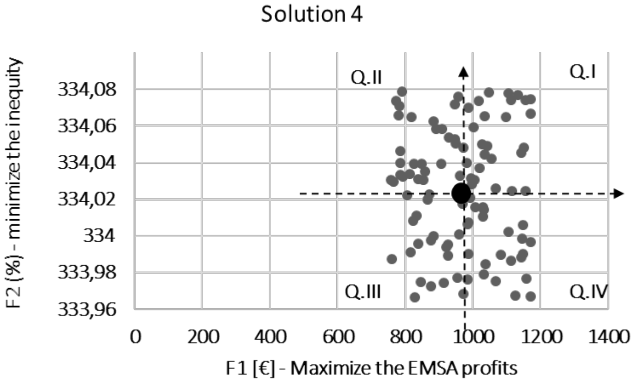

| $\eta_k$ - neighborhood around f(x) | % of sol | Quadrant | % of sol |
|---|---|---|---|
| $\eta_1 \in ]-0,05.f(x);\ 0,05.f(x)]$ | 31 | Q. I | 21 |
| $\eta_2 \in ]-0,10.f(x);\ 0,10.f(x)]$ | 63 | Q. II | 25 |
| $\eta_3 \in ]-0,15.f(x);\ 0,15.f(x)]$ | 86 | Q. III | 26 |
| $\eta_4 \in ]-0,20.f(x);\ 0,20.f(x)]$ | 100 | Q. IV | 28 |
| $\eta_5 \in ]-0,25.f(x);\ 0,25.f(x)]$ | 100 | | |

Fig. 6 - Robustness information of solution 3.



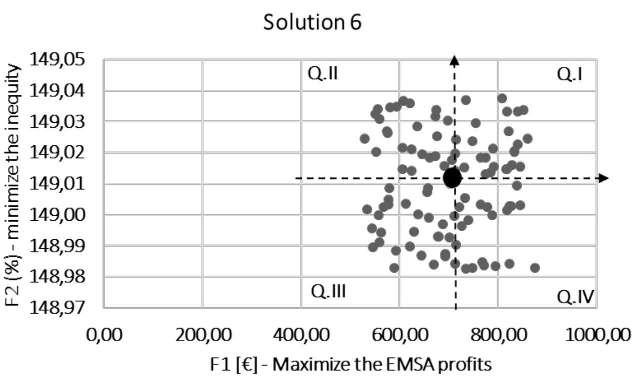

| $\eta_k$ - neighborhood around f(x) | % of sol | Quadrant | % of sol |
|---|---|---|---|
| $\eta_1 \in ]-0,05.f(x);\ 0,05.f(x)]$ | 28 | Q. I | 36 |
| $\eta_2 \in ]-0,10.f(x);\ 0,10.f(x)]$ | 50 | Q. II | 23 |
| $\eta_3 \in ]-0,15.f(x);\ 0,15.f(x)]$ | 77 | Q. III | 22 |
| $\eta_4 \in ]-0,20.f(x);\ 0,20.f(x)]$ | 99 | Q. IV | 20 |
| $\eta_5 \in ]-0,25.f(x);\ 0,25.f(x)]$ | 100 | | |

Fig. 7 - Robustness information of solution 4.




| $\eta_k$ - neighborhood around f(x) | % of sol | Quadrant | % of sol |
|---|---|---|---|
| $\eta_1 \in \left]-0,05.f(x);\ 0,05.f(x)\right]$ | 28 | Q. I | 28 |
| $\eta_2 \in \left]-0,10.f(x);\ 0,10.f(x)\right]$ | 50 | Q. II | 28 |
| $\eta_3 \in \left]-0,15.f(x);\ 0,15.f(x)\right]$ | 67 | Q. III | 19 |
| $\eta_4 \in \left]-0,20.f(x);\ 0,20.f(x)\right]$ | 93 | Q. IV | 25 |
| $\eta_5 \in \left]-0,25.f(x);\ 0,25.f(x)\right]$ | 100 | | |

Fig. 8- Robustness information of solution 6




| $\eta_k$ - neighborhood around f(x) | % of sol | Quadrant | % of sol |
|---|---|---|---|
| $\eta_1 \in \left]-0,05.f(x);\ 0,05.f(x)\right]$ | 33 | Q. I | 24 |
| $\eta_2 \in \left]-0,10.f(x);\ 0,10.f(x)\right]$ | 64 | Q. II | 33 |
| $\eta_3 \in \left]-0,15.f(x);\ 0,15.f(x)\right]$ | 100 | Q. III | 31 |
| $\eta_4 \in \left]-0,20.f(x);\ 0,20.f(x)\right]$ | 100 | Q. IV | 12 |
| $\eta_5 \in \left]-0,25.f(x);\ 0,25.f(x)\right]$ | 100 | | |

Based on this analysis it may be concluded that solution 1, 3, 4 and 6 present a degree of robustness of 3, 4, 4 and 3, respectively, when subject to small random perturbations around the nominal values. The extreme solutions (i.e. the non-dominated solutions that individually optimize each objective function) present a better degree of robustness in comparison to the intermediate solutions.

## V. CONCLUSION

This paper presents a methodology for robustness analysis of non-dominated solutions, which have been obtained by a hybrid evolutionary approach coupling NSGA-II and DE to solve a multi-objective optimization problem of the EMSA considering maximizing the EMSA profits and minimizing the inequity between the amounts of load flexibility provided by the end-user clusters to satisfy SO requests.

The non-dominated solutions were considered robust until certain level of perturbation, i.e., until a perturbation [-3%, 3%] is applied in the coefficients of the nominal solutions. In this range the derived perturbed solutions are considered admissible whenever they lie in the interval *[-0.25 f(x); 0.25 f(x)]* in the objective function space. Solutions out of this interval are considered non-robust. This scenario only happens when the perturbation is higher than ±3% in all solutions obtained in the (nominal) Pareto front.

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