Multi-Objective Optimal Power Management in Microgrids: A Comparative Study

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***Abstract*— the design of Energy Management System involves important technological challenges to obtain optimal power management in microgrids, especially when two or more objectives must be reached. As an approach, several constrained multi-objective optimization (MO) algorithms partially can address optimal power management. For these cases, a decision-maker must choose not only the final set-points, but the best MO algorithm applied to the process. This paper presents a comparative study among four MO algorithms: MOGA, NSGAII, SPEA2 and IMOPSO to propose a comparative framework to ease choosing of a better MO algorithm. The comparative study proposes five criteria to evaluate the performance based on the average of: total operation costs, total emissions, energy share, runtime and non-dominated solutions in grid-connected mode. Results show IMOPSO offers overall better performance while MOGA provides good behavior in average of emissions and runtime. Nonetheless, this framework could improve decisions by increasing the set of criteria properly.**

***Index Terms*-- decision maker, energy management system, microgrids, multi-objective optimization, optimal power management.**

I. Introduction

Microgrids are a new concept of power system, developed to avoid illness an unsuitability of conventional power grids. However, microgrid deployment expectation includes optimal performance in terms of lower operational costs, lower pollutant emissions, a safety operation, among other objectives [1]. The above implies microgrid must properly manage power output from all distributed generators that comprise it [2]. Researchers commonly call this task as an optimal power management (OPM) in microgrids. To perform it, a specialized and qualified energy management system (EMS) must be designed [3], [4].

Recently, researchers have proposed to base the EMS optimization design using constrained multi-objective optimization (MO) [5], with good results. Notwithstanding, MO delivers a solution-set instead a single optimal solution. This feature involves the need for developing a design process, where a decision-maker (DM) must select only one solution and subsequently apply it to microgrid state.

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$x \in E^n$	n-dimensional decision variable
$F(x) \in E^k$	Vector to optimize
k	Number of objective functions
E^n	n-dimensional feasible set of an optimization problem
$g(x)$	Inequality constraint
$h(x)$	Equality constraint
m	Number of inequality constraints
e	Number of equality constraints
P_i	Output power of generating unit i
$CF(\boldsymbol{P})$	Operation cost of microgrid [$/h]
$E(\boldsymbol{P})$	Overall total emissions of NO_x, SO_x and CO_2 [kg/h]
$\boldsymbol{P} = (P_1, P_2, \dots, P_N)$	Power vector of N decision variables
N	Number of generating units
M	Emission type (NO_x, SO_x, CO_2)
C_i	Fuel cost of generating unit i.
$F_i(P_i)$	Fuel consumption rate of generating unit i
$OM_i(P_i)$	Operation and maintenance cost for Generating unit i
CEI	Cost of imported energy from main grid
CEE	Cost of exported energy to main grid
EF_{ij}	Type j emission factor of generating unit i
σ_j	Constant externality cost for type j emission
$\alpha_i, \beta_i, \gamma_i, \zeta_i, \lambda_i$	Parameters of characteristic emission of Generating unit i
$\sum_{i=1}^{N} P_i$	Total power generated by generating units
P_L	Power load demand
P_{PV}	Output power of photovoltaic array PV
P_{WT}	Output power of wind turbine WT
P_{SHP}	Output power of small hydro-power SHP
P_{DS}	Output power of distributed store DS
P_G	Power of main grid
P_i^{min}	Minimum set-point of generating unit i
P_i^{max}	Maximum set-point of generating unit i
DG01	Diesel generator number one
MT01	Micro Turbine generator number one
FC01	Fuel Cell generator number one
BG01	Biodiesel generator number one
BG02	Biodiesel generator number two
BG03	Biodiesel generator number three

Figure 1. Nomenclature

Nevertheless, due several algorithms of MO can address the OPM, before DM faces the above decision, he must address the challenge of choosing an MO algorithm to perform the best optimization process [6]. A common comparison methodology could be useful to choose the best algorithm for microgrid operation. Although specialized literature shows some approaches, each one of them has its own framework and the lack of optimization parameters makes the comparison among algorithms more difficult. To the best of our knowledge, very few comparative studies among MO techniques applied to OPM in microgrids have been published.

This paper presents a comparative study of four MO algorithms applied to optimize two conflicting objectives over the same microgrid model: i) minimize operational costs in the microgrid and ii) minimize overall pollutant emissions (CO_2, SO_x and NO_X). We use MOGA , NSGAII, SPEA2 and IMOPSO algorithms due they are known for its ability to provide solutions to large–scale distributed optimization, often more effectiveness and robustness than traditional approaches [7]. Thus, we propose a methodology to perform the comparative study using five criteria to evaluate the performance of each MO algorithm based on average of: total operation costs, total emissions, energy share, the amount of non-dominated solutions delivered and runtime. The remainder of this paper is organized as follow: section II presents problem formulation and some relevant previous research. Section III presents the comparison methodology in terms of the microgrid model, MO algorithms applied and the framework implemented to evaluate its performance. Section IV shows the outcomes using the proposed comparison framework. Section V presents some discussions and conclusions.

II. Problem Formulation and State of the Art

A specialized EMS for microgrids could be base OPM core using MO. Researches have considered this kind of formulation, among other features, due MO allows to depict this problem through formal definitions [8]. See (1)–(3).

Minimize:

$$F(x) = [F_1(x), F_2(x), \dots, F_k(x)]^T \tag{1}$$

Subject to:

$$g_j(x) \le 0,\ j = 1,2,\dots,m \tag{2}$$

$$h_l(x) = 0,\ l = 1,2,\dots,e \tag{3}$$

Interest in modeling the problem of OPM in microgrids using MO has grown in recent years, getting promising results. Some of these studies use different MO algorithms to face two or more non-lineal objective functions to depict a minimization of operational costs and greenhouse emissions [9]–[14]. Others have proposed the minimization of economic costs and the maximization of distributed generation use [15], the minimization of lost in transmission lines and fuel consumption [16], or the maximization of profits and risk minimization due to price variability [17]. Nevertheless, when MO is involved is necessary to consider two design aspects. From work of Mattson and A. Messac in [6], these design aspects are called *design alternatives* and *design concepts*. Due the output of a MO algorithm is not a single solution, but a set, *design alternatives* implies that a DM must choose only one solution from the set and apply it to microgrid. However, before that this selection happens, DM should make a decision on which MO algorithm (concept) he must use to perform a better optimization procedure. To address this *design concept*, a common methodology to compare performance among different MO algorihtms could be a helpful tool to ease labor of DM. The state of the art refers some studies which include a different methodologies about *design concepts* to help work of DM, however they are tailored for another specific areas of engineering [18], [19] or in the field of math [20], [21], with no relation with optimal microgrids operation.

III. Comparison Framework

A. Microgrid Model

The proposed microgrid model is based on a cluster of electrical power loads fed by a group of distributed generators: distributed energy resources (DER): DG01, MT01, FC01, BG01, BG02 and BG03, and alternative energy distributed generators (AEDG): Photovoltaic array–PV, Wind Turbine–WT and Small Hydro Power–SHP. Fig. 2 shows a conceptual scheme for the model, where is indicated the maximum output power of each distributed generator.

B. Objective Functions

From model presented in Fig. 2, we describe a cost function optimization model based on operational cost [$], emissions [kg] and constraints. See [22] for more details of this model.

1) Economic cost function: Equation (4) shows the operational cost function where fuel, operation and maintenance (O&M), energy importation/exportation and externality costs (due pollutant gases, NO_x, SO_2 and CO_2, see Table I) are added in the expression:

$$CF(\boldsymbol{P}) = \sum_{i=1}^{N}(C_i \times F_i(P_i) + OM_i(P_i) + CEI - CEE) + \sum_{i=1}^{N}\sum_{j=1}^{M} \alpha_i\left(EF_{ij}\, P_i\right) \tag{4}$$

2) Emission function: Equation (5) shows emissions of NO_x, SO_2 and CO_2 [kg], as a function of power output per DER unit and main grid power (used to supply deficits in microgrid). Here, *L* is the number of DER units plus one, *L=N+1*:

$$E(P_i) = \sum_{i=1}^{L} 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \zeta_i \exp(\lambda_i P_i) \tag{5}$$

3) Constraints: To keep a well operated system, a balance among output power must be introduced. At same time, each generating unit must be bounded between its own output power limits. See (6) and (7).

$$\sum_{i=1}^{N} P_i = P_L - P_{PV} - P_{WT} - P_{SHP} - P_G \tag{6}$$

$$P_i^{min} \le P_i \le P_i^{max},\ \forall_i = 1, \dots, N \tag{7}$$

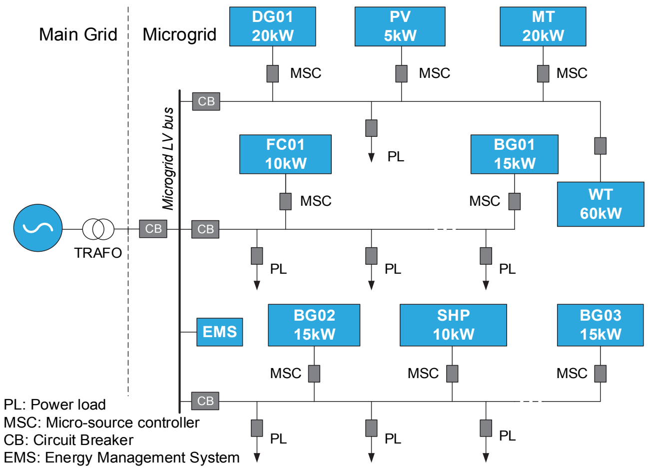

Figure 2. Microgrid conceptual scheme. Based on [22].

C. MO Algorithms

Four MO algorithms are used in this study: the non-domination sorting genetic algorithm NSGAII [23], the multi-objective genetic algorithm MOGA [24], the improved strength Pareto evolutionary algorithm SPEA2 [25] and the improved multi-objective particle swarm optimization IMOPSO [20]. Different optimization approaches uses these algorithms for many areas of engineering, obtaining satisfactory results. Here, for each algorithm used, the initial population = 100, the final population = 100 and the number of iterations = 500.

D. Performance Criteria

Based on Lopez's work in [22], a comparison framework among MO algorithms is proposed to evaluate the average of: costs [\$/h], emissions [kg/h], distribution of energy (energy share), runtime and non-domination, in 24 hours of operation. This procedure is tested ten times, i.e., we get 960 simulation routines (24 runs per day, 4 algorithms, 10 test).

In accordance with Zitztler in [26], metrics about non-domination (ND) solution-set can be depicted according to (8). To calculate non-domination average, we perform 10 routines.

$$(X',X'') = \frac{|\{a'' \in X'' ; \exists a' \in X' : a' \preccurlyeq a''\}|}{|X''|} \qquad (8)$$

Where X', $X'' \subseteq X$, are two decision vector set. a'' and a' are individual solutions from X' and X'' respectively. Function C maps ordered pair (X', X'') to the interval [0, 1]. $C(X',X'') = 1$, means all solutions in X'' are dominated or are equals to solutions in X'. $C(X',X'') = 0$, means no solutions are dominated by X' set. Note that $C(X',X'')$ is not necessarily equal to $1 - C(X'', X')$.

E. Input Information

Fig. 3 shows how using only AEDG resources does not cover total power load (PL) demand. Due this, is necessary to carry up a power management strategy using a combination among DER units and even main grid. Fig. 4 presents the evolution of energy price for the main grid. Between both curves (bought and sold energy), there is a commercial brokerage rate close to 30%.

TABLE I. EXTERNALITY COSTS AND EMISSION FACTORS

Emission Type	α [\$/kg]	DG/GRID [kg/kWh]	FC [kg/kWh]	MT [kg/kWh]	BG [kg/kWh]
NO_x	4.200	0.021800	0.000030	0.000440	0.030800
SO_2	0.990	0.000454	0.000006	0.000008	0.000000
CO_2	0.014	0.001432	0.001078	0.001596	0.000750

TABLE II. EMISSION COEFICIENTS

Source	α	β	γ	ζ	λ
DG/BG /GRID	0.2125	0.2404	0.2809	8.70×10^{-6}	0.1237
MT	0.0110	0.0120	0.0140	4.35×10^{-7}	0.0062
FC	0.212×10^{-3}	0.240×10^{-3}	0.014×10^{-3}	4.35×10^{-10}	0.62×10^{-5}

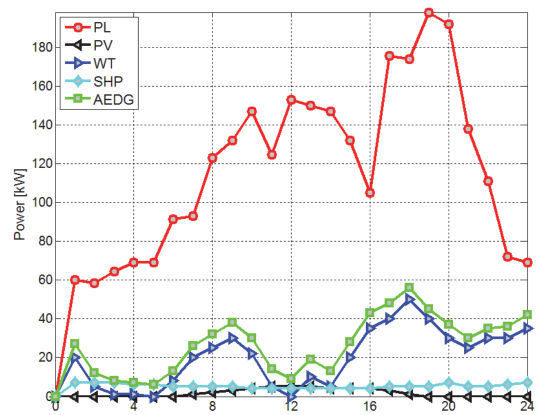

Figure 3. Power load demand and AEDG power output

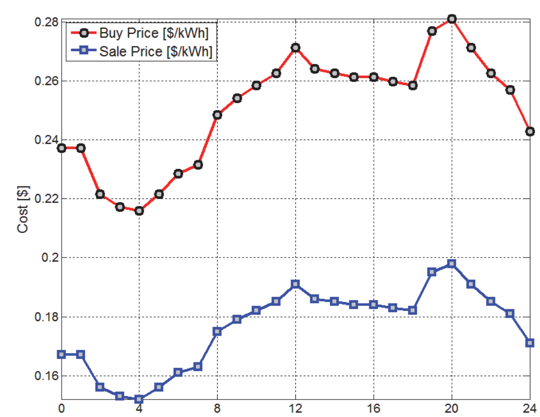

Figure 4. Curves of sale and buy prices

F. Optimization Strategy

1) At the beginning of each hour, calculate total PL demand.
2) Calculate output power of renewables generation units and use with priority.
3) If total use of AEDG are not enough, run MO algorithm with constraints, operational cost, and emission to obtain a solution-set. See (4)–(7).
4) Choose one solution from solution-set (set-points vector $\boldsymbol{P}_i$). This vector is formed by only DER units, or can be complemented with power importation from main grid. Here, the DM makes a selection based on follow rules:
   i. Calculate cost [$] of importing total power demand from main grid. This means equal to zero all output power in DER units (total importation strategy).
   ii. From MO solution-set, to select the first individual such as its operation cost value is lower or equal to the value calculated in i.
5) Apply selected set-point.
6) Repeat steps 1 to 5 until 24 hours are achieved.
7) Repeat this procedure 10 times for each MO Algorithm.

IV. Results

A. Cost average:

Chart in Fig. 5 shows comparison among economical cost average. IMOPSO gets a cheaper performance with $395.61 of average, followed by: SPEA2 (10.35%), MOGA (12.01%) and NSGAII (21.89%) respect of the cost of IMOPSO. See Table III.

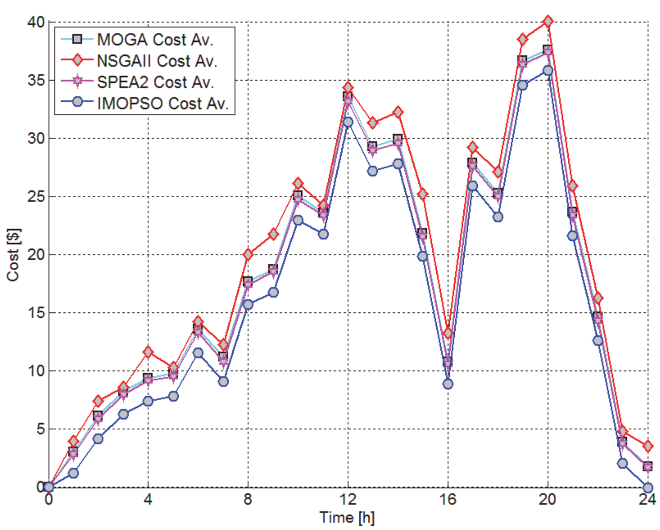

Figure 5. Cost average comparison.

B. Emissions average

Fig. 6 depicts a comparative chart among total emissions (GRID+DER). Here, MOGA gets the greener performance with 33,536.54 kg of gases thrown to atmosphere, followed by results that are more pollutants: IMOPSO (5.34%), SPEA2 (5.38%) and NSGAII (8.35%). Notice that, IMOPSO and SPEA2 are close to MOGA emissions performance. Table III also presents these results.

C. Energy share average

Fig. 7 shows MO algorithms distribute energy from DER sources. SPEA2, MOGA and NSGAII present a trend to shutdown diesel/biodiesel sources, while IMOPSO trends to distribute the production in all sources.

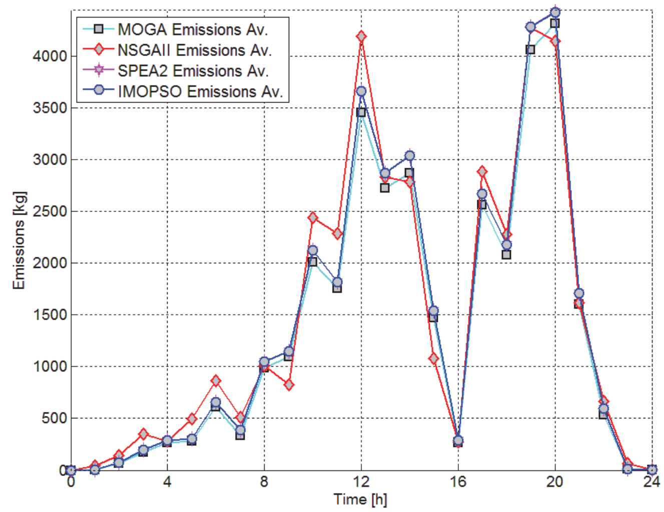

Figure 6. Emissions average comparison.

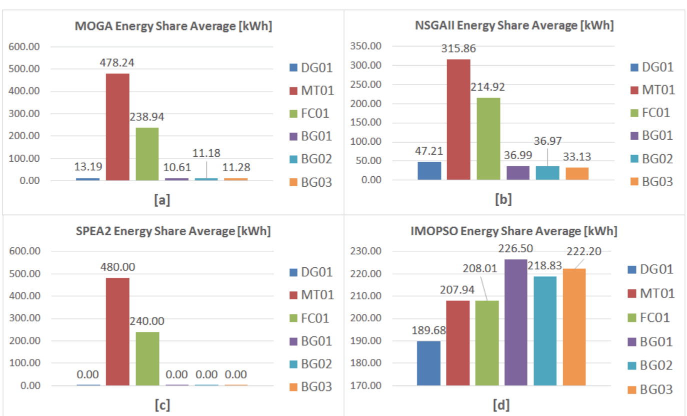

Figure 7. Energy share average comparison. (a) MOGA; (b) NSGAII; (c) SPEA2; (d) IMOPSO.

TABLE III. Performance Index

Performance Index	MOGA	NSGAII	SPEA2	IMOPSO
Total cost av. [$]	443.13	482.23	436.55	395.61
Total emission av. [kg]	33,536.54	36,338.02	35,340.94	35,325.87
Runtime average [s]	22.40	30.27	107.75	164.45
Coefficient of variation	1.48%	1.59%	2.28%	1.99%

D. Runtime average

Table III shows runtime average from 24h operation among MO algorithms. MOGA is the fastest (22.40s), and is followed by NSGAII (35.15%), SPEA2 (381.10%) and IMOPSO (334.25%) respectively. Table III shows that the coefficient of variation obtains similar data consistency for whole of the algorithms tested.

E. Non-domination average

Table IV shows first comparison about amount of non-dominated solutions average based on (8). Here, we observe that IMOPSO offers more non-dominated solutions since it exceeds the amount of non-dominated solutions of other algorithms. Following the order, SPEA2, MOGA and NSGAII complete ranking. Sensitive data variation is perceived when the amount of non-dominated solutions tends to be smaller.

TABLE IV. NON-DOMINATION STUDY

Study after 10 runs	Non-Domination Average	Coefficient of Variation
MOGA vs NSGAII	0.78608	5.49368%
NSGAII vs MOGA	0.00008	200.02899%
MOGA vs SPEA2	0.00542	42.49079%
SPEA2 vs MOGA	0.70984	5.48675%
MOGA vs IMOPSO	0.01317	22.51955%
IMOPSO vs MOGA	0.69646	3.41146%
NSGAII vs SPEA2	0.00000	0.00000%
SPEA2 vs NSGAII	0.84629	4.23911%
NSGAII vs IMOPSO	0.00004	300.00000%
IMOPSO vs NSGAII	0.84242	3.99599%
SPEA2 vs IMOPSO	0.07438	8.64725%
IMOPSO vs SPEA2	0.52496	1.60025%

V. DISCUSSIONS AND CONCLUSIONS

Here, we present a first approximation of a framework to help DM to get a better algorithm to solve multi-objective OPM in microgrids using algorithms based on computational intelligence.

The results show that IMOPSO has the best features to obtain lower costs and solutions where a more combined mix of DER generation units are used. The IMOPSO good performance is explained through of a greater amount of non-dominated solutions delivered in each test. This distribution gets the best result as far as production costs and avoid to keep the sources on their limits which could guarantee the useful life of equipment on the grid. However, this technique could be limited by runtime, for those EMS where lower sampling times are required.

Despite MOGA in literature review is an evolutionary algorithm which tends to fall into disuse, it offers the best performance in emissions average and also a competitive performance in cost average. Furthermore, MOGA takes advantage where a faster response is imperative. At same time, MOGA provides the lower coefficient of variation, which means more repeatability in data, although other algorithms are close to these values.

However, a DM still must choose the more convenient algorithm even before start the optimization procedure, since time available to assess the performance on-line may limit the quality of the results. Thus, an evaluation off-line could be recommended, at least to select the best algorithms in according to nature of microgrid model. This means that the DM should make decisions on two different stages, first in off-line mode and likely later in on-line mode.

Beyond this, an extended comparison framework, which includes other performance indexes, could develop better evaluations and therefore more accurate decisions. On the other hand, new studies and MO algorithms would enhance the methodology and expanding the DM´s possibilities to get an optimal performance.

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