Multi-objective Particle Swarm Optimization to Solve Energy Scheduling with Vehicle-to-Grid in Office Buildings Considering Uncertainties

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Abstract: This paper presents a Multi-Objective Particle Swarm Optimization (MOPSO) methodology to solve the problem of energy resource management in buildings with a penetration of Distributed Generation (DG) and Electric Vehicles (EVs). The proposed methodology consists in a multi-objective function, in which it is intended to maximize the profit and minimize CO_2 emissions. This methodology considers the uncertainties associated with the production of electricity by the photovoltaic and wind energy sources. This uncertainty is modeled with the use of a robust optimization. A case study is presented using a real building facility from Portugal, in order to verify the feasibility of the implemented robust MOPSO.

Keywords: CO_2 Emissions, Electric Vehicles, Energy Resources Management, Multi-Objective Particle Swarm Optimization, Robust Optimization.

1. INTRODUCTION

The buildings, in terms of energy consumption, represents about 20 to 40% of total energy consumption in a developed country (Juan, Gao, and Wang 2010). For example, in the European Union buildings are responsible for 40 % of total consumption (Zhao and Magoulès 2012) and 37 % in the United States (Juan, Gao, and Wang 2010).

The buildings energy consumption is expected to grow up, especially in residential buildings due to requirements for the comfort levels and increasing number of household appliances. Another factor is that less developed countries are growing and becoming wealthier. The improvements in the quality of life of these countries lead to an increase in the energy consumption of its buildings.

The increase of the power consumption in buildings is directly linked to the increase of CO_2 emissions, creating environmental problems. A large number of policies to control the CO_2 emissions levels are currently in force, creating a direct impact to reduce the emissions in the electrical sector (Zhao and Magoulès 2012). With the growing concern about global climate change, global warming and pollution of air, policies have been released with the aim to promote electricity production from Renewable Energy Sources (RES). The increase of the Distributed Generation (DG) based on renewable sources, such as Photovoltaic (PV) panels, wind turbines, small hydro, etc. is presented as a solution to reduce CO_2 emissions significantly.

In the scope of Smart Grids (SGs), the consumer can be a flexible entity, participating as an active actor on the energy network. This flexibility can be achieved with the successful use of energy resource management, including loads, generators units, Energy Storage Systems (ESSs) and Electric Vehicles (EVs). The SGs are directed associated with development of reability and power quality of the electric network, being able to control and manage energy production and consumption of all players. As described in (Venayagamoorthy 2011), SG aims to maximize the penetration of RES and, on the other hand, to include Demand Response programs (DR) on consumers. The DR is a change from the normal pattern of electricity use (consumption) by end customers in response to an electricity price change or due to incentive payments (North American Electric Reliability Corporation 2007).

The increase of the use of renewable energy production facilities, such as wind and PV, contributes positively to the reduction of the carbon footprint. However, in contrast to conventional generation units, renewable sources are characterized by a high degree of uncertainty and variability. Given this degree of uncertainties it is necessary the use of advanced programming models, using robust control and predictive models, able to handle with this stochastic and uncertain behavior. The motivation to establish a stochastic modeling is associated with the challenge of facing the variability and uncertainty of renewable energy resources in microgrids, since these resources can be a major part of the total production.

The energy resources management in SG environment, considering the stochastic component needs attention in the current literature. Robust optimization has proved to be a promising method to deal with the uncertainties in the optimization problems. Several studies have been reported in the recent literature. In the context of smart homes, the robust optimization is used in reference (Wang et al. 2015), in order to model the input uncertainties from the production of a PV system. The main objective of this methodology is perform the scheduling for the various types of electrical loads present in the residence. The work presented in (Chen, Wu, and Fu 2012) evaluates the DR program based on the real time price in the management of residential loads, through two approaches, the stochastic optimization and robust optimization. The stochastic optimization adopts the scenario-based approach via Monte Carlo (MC) simulation for minimizing the expected electricity payment for the entire day, while controlling the financial risks associated with real time electricity price uncertainties. Price uncertainty intervals are considered in the robust optimization for minimizing the worst-case electricity payment while flexibly adjusting the solution robustness. Both approaches are formulated through a mixed integer linear programming (MILP). Reference (Akbari et al. 2014) focused in energy management system of a building under the influence of multiple sources of uncertainty, such as, the energy demand level in relation to cost (as the cost of carbon emissions , the primary energy savings, etc.) and prices (as prices of fuel and electricity tariffs). The optimization depicts a multi-objective problem for a commercial building, where one objective is minimizing costs and the other is minimize the energy consumption. To overcome the environment of the uncertainties mentioned above, this model uses a robust optimization. It is important to refer that in the current literature, the subject of robust optimization applied to meta-heuristics is not very well exploited. The current robust models are usually converted to linear and deterministic optimization. However, in situations with a large number of variables and/or considering nonlinear models, the deterministic approach may be impractical.

The main contribution of this paper focuses on the development of a methodology to solve the day-ahead energy resource management problem in buildings, considering the uncertainties associated with the energy production from PV and wind units. To model this uncertainty a robust optimization was incorporated in Multi-Objective Particle Swarm Optimization (MOPSO). The robust optimization applied to a meta-heuristic, taking into account the scarcity of studies addressing this subject, especially in the area of building management, is an important contribution of this work. This approach allows a more conservative solution, which is the best solution considering the worst-case scenarios. The proposed problem in this paper considers two conflicting objectives, maximizing profits and minimizing CO_2 emissions. Other relevant contributions are the business models considered, namely the fact that the building can buy energy from different external suppliers in each period, the use of vehicle-to-building, in which the electric vehicle can supply energy to the building. In addition, an innovative DR model has been proposed, which considers a daily peak power pricing and an incentive to minimize it. A case study is presented using a real building facility from Portugal, with DG, EVs and ESS, in order to verify the feasibility of the robust algorithm implemented. Two scenarios are assessed and evaluated using the multi-objective approaches. The first scenario considers a robust optimization giving more importance to the criterion of profit and the second scenario considers a robust optimization giving more importance to the criterion of CO_2 emissions. The robust model development in this paper is based in (by Robert Marijt and Hensen 2009).

This paper is organized as follows: after this introduction, section 2 presents the mathematical formulation of the Energy Resources Management problem, section 3 presents the case study and finally section 4 the conclusions.

2. META-HEURISTIC APPROACH

2.1 Mathematical model

The envisaged problem is a hard combinatorial Mixed-Integer Non-Linear Programming (MINLP) problem due to the continuous, discrete and binary variables. The two conflicting objectives of the building management are to maximize profits and minimize CO_2 emissions, as shown in (1).

$$\text{Minimize} \quad Z = C - R + E \tag{1}$$

The building receives a revenue (R) from two sources, as illustrated in (2): the revenue from the EVs charging and the DR incentive to keep the energy demand (from the grid) relatively low.

$$\text{Maximize} \quad R = \sum_{t=1}^{T}\left[\left(\sum_{v=1}^{N_v} P_{\text{charg}}^{v}(t)\cdot c_{\text{charg}}^{v}(t)\right)\right] + r_{peakPower} \tag{2}$$

The parameters are described by: N_v is the number of EVs; $c_{\text{charg}}^{v}(t)$ is the price for the charge process of EV v in period t (m.u.); $r_{peakPower}$ is the incentive for achieving a maximum peak power value.

The variables are: R is the building revenue (m.u.); $P_{\text{charg}}^{v}(t)$ is the active power charge of EV v in period t (kW);

Function C (3) represents the cost of the resources managed by the building. It considers the cost with DG, external suppliers, discharge of EVs, and the cost of power peak value.

$$\text{Minimize} \quad C = \sum_{t=1}^{T}\left[\left(\begin{array}{l}\displaystyle\sum_{d=1}^{N_d} P_{\text{dg}}^{d}(t)\cdot c_{\text{dg}}^{d}(t) + \\ \displaystyle\sum_{s=1}^{N_{sp}} P_{\text{sp}}^{s}(t)\cdot c_{\text{sp}}^{s}(t) + \sum_{v=1}^{N_v} P_{\text{disch}}^{v}(t)\cdot c_{\text{disch}}^{v}(t)\end{array}\right)\right] + c_{peakPower} \tag{3}$$

The indices are represented by: d is an index of DG units; l is an index of loads; s is an index of external suppliers; t is an index of time periods; v is an index of EVs.

The parameters are described by: N_d is the number of DG units; N_{sp} is the number of external electricity suppliers;

$c_{\mathrm{dg}}^{d}(t)$ is the generation price of DG unit d in period t (m.u.); $c_{\mathrm{sp}}^{s}(t)$ is the energy price of external supplier s in period t (m.u.); $c_{\mathrm{disch}}^{v}(t)$ is the discharging cost of EV v in period t (m.u.); $c_{peakPower}$ is the peak power cost.

The variables are described by: C is the total cost (m.u.); $P_{\mathrm{dg}}^{d}(t)$ is the active power generation of DG unit d in period t (kW); $P_{\mathrm{sp}}^{s}(t)$ is the active power generation of the external supplier s in period t (kW); $P_{\mathrm{disch}}^{v}(t)$ is the active power discharge of EV v in period t (kW);

Equation (4) shows the objective function to minimize the CO_2 emissions.

$$\text{Minimize } E = \sum_{t=1}^{T}\left[\begin{pmatrix} \sum_{d=1}^{\Omega_{\mathrm{dg}}^{d}} P_{\mathrm{dg}}^{d}(t)\cdot E_{\mathrm{dg}}^{d}(t) + \\ \sum_{s=1}^{\Omega_{\mathrm{sp}}^{e}} P_{\mathrm{sp}}^{s}(t)\times E_{\mathrm{sp}}^{s}(t) \end{pmatrix}\right] \quad (4)$$

The sets are described by: Ω_{dg}^{d} is a set of DG units with CO2 emissions; Ω_{sp}^{e} is a set of external suppliers with CO2 emissions.

The parameters are described by: E_{dg}^{d} is the CO_2 emissions of DG unit d in period t (kgCO2/kWh); E_{sp}^{s} is the CO_2 emissions of external supplier S in period t (kgCO2/kWh).

The variables are described by: E is the total emissions CO_2 (kg).

Some constraints of this problem can be found in (Soares et al. 2016), such as, EV charging and discharging rates, battery capacity and balance considering predicted demand and location, technical limits of ESSs, balance and capacity in each period, dispatchable DG capacity and supplier's limits. In additional, an innovative DR model has been proposed, which considers a daily peak power pricing ($c_{peakPower}$) and an incentive to minimize it ($r_{peakPower}$). The daily peak power pricing depends from the peak power value (P_{peak}), that represents the maximum energy supplied by the external supplier for the entire day. The $c_{peakPower}$ can been calculated with the equation (5)

$$c_{peakPower} = \begin{cases} if\ \lim_{\min}(1) \le P_{peak} \le \lim_{\max}(1), p_{\mathrm{level}}(1) \\ if\ \lim_{\min}(2) \le P_{peak} \le \lim_{\max}(2), p_{\mathrm{level}}(2) \\ \\ if\ \lim_{\min}(\mathrm{n}) \le P_{peak} \le \lim_{\max}(\mathrm{n}), p_{\mathrm{level}}(\mathrm{n}) \end{cases} \quad (5)$$

The parameters are described by: $\lim_{\min}$ is the minimum power limit; $\lim_{\max}$ is the maximum power limit; p_{level} is the peak power price by level.

The $r_{peakPower}$ is paid if the P_{peak} of the building does not exceed 200% of the average daily demand (P_{mean}), as you can seem in equation (6).

$$r_{peakPower} = \begin{cases} if\ P_{peak} \le 2P_{mean},\ \dfrac{c_{peak}}{2} \\ if\ P_{peak} > 2P_{mean},\ 0 \end{cases} \quad (6)$$

2.2 Multi-Objective Particle Swarm Optimization (MOPSO)

MOPSO is an advanced optimization algorithm to solve multi-objective problems (Coello, Pulido, and Lechuga 2004) used in this work to handle the envisaged energy problem. The traditional MOPSO relies on externally fixed particles' velocity limits, inertia, memory and cooperation weights without changing these values along the swarm search. In the proposed method we employ mutation of the strategic parameters used in Evolutionary PSO (Miranda, Keko, and Jaramillo 2007) instead of the usual fixed parameters. This modification improved the cover rate and the overall front of the non-dominated solutions as higher exploratory properties were introduced in the search procedure. The first step of the MOPSO is the creation of 10 initial particles, each of which contains the decision variables and variables with uncertainty. Each initial particle is evaluated and the better particles are stored in a repository. The next step is to identify or update the repository leader (global best solution). Then it is performed the mutation rate of the strategic velocity coefficients. That said, it is performed the calculation of the new velocities and positions for each particle. After this, a mutation in the position of some particles (randomly selected) is made. For each particle, the variables with uncertainty (wind and PV), which in this case correspond to the production forecast values for the next day, are disturbed by a prediction error value, creating 10 different scenarios for the PV and wind production. These scenarios are generated by using the MC method, following a normal distribution and assuming a 15% prediction error (Su, Wang, and Roh 2014). Each perturbation solution is evaluated in the objective function and the solution that represent the worst case is chosen. For this case study 2 different scenarios were developed: the first scenario considers a robust optimization giving more importance to the criterion of profit, select the worst profit. The second scenario considers a robust optimization giving more importance to the criterion of CO_2 emissions, considers the worst value of CO_2 emissions. After the selection of all robust particles, each robust solution is evaluated and the non-dominated solutions are stored in the repository in order to represent the Pareto front. This entire cycle will be repeated until a set number of iterations (see Fig. 1).

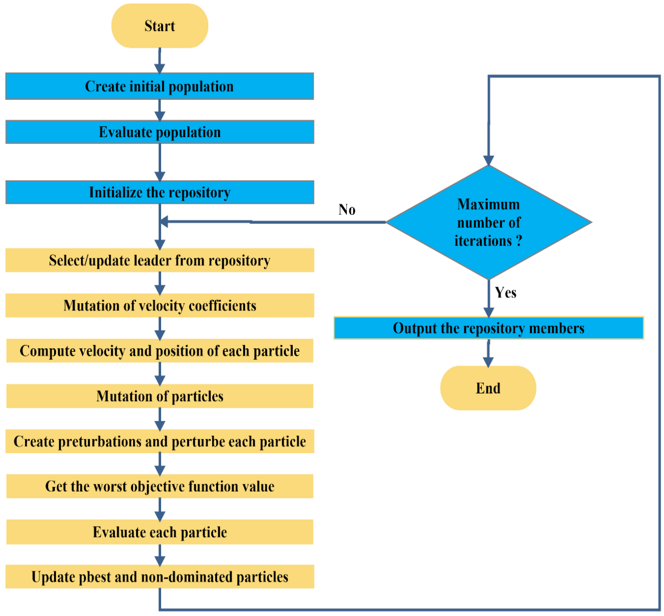

Fig. 1. Flowchart of the developed MOPSO

The fitness function (7) in MOPSO considers the total profit and the emission of CO_2. The total profit is achieved by the minimization of this function.

$$\text{fitness} = \left[(C - R) + E \right] + \text{penalties} \tag{7}$$

3. CASE STUDY AND RESULTS

The proposed methodology is tested using a case study of a real building, in Porto, Portugal, namely the GECAD building from ISEP/IPP (Institute of Engineering – Polytechnic of Porto). The building is able to manage 2 DG units (PV and wind), 4 external suppliers, 1 ESS and 3 EVs. Table 1 shows the energy resources data, regarding the information of price in monetary units per kWh (m.u./kWh) and availability in MW.

Table 1. Energy resource data

Energy resources		Availability (kW)	Prices (m.u./kWh)	Units
		min – max	min – max	
PV		0 – 7.50	0.00	1
Wind		0 – 1.00	0.00	1
External Supplier		0 – 15.00	0.07 – 0.32	4
Storage	Charge	0 –10.00	0.00	1
	Discharge	0 – 10.00	0.00	
Electric Vehicle	Charge	0 – 9.00	0.13	3
	Discharge	0 – 9.00	0.15	
Load		1.02 – 11.96	0.00	1

To make the problem more innovative, four external suppliers were considered with different emission rates and energy prices. Table 2 represents the different types of external suppliers used in this case study based in four different European countries (Portugal, Spain, Germany and France) (Red Eléctrica de España 2016; ERSE 2016; E.ON 2016; EDF 2016; European Commission 2014).

Table 2. External suppliers data

Scenario	CO_2 emissions ($kgCO_2$/kWh)	Prices (m.u./kWh)	Tariff type
Portugal	0.23	0.0927 - 0.3177	Tri tariff
Spain	0.25	0.0742 – 0.0993	Hourly tariff
France	0.07	0.1150 – 0.1636	Bi tariff
Germany	0.35	0.2013	Simple tariff

Table 3 presents the parameters used for this case study in the meta-heuristic approach, namely MOPSO. These parameters were obtained by extensive experimental tests and by previous recommendations made in the literature (Coello, Pulido, and Lechuga 2004). The repository size was set to 100, as suggested in the literature, in order to obtain a very high quality of the Pareto front.

Table 3. MOPSO parameters

Parameter		Description
Number of particles		10
Repository size		100
Inertia Weight		Gaussian mutation weights (initial weights randomly generated between 0 and 1)
Acceleration Coefficient Best Position		
Cooperation Coefficient		
Perturbation Coefficient		
Mutation learning parameter (δ)		0.20
Number of divisions		30
Initial swarm population		Randomly generated between the upper and lower bounds of variables
Mutation rate of particles		0.50
Mutation dimensions		Random 10% dimensions
Velocity clamping factor (C_{factor})		1
Stopping Criteria	Max.	2000 iterations (cycles)
Max. Positions (x_{max})		Equal to the upper bounds of the variables
Min. Positions (x_{min})		Equal to the lower bounds of the variables
Max. Velocities (v_{max})		$\frac{x_{max} - x_{min}}{2} \cdot C_{factor}$
Min. Velocities (v_{min})		$-v_{max}$

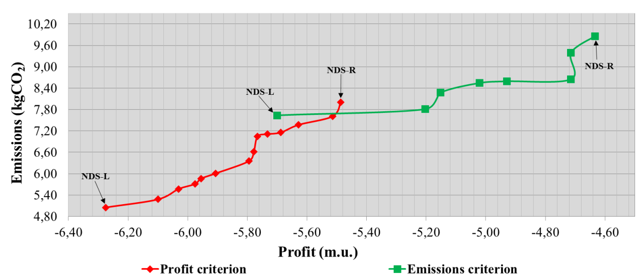

Fig. 2. Pareto fronts for the profit and CO_2 emissions criterion

The number of NDS obtained was 14 and 8, for the profit and CO_2 criterion, respectively, and we selected the solutions from the Pareto front: lowest total emissions of CO_2 (NDS-L) and higher profit (NDS-R), i.e. left and right solutions of Pareto front, respectively as presented in Fig. 2. The first, NDS-L, to obtain less CO_2 emissions, is achieved a lower profit. In the second solution, NDS-R, unlike the NDS-L, to achieve higher profit, the CO_2 emissions tend to be higher as well.

In the robust approach with the emissions criterion, the Pareto front solutions present a higher value in both terms (profit and CO_2 emissions) than the profit criterion (see Fig. 2). The solutions with higher CO_2 emissions generally present more profit. It may sound contradictory that the profit criterion obtains worse solutions (in terms of profit) than the emissions criterion. However, the robust approach looks for the best solution in the worse-case scenario during the search procedure. For example, this means that under the scenarios that lead to the worse profit, the robust approach can provide the best solutions (red line) for the worse profit situation. The combination of the both Pareto fronts constitute a set of solutions with a broader range.

Table 4 show the selected NDS from the Pareto curve. The PV and wind production is insufficient to feed the total consumption, therefore the solution presents negative profits, i.e. energy costs instead of profits.

Table 4. Selected non-dominated solutions

	Profit criterion		Emissions criterion	
NDS	**L**	**R**	**L**	**R**
Profit(m.u)	-6.275	-5.487	-5.700	-4.633
CO_2 emissions (kg)	5.053	7.999	7.636	9.856

Fig. 3 and Fig. 4 depict the energy scheduling results for NDS-L, for the profit and emission criterion, respectively. The storage discharge is a resource used in both solutions, this is due by the fact that it is a resource that does not involve any cost to the building, since the storages are considered its property. The vehicles' discharge, where the building has to pay an incentive to the vehicle owner use this feature, is scheduling in periods when the external supplier has an energy price greater than the cost of this incentive. Resources such as the vehicles and battery discharge are used in order to decrease the energy supply by the external suppliers. The energy from external suppliers in the emission criterion solution is 14.94% lower than the solution in the profit criterion. This variation is mainly due by the fact than the DG is 5.64% higher in the solution that considers the emission criterion, since the higher is the energy value produced by the DG, less is the need to buy energy from external suppliers, to support the building consumption. On the other hand, the profit criterion solution has a higher need to buy energy from external suppliers, leading to a worse profit in this solution. The vehicles' discharge in the emission criterion solution is decreased by 53.69%, compared with the profit criterion, resulting in a profit increased, but the emissions levels are reduced simultaneously. The battery discharge had a decrease of 16.91% in the emission criteria solution, compared to the profit criterion.

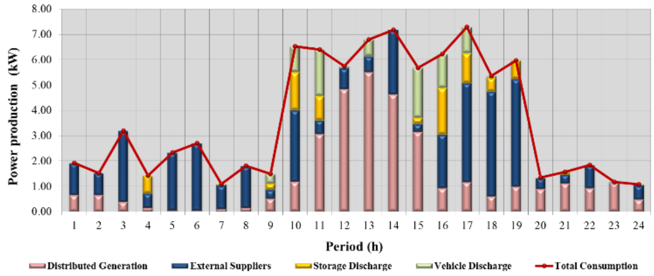

Fig. 3. Optimal resource scheduling of NDS-L for the profit criterion

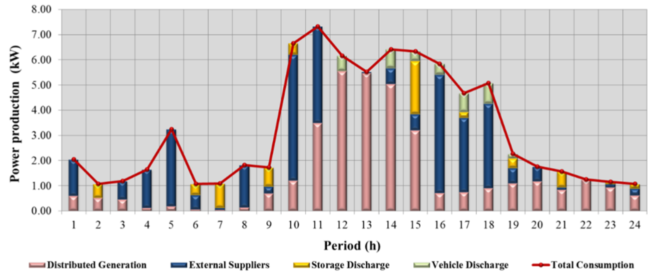

Fig. 4. Optimal resource scheduling of NDS-L for the CO_2 emissions criterion

Fig. 5 and Fig. 6 depict the power consumption results for NDS-L, for the profit and CO_2 emissions criterion, respectively. The EVs charge is made mainly in the afternoon periods (16h - 19h) so the owners have the minimum battery requirement to make the return trip to home. In addition, the charging of EVs is still performed during periods of high DG production (11h-13h). Regarding the storage charging, this is carried out in periods when the building can buy energy to the external suppliers with a cheaper price, corresponding essentially to night periods (23h-4h). The vehicles' charging has a large decrease (70.55%) in the emissions criterion solution, compared with the solution obtained in profit criterion, justified by the smaller use of vehicles' discharge verified in this solution. In terms of storage charging, there is a decrease of 17.42% in the emissions criterion solution, compared to the profit criterion solution.

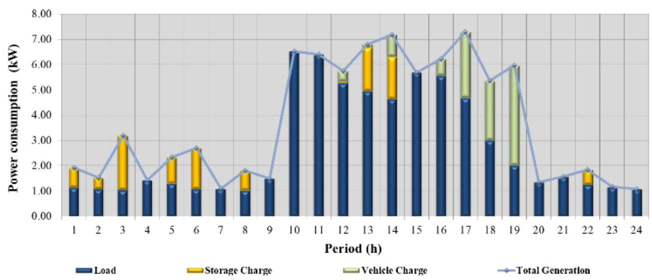

Fig. 5. Consumption scheduling of NDS-L for the profit criterion

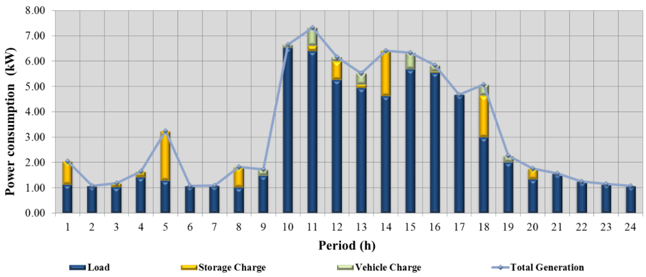

Fig. 6. Consumption scheduling of NDS-L for the CO_2 emissions criterion

The developed MOPSO algorithm took an average execution time of 30 minutes using six cores. This time could be reduced to about 5 minutes using GECAD's computing cluster with 6 machines, 36 workers (cores) configured with MATLAB distributed computing environment. Each worker can execute code independently and simultaneously.

4. CONCLUSIONS

This paper presented a method for intelligent energy management of a building using Multi-Objective Particle Swarm Optimization (MOPSO) based in multi-objective optimization, aiming to maximize the profit and minimize the CO_2 emissions. MOPSO is responsible for finding a set of possible solutions, in the two cases and with two different approaches. The first approach considers a robust optimization giving more importance to the criterion of profit and the other approach giving more importance to the criterion of CO_2 emissions.

The robust optimization can do not get the best solution, however, represents a method able to safeguard the building's operator with an adverse to the risk solution. Certain input parameters in the proposed optimization model are not deterministic, e.g. the energy production from RES, and can change significantly after the optimization has been made. This is particularly true in day-ahead forecasts, with a larger time horizon can significantly change after performing the optimization. With the use of the robust approach presented in this paper this risk is reduced. Faced with an optimization performed for the next day, which not handle with the uncertainty, can result in a worse production than the expected, forcing to a rescheduling in real time, which would lead to penalties and excessive costs to accomplish certain restrictions.

Taking into account its processing time, the robust optimization model developed in this work can be a useful method to obtain a quick solution for the next day, allowing that the building operator solve the problem with a more conservative approach to deal with uncertainties from the next day.

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