

Robust Metaheuristic for Day-ahead Microgrid Dispatch Considering Uncertainties

Nuno Borges* João Soares* Zita Vale*

*GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
Polytechnic of Porto (ISEP/IPP)
Rua Dr. Almeida, 431, 4200-072, Porto, Portugal
(e-mail: {ndsbs, joaps, zav}@isep.ipp.pt)

Abstract: This paper presents a robust Particle Swarm Optimization (PSO) methodology to solve the problem of day-ahead microgrid (MG) dispatch with high penetration of Distributed Generation (DG) and considering uncertainties. The proposed methodology has the objective to satisfy demand aiming at obtaining the maximum profit, corresponding to the difference between the income and costs. 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 approach in PSO. A case study is presented using a 21-bus MG from Portugal, a real university campus, and the projection of distributed energy resources based on the evolution scenario for the year 2050 managed by an aggregator.

Keywords: Energy Resources Management, Microgrids, Particle Swarm Optimization, Robust Optimization.

1. NOMENCLATURE

Indices

I	Index of DG units
t	Index of time periods
L	Index of loads
S	Index of external suppliers
V	Index of EVs
E	Index of ESSs
M	Index of energy buyers

Parameters

N_{DG}	Total number of distributed generators
N_L	Total number of loads
N_{ST}	Total number of storage units
N_S	Total number of external suppliers
N_V	Total number of EVs
N_E	Total number of ESSs
N_M	Total number of energy buyers
$c_{Discharge(V,t)}$	Discharging cost of EV V in period t (m.u.)
$c_{Discharge(E,t)}$	Discharging cost of ESS E in period t (m.u.)
$c_{DG(I,t)}$	Generation price of DG unit I in period t (m.u.)
$c_{GCP(I,t)}$	Generation curtailment power price of DG unit I in period t (m.u.)
$c_{NSD(L,t)}$	Non-supplied demand price of load L in period t (m.u.)
$c_{Supplier(S,t)}$	Energy price of external supplier S in period t (m.u.)
$c_{LoadDR(L,t)}$	Demand response cost of load L in period t (m.u.)
$MP_{Charge(E,t)}$	Price for the charge process of ESS E in period t (m.u./kWh)
$MP_{Charge(V,t)}$	Price for the charge process of vehicle V in period t

(m.u./kWh)

$MP_{Load(L,t)}$	Price of load L in period t (m.u./kWh)
$MP_{Sell(M,t)}$	Price energy sale to market M in period t (m.u./kWh)

Variables

$P_{DG(I,t)}$	Active power generation of I unit in period t (kW)
$P_{Supplier(S,t)}$	Active power generation of the external supplier S in period t (kW)
$P_{LoadDR(L,t)}$	Demand response program active power activated for load L in period t (kW)
$P_{Discharge(E,t)}$	Power discharge of ESS unit E in period t (kW)
$P_{Discharge(V,t)}$	Power discharge of EV V in period t (kW)
$P_{Charge(E,t)}$	Power charge of ESS unit E in period t (kW)
$P_{Charge(V,t)}$	Power charge of EV V in period t (kW)
$P_{NSD(L,t)}$	Non-supplied demand for load L in period t (kW)
$P_{GCP(I,t)}$	Generation curtailment power in DG unit I in period t (kW)
$P_{Load(L,t)}$	Active power demand of load L in period t (kW)
In	VPP income (m.u.)
C	Total operation cost (m.u.)

2. INTRODUCTION

The introduction of electricity markets and the integration of large amounts of Distributed Energy Resources (DERs), namely Distributed Generation (DG), are the reasons behind the new power system paradigm. It is possible to use several types of DERs, namely DG units, Demand Response (DR), Energy Storage Systems (ESSs) and Electric Vehicles (EVs).

The operation and management points of view, the high utilization of the DGs in small and medium players makes the

network management more difficult and instable (Siano 2014). In order to solve this problem, new concepts have been implemented, such as, microgrids (MGs) (Fu et al. 2012). An MG is an electric power distribution network with distributed capable of operating as a single controllable system (Moghaddam et al. 2011) In definition, the MG problem is the aggregation of DGs, electrical loads and generation interconnected among themselves and with distribution network (Moghaddam et al. 2011). This type of aggregator can manage and control a small or medium geographic area in order to change the electrical network to a distributed system. A MG can either operate in islanded mode or be grid-connected: in the second case the MG operates in parallel with the main grid and it can buy and sell energy. The energy efficient operation of MGs requires the development of an appropriate Energy Management System (EMS), that manages all the DERs.

The increasing of the number of Renewable Energy Sources (RES), such as wind and photovoltaic, contributes positively to the reduction of the CO₂ emissions, and highly contribute to the independence from fossil fuel electricity generation units. However, the RES are characterized by a high level of uncertainty related to weather aspects. The motivation to establish a robust modeling is associated with the increased challenge of facing the uncertainty of RES in MGs, since these resources can be a major part of future production.

Several studies have been reported in the recent literature using the robust optimization to deal with the uncertainty variables for energy scheduling in MGs. In (Kuznetsova et al. 2015) is developed one framework capable to performing a power management in a micro grid based on a robust optimization. Various types of uncertainty are considered, such as, the production based on unpredictable renewable sources, the cost of production and the energy consumption. The uncertainty is represented by prediction intervals, estimated by a neural network and by the Non-dominated Sorting Genetic Algorithm (NSGA -II), allowing to obtain the upper and lower limits, representing a range of values where it is expected that the parameter with uncertainty values tend to match, with a certain confidence level. In (Zhang, Gatsis, and Giannakis 2013) is presented a method to deal with the optimization of energy management for the production and consumption of a micro grid connected to the network and incorporating renewable production technologies. The main goal is to minimize costs in the micro grid network, such as the production of conventional DG, penalties of storage units, the use of elastic loads and transaction costs (sell excess energy to the main network or buy energy power in case of need). To deal with the uncertainty in RES production units, a robust formulation was used. It is important refer that in the current literature, the subject of robust optimization applied to meta-heuristics is not very exploited, being more used through the mathematical model, based in a deterministic optimization. However, in situations with a large number of variables, it is impractical use this approach. In the context of smart homes, the robust optimization was used in reference (Wang et al. 2015), in order to model the uncertainties concerning the production of a photovoltaic system. The main objective of

this methodology is perform the analysis of various types of charges present in the residence.

This paper presents a robust Particle Swarm Optimization (PSO) to solve the day-ahead Energy Resource Management (ERM) problem in MGs, considering the uncertainties associated with the energy production from photovoltaic and wind units. To model this uncertainty a robust optimization was incorporated in this metaheuristic. This approach allows a more conservative solution, the best solution considering the worst-case scenarios. The proposed methodology has the objective to satisfy demand aiming at obtaining the maximum profit, corresponding to the difference between the income and costs. A case study is presented using a real university campus MG, from Portugal, based on the evolution scenario of distributed energy resources for the year 2050. The case study includes DR programs, several types of RES, ESS and EVs managed by an aggregator. The main contribution of the paper is the robust optimization model used in metaheuristic approach.

After this introductory section, the mathematical formulation of the ERM problem is presented in Section 3. Section 4 presents the case study and the main results, discussing the advantages of the proposed approach. The main contributions of this work are presented in Section 5.

3. ERM PLATAFORM

The ERM methodology optimizes the distributed energy resources that are available in a smart grid managed by a MG operator. It considers all the available resources: distributed generation, storage units, and DR, and supports the negotiation with external players. The goal is to satisfy demand aiming at obtaining the maximum profit. The ERM is executed for the day-ahead scheduling considering all available resources and the day-ahead forecast for each of the involved resources.

3.1 Mathematical model

The envisaged problem is a hard combinatorial Mixed-Integer Non-Linear Programming (MINLP) problem due to high number of continuous, discrete and binary variables. The MG operator focuses on maximizing the profits (1), the goal is to use cheaper resources, but also to increase the incomes (In).

$$\text{Maximize } Z = In - C \quad (1)$$

The MG can receive his income (In) from four sources, as illustrated in (2): the revenue from the consumers' demand; the energy to sell to the electricity market and the revenue from the charging process of storage units.

Function C (3) represents the operation cost of the resources managed by the MG aggregator. It considers the cost with DG, external suppliers, discharge of storage, DR programs, penalization with non-supplied demand and penalization with DG units' generation curtailment.

$$\text{Maximize } In = \left[\sum_{L=1}^{N_L} P_{Load(L,t)} \cdot MP_{Load(L,t)} + \sum_{M=1}^{N_M} P_{Sell(M,t)} \cdot MP_{Sell(M,t)} + \sum_{E=1}^{N_E} P_{Charge(E,t)} \cdot MP_{Charge(E,t)} + \sum_{V=1}^{N_V} P_{Charge(V,t)} \cdot MP_{Charge(V,t)} \right] \quad (2)$$

$$\text{Minimize } C = \left[\sum_{I=1}^{N_{DG}} P_{DG(I,t)} \cdot C_{DG(I,t)} + \sum_{S=1}^{N_S} P_{Supplier(S,t)} \cdot C_{Supplier(S,t)} + \sum_{L=1}^{N_L} P_{LoadDR(L,t)} \cdot C_{LoadDR(L,t)} + \sum_{E=1}^{N_E} P_{Discharge(E,t)} \cdot C_{Discharge(E,t)} + \sum_{V=1}^{N_V} P_{Discharge(V,t)} \cdot C_{Discharge(V,t)} + \sum_{L=1}^{N_L} P_{NSD(L,t)} \cdot C_{NSD(L,t)} + \sum_{I=1}^{N_{GCP}} P_{GCP(I,t)} \cdot C_{GCP(I,t)} \right] \quad (3)$$

The problem constraints are equal to the constraints found in (Marco Silva et al. 2013).

3.2 Robust Particle Swarm Optimization (PSO)

The particle swarm paradigm, that was only a few years ago a curiosity, has now attracted the interest of researchers around the globe, this method has undergone many changes since its introduction in 1995 (Poli, Kennedy, and Blackwell 2007). The initial ideas on particle swarms of Kennedy (a social psychologist) and Eberhart (an electrical engineer) were essentially aimed at producing computational intelligence by exploiting simple analogues of social interaction, rather than purely individual cognitive abilities.

Table 1. Parameters of PSO

Parameter	Description	
Number of particles	10	
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	
Initial swarm population	Randomly generated between the upper and lower bounds of variables	
Stopping Criteria	Min.	500 iterations
	Max.	2000 iterations
	Threshold	10^{-9}
	Threshold iterations	400
Velocity Clamping Factor (C_{factor})	1	
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})	According to velocity clamping factor equation [8]	
Min. Velocities (v_{min})	According to velocity clamping factor equation [8]	

The particle swarm is a population-based stochastic algorithm for optimization which is based on social-psychological principles like flocks of birds or schools of fish. In PSO a number of particles are placed in the search space and each particle evaluates the objective function at its current location. Each particle keeps track of the coordinates associated with best solution found for it so far, this value is named of "personal best" (pbest). The particle also has access to information on the best solution found in their vicinity, this value is called "global best" (gbest). The basic idea of PSO is to accelerate every particle in the direction for the local of pbest and gbest. The value of acceleration varies randomly during the research. While searching each particle uses the information from her best position in the past and the current best position among its neighbors. The movement is determined from the combination linear vectors with different weights. Table 1 presents the parameters used for this case study in the meta-heuristic approach, namely PSO. The work was developed in MATLAB R1014a 64bits software (Moore 2014).

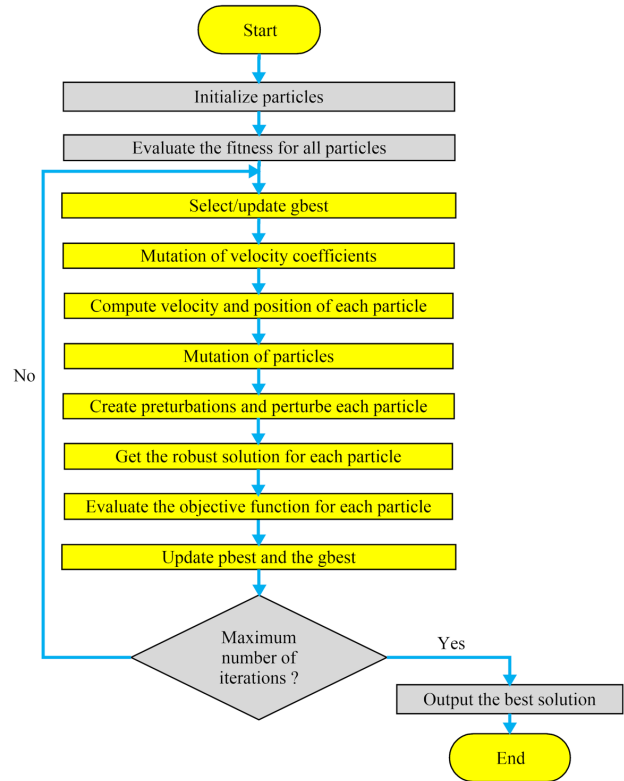


Fig. 1. Flowchart of the developed PSO

Fig. 1. show the flowchart of PSO implemented algorithm to solve the ERM problem. It is important to note that the main factor of innovation presented in this model focuses on the consideration of the uncertainties regarding production from photovoltaic panels and wind turbine. This algorithm is based in robust optimization approach that focuses on finding robust solutions that represent the worst case scenario. After being performed the typical steps of PSO, for each particle the variables with uncertainty are disturbed by a set of scenarios generated by MCS. For each particle, the variables with uncertainty (wind and photovoltaic), which in this case correspond to the production forecast values for the next day,

are disturbed by a prediction error value, creating a 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% forecast error (Su, Wang, and Roh 2014). The 15% error is assumed for the PV and wind forecast because represents a pessimistic error taking into account the current forecast models, that can achieve even lower predictions errors, creating this way an extended set of scenarios. Each perturbation solution is evaluated in the objective function and the solution that represent the worst case is chosen. This process is made for each particle of the initial population and the cycle will be repeated until a set number of iterations. It can be concluded that are evaluated a total of 200 000 different scenarios for photovoltaic and wind power generation, since 10 different scenarios are created for each particle (10) and this process being repeated to 2000 iterations.

4. CASE STUDY

The proposed methodology is tested using a case study of a 21-bus MG of the university campus located in Portugal, as shown in Fig. 2. The case study uses data collected from a university campus and adapted data from measurements collected by GECAD (e.g. classrooms, laboratories, lecture theatre, canteen, restaurant, gym, bank and so on). The data measures were taking place between 5 of September 2014 and 27 of January 2015 Due to confidentiality reasons the detailed content of the data used in this case study will not be shown. The university campus MG distribution network is connected to the main grid through a medium voltage/low voltage Transformer (Bus 21). The distribution transformer is the connection point of electrical energy between the MG operator and external suppliers. A total of 23 lines with 3.35 km length represent the radial MG (see Fig. 2). The technical limits of the lines can be seen in (M. Silva et al. 2015).

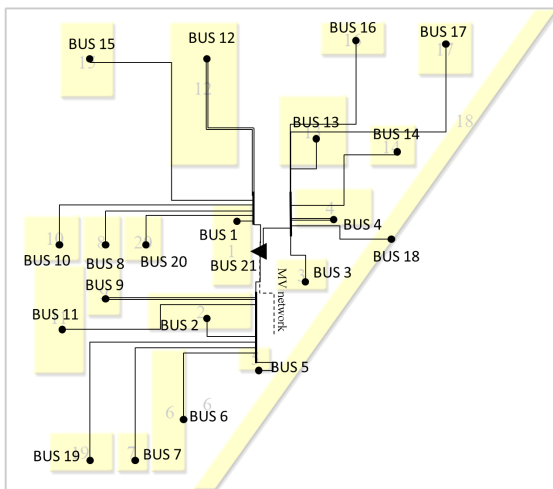


Fig. 2. MG network used in the case study

The considered characteristics of the case study took into account several research works and the forecasts carried out in the literature for 2050. According to (Zervos, Lins, and Muth 2010) the forecasted penetration of renewable generation will amount to 100% to the satisfaction of electricity consumption, than 50% in the wind and solar

power. The production of RES connected to distribution networks will have greater impact on photovoltaic, biomass and wind, which will represent 86%, 89% and 50%, respectively, compared with the transmission network (Frias et al. 2010). The consumption will rise by 48% for 2050, in comparison with 2007. This increase is particularly justified by the EVs sector that will represent in 2050 15% of global electricity demand (Zervos, Lins, and Muth 2010). The storage systems will represent up to 20% of this variable renewable electricity (Nijs et al. 2014).

The penetration of resources in this university campus was projected to the year of 2050, resulting in the accommodation of 25 DG units (20 PV panels, 4 wind generators and 1 biomass unit), 1 external supplier (main grid supply in bus 21), 20 consumers with DR programs (load reduce program), 7 energy storage units and 300 EVs, with charge and discharge capacity located in car parks, which are integrated in the load consumption buildings.

Table 2 presents the data of the energy resources that are managed by the MG operator and the bid coefficients, expressed in monetary unit per kWh, the maximum power limits and the location of resources. The price of PV panels, wind generators and biomass unit have a price equal to zero, because they are endogenous resources of the MG operator. On the other hand, the operator has to remunerate the external supplier, the loads that activate their DR programs (reduce the university campus loads, at maximum until 30%), the discharge from storage systems or EVs. The MG operator will receive from charging the EVs in the parking lot of the university campus. The charging price is equal to 0.095 m.u./kWh to the EVs with id from 1 to 239, while the rest (EVs with id from 240 to 300) have a charging price of 0.11 m.u./kWh. The first charging price is applied to regular users of the university campus, such as professors, university staff and students. The second charging price is applied to visitors of the university campus.

Table 1. Energy resource data

Energy resources	BUS	Rated Power (kW/BUS)	Prices (m.u./kWh)	Units	
Photovoltaic	1 to 20	23.75	0.00	19	
Wind	2, 2, 6, 21	100.00	0.00	4	
Biomass	21	40.00	0.00	1	
External Supplier	21	500	0.10	1	
Storage	Charge	2, 6, 8, 10, 12, 13, 17	5	0.00	
	Discharge		5	0.06	7
EV	Charge	2, 3, 6, 10, 12, 13, 19	5	0.095-0.11	
	Discharge		5	0.15	300
DR	Reduce	1 to 20	-	0.12	20
Upstream link	21	500	0.06	1	

^aStorage or EV system capacity.

The power demand and the generation profiles are based on real data. Fig. 3 presents the total consumption for the 20 load points and the set of 200,000 samples obtained for wind and PV production. The PV production is show in red (and light red area) indicating the range of PV production variation obtained using a MC method. On another hand, the wind production and respective variation is show in blue (and light blue area).

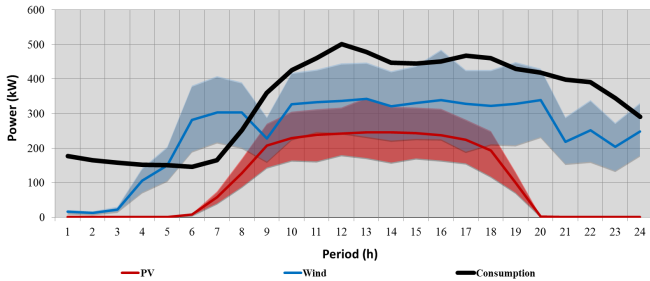


Fig. 3. Total power demand and wind and PV samples during the 24 periods.

The MG operator requires the use of other resources (external suppliers, DR programs, discharge from storage or EVs) to support the load between periods 20 to 24 and between periods 1 to 4. In the remaining periods, the excess of generation from endogenous resources can be used to charge of storage/EVs or to sell energy to the electricity market. The Electric Vehicles (EVs) parked in the parking lot of the university campus were also considered in the management of the MG. The charging and discharging of their batteries can be controlled by the MG operator. The same control stands for the storage systems. The EVs will remunerate the MG operator for charging their batteries until a minimum energy required by the EV users. On the other hand, the MG operator will have to pay discharging energy of the EVs. Thus, the EVeSSi simulator tool (Soares et al. 2012). was used to generate a scenario for the university campus, determining the EVs movements and their trip consumption during the day that are shown in Fig.4.

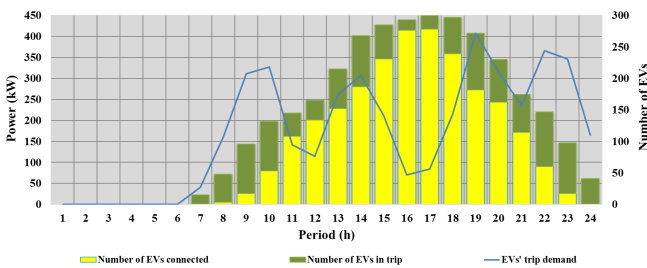


Fig. 4. Trip consumption and number of EVs connected and in trip

For this case study, the robust technic obtained an optimal solution with a profit of 76.61 m.u. The methodology took around 2360 seconds to find the optimal solution. Fig. 5 depicts the energy scheduling result. Fig. 6 depicts the percentage of each resource in the optimal resource scheduling. Through Fig. 6 it is possible to see that the DG contributes with 79% of the total generation. 20% is given by the external suppliers, while storage discharge contributes with 1%.

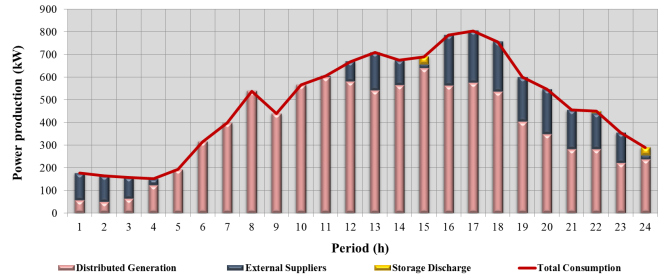


Fig. 5. Optimal resource scheduling

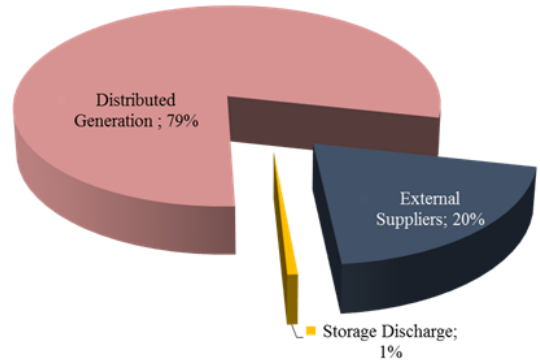


Fig. 6. Percentage of each resource in the energy scheduling

Fig. 7 presents the load diagram, which contains the consumption of loads, EVs and storage charge and energy sale to the electricity market. Fig 8 depicts the percentage of each resource in the consumption scheduling.

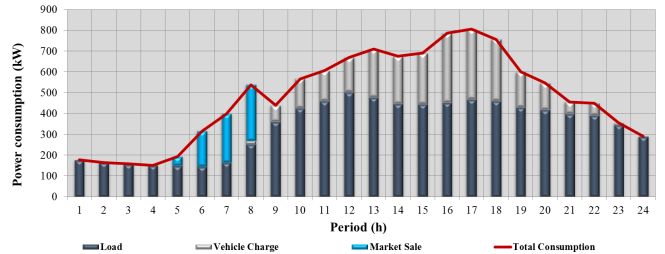


Fig. 7. Power consumption results

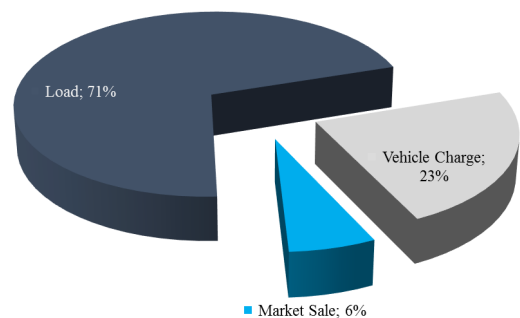


Fig. 8. Percentage of each resource in the consumption scheduling

Analyzing the Fig. 7, the MG operator is able to sell energy in the electricity market between periods 5 and 8. In these periods, there is an excess of PV and wind generation that is not possible to charge EVs, because the EVs are not in the university campus. In fact, they come to the university from

the period 8. In the remaining periods, the excess of PV and wind generation is used to charge the EVs, instead of selling to the electricity market. The total power consumption was divided in 71% for the consumption in load points, 23% for charging the EVs and 6% for the sale of generation excess to the electricity market.

To measure the advantage of using the robust MOPSO over the deterministic solution we evaluate the scheduling solution for the average scenario (average of the 200,000 scenarios evaluated in MOPSO) with a technique implemented in TOMLAB/CPLEX (TOMLAB 2016), which is an advanced optimization toolbox for MATLAB. The worst-case scenario captured by MOPSO is selected to be evaluated with the result from the deterministic solution under the average scenario. In this case the deterministic solution may present energy imbalances (due to the differences in wind/PV generation), and therefore a rescheduling is made. With this procedure we estimate what would be the expected profit with a deterministic solution. In the rescheduling procedure, the MG can only buy energy to external supplier, or in the case it has already reached the maximum generation capacity, a penalty for the non-supplied energy. On other hand, if the real production is higher than expected, the excess energy is sent to the upstream grid. Table 3 summarizes the obtained results regarding the performance of the robust optimization. The advantage of the robust MOPSO approach over the deterministic optimization is 11.12 m.u., namely the solution evaluated under the worst-case scenario. The robust MOPSO approach expected profit is 76.61 m.u., while using a deterministic solution is 65.49 m.u. The average scenario (deterministic) presents an expected profit of 122.40 m.u. It can be seen that the profit value varies significantly in the worst-case scenario (122.40 to 65.49, almost 50%). It means that adopting a robust approach will protect the MG operator from worse profits than the one achieved by MOPSO or an equivalent approach. Under other scenario circumstance the profit obtained by robust MOPSO will certainly increase over the worst-case scenario, e.g. with more wind/PV generation.

Table 2. Advantage of robust optimization approach

Solution	Robust MOPSO	Deterministic Optimization (CPLEX)	
	Worst Scenario	Average Scenario	Worst Scenario
Profit (m.u.)	76.61	122.40	65.49

5. CONCLUSIONS

This paper presented a method for intelligent energy management of a MG using PSO, aiming to maximize the profit. This methodology considers a robust optimization.

The robust optimization model developed in this work can do not get the best solution, however, the resulting solution represents an averse to the risk solution that able to safeguard the MG operator. The results reveal that the robust optimization can be used as an efficient approach to deal with the uncertainty in ERM. In the tested case study, the method

appears to be more advantageous, compared to an optimization performed for the next day, which not handle with the uncertainty.

REFERENCES

- Frias, P, C Fernandes, R Cossent, and L Olmos. 2010. "D2. 6-Report from the Regional Study Case: South-Western Europe (Spain)." *JOUR. Univ. Pontif. Comillas*.
- Fu, Qiang, Luis F. Montoya, Ashish Solanki, Adel Nasiri, Vijay Bhavaraju, T. Abdallah, and David C. Yu. 2012. "Microgrid Generation Capacity Design With Renewables and Energy Storage Addressing Power Quality and Surety." *IEEE Transactions on Smart Grid* 3 (4): 2019–27. doi:10.1109/TSG.2012.2223245.
- Kuznetsova, Elizaveta, Carlos Ruiz, Yan-Fu Li, and Enrico Zio. 2015. "Analysis of Robust Optimization for Decentralized Microgrid Energy Management under Uncertainty." *International Journal of Electrical Power & Energy Systems* 64 (January): 815–32. doi:10.1016/j.ijepes.2014.07.064.
- MathWorks. 2016. "MATLAB - The Language Of Technical Computing." Web Page. <http://www.mathworks.com/products/matlab/>.
- Moghaddam, Amjad Anvari, Alireza Seifi, Taher Niknam, and Mohammad Reza Alizadeh Pahlavani. 2011. "Multi-Objective Operation Management of a Renewable MG (Micro-Grid) with Back-up Micro-Turbine/fuel Cell/battery Hybrid Power Source." *Energy* 36 (11): 6490–6507. doi:10.1016/j.energy.2011.09.017.
- Moore, Holly. 2014. *MATLAB for Engineers*. BOOK. Prentice Hall Press.
- Nijs, Wouter, Sofia Simoes, Pablo Ruiz, Alessandra Sgobbi, and Christian Thiel. 2014. "Assessing the Role of Electricity Storage in EU28 until 2050." In *11th International Conference on the European Energy Market (EEM14)*, 1–6. IEEE. doi:10.1109/EEM.2014.6861273.
- Poli, Riccardo, James Kennedy, and Tim Blackwell. 2007. "Particle Swarm Optimization." *Swarm Intelligence* 1 (1). Springer US: 33–57. doi:10.1007/s11721-007-0002-0.
- Siano, Pierluigi. 2014. "Demand Response and Smart grids—A Survey." *Renewable and Sustainable Energy Reviews* 30: 461–78. doi:10.1016/j.rser.2013.10.022.
- Silva, M., F. Fernandes, H. Morais, S. Ramos, and Z. Vale. 2015. "Hour-Ahead Energy Resource Management in University Campus Microgrid." In *2015 IEEE Eindhoven PowerTech*, 1–6. IEEE. doi:10.1109/PTC.2015.7232449.
- Silva, Marco, Hugo Morais, Tiago Sousa, and Zita Vale. 2013. "Energy Resources Management in Three Distinct Time Horizons Considering a Large Variation in Wind Power." Conference Proceedings. In *European Wind Energy Conference & Exhibition 2013*.
- Soares, J, B Canizes, C Lobo, Z Vale, and H Morais. 2012. "Electric Vehicle Scenario Simulator Tool for Smart Grid Operators." *Energies* 5 (6): 1881–99. doi:10.3390/En5061881.
- Su, Wencong, Jianhui Wang, and Jaehyung Roh. 2014. "Stochastic Energy Scheduling in Microgrids With Intermittent Renewable Energy Resources." *IEEE Transactions on Smart Grid* 5 (4): 1876–83. doi:10.1109/TSG.2013.2280645.
- TOMLAB. 2016. "TOMLAB Optimization." Web Page. <http://tomopt.com/tomlab/about/>.
- Wang, Chengshan, Yue Zhou, Bingqi Jiao, Yamin Wang, Wenjian Liu, and Dan Wang. 2015. "Robust Optimization for Load Scheduling of a Smart Home with Photovoltaic System." *Energy Conversion and Management* 102 (September): 247–57. doi:10.1016/j.enconman.2015.01.053.
- Zervos, Arthouros, Christine Lins, and Josche Muth. 2010. *RE-Thinking 2050: A 100% Renewable Energy Vision for the European Union*. Book. EREC.
- Zhang, Yu, Nikolaos Gatsis, and Georgios B. Giannakis. 2013. "Robust Energy Management for Microgrids With High-Penetration Renewables." *IEEE Transactions on Sustainable Energy* 4 (4): 944–53. doi:10.1109/TSST.2013.2255135.