VPP Energy Resources Management considering Emissions: The case of northern Portugal 2020 to 2050

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***Abstract*— In SGs context, Distributed Generation (DG) based on renewable sources represents an alternative paradigm of energy supply and the opportunity for significant reduction in CO_2 emissions. However, strict emissions regulations might impact profit seeking Virtual Power Plants (VPP) operation. This paper addresses energy management at distribution level and evaluates if electricity emissions are worth to be considered in different time horizons. A realistic case study is developed for a chosen area of the northern region of Portugal, namely one part of the distribution grid from Vila Real managed by a VPP, with estimated penetration of Electric Vehicles (EV), several Distributed Generation (DG), Demand Response (DR) and Energy Storage Systems (ESS). The considered characteristics of the case study took into account several studies and the forecasts made in the literature. For 2030 it is expected an average CO_2 grid emission of 50 $kgCO_2/MWh$ in Portugal. The repository-based multi-objective Particle Swarm Optimization (MOPSO) is used to tackle the developed optimization problem. Three scenarios are evaluated for the profit seeking VPP in 2020, 2030 and 2050 perspectives.**

***Index Terms*— Energy Resources Management, Multi-objective Particle Swarm Optimization, Virtual Power Plant, Smart Grid.**

I. 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

Sets

Ω_{DG}^{d}	Set of DG units with CO2 emissions
Ω_{SP}^{e}	Set of Suppliers with CO2 emissions

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.)
$E_{DG(DG,t)}$	CO2 emissions of DG unit in period t (kgCO2/MWh)
$E_{SP(SP,t)}$	CO_2 emissions of the external supplier S in period t ($kgCO_2/MWh$)
$MP_{Discharge(E,t)}$	Price for the discharge process of ESS E in period t (m.u./MWh)
$MP_{Discharge(V,t)}$	Price for the discharge process of vehicle V in period t (m.u./MWh)
$MP_{Load(L,t)}$	Price of load L in period t (m.u./MWh)
$MP_{Sell(M,t)}$	Price of the energy sale to the market M in period t (m.u./MWh)

Variables

$P_{DG(I,t)}$	Active power generation of I unit in period t (MW)
$P_{Supplier(S,t)}$	Active power generation of the external supplier S in period t (MW)
$P_{LoadDR(L,t)}$	Demand response program active power activated for load L in period t (MW)
$P_{Discharge(E,t)}$	Power discharge of ESS unit E in period t (MW)
$P_{Discharge(V,t)}$	Power discharge of EV V in period t (MW)
$P_{NSD(L,t)}$	Non-supplied demand for load L in period t (MW)

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$P_{GCP(I,t)}$	Generation curtailment power in DG unit I in period t (MW)
$P_{Load(L,t)}$	Active power demand of load L in period t (MW)
E	Total emissions CO_2 (kg)
In	VPP income (m.u.)
OC	Total operation cost (m.u.)

II. Introduction

The power industry represents a significant portion of the global carbon dioxide (CO_2) emissions corresponding to about 40% [1]. Nevertheless, regulations are currently in place for controlling the level of emissions in this sector [2]. Distributed Generation (DG) based on renewable sources presents an opportunity to decrease this level considerably. In Portugal the 2000s level of CO_2 emissions from electricity generation was 500 kgCO_2/MWh. In 2050 it is expected that this level will drop to 20 kgCO_2/MWh [3]. This raises an interesting research question that is discussed in this work, namely understanding the impact of considering CO_2 emissions in the energy management problem up to 2050. Energy management problems are of trivial importance in particular for Virtual Power Plants (VPP), VPPs are a relatively new idea emerged in Smart Grids (SG) context, whose main role is to aggregate DG and demand with the aim to raise their participation in market environments [4].

Several approaches have been reported in the literature regarding Energy Resources Management (ERM) considering emissions. In [5] the tradeoff between cost and emissions is presented using a regular and a binary Particle Swarm Optimization (PSO). Intelligent scheduling seems promising to reduce cost, emissions while maximizing the utilization of renewables. The multi-objective problem is solved using a weighted sum approach in the PSO, instead of a multi-objective evolutionary algorithm or multi-objective PSO (MOPSO). Moreover, the network constraints are not considered in the mentioned approach. In [6] a multi-objective energy management for a micro-grid using both intelligent techniques and linear programming is presented to minimize operation costs and environmental impacts. However, the work solves the day-ahead energy scheduling using a linear formulation without network constraints and not considering the possibility of Vehicle-To-Grid (V2G). In [8] a methodology was applied for a multi-objective day-ahead energy resource scheduling for smart grids considering intensive use of distributed generation and V2G. However, this work not considers Demand Response (DR), energy storage and market energy sale. In [7] a multi-objective is proposed to optimize the operation cost and the net emissions. However, the model considers a simple load balance and does not consider the presence of Electric Vehicles (EVs) neither any type of Demand Response (DR). In [8] a Fuzzy Self Adaptive PSO (FSAPSO) to dispatch the generation and minimize the total operation cost and the emissions in a typical micro-grid. The work only considers a simple load balance (linear constraints) and does not include EVs, DR, Energy Storage Systems (ESS) or market energy sale. Furthermore, in none of those papers the raised research question is discussed.

The problem handled in this work concerns a profit seeking VPP managing several resources solving the ERM problem, which is large-scale non-linear combinatorial Distributed Energy Resources (DER) scheduling problem including DGs, V2G resources, DR, ESS, sales and/or purchases to the market and to external suppliers. A multi-objective function is used to maximize the profit corresponding to the difference between the income and the operating costs and at the same to minimize the CO_2 emissions.

The work includes a case study concerning a real 233-bus distribution network from a northern region of Portugal, namely a part of a grid from Vila Real. Three scenarios are assessed and evaluated using the multi-objective ERM. The grid is updated up to 2050, namely expanding the capacity of the 135 DG units to supply load to circa 14,000 consumers. The scenarios of EVs were also expanded to 5080 EVs with V2G in 2050.

This paper is organized as follows: after this introductory section III presents the MOPSO approach of the Energy Resources Management problem, section IV presents the case study and finally section V the conclusions.

III. Multi-objective Particle Swarm Optimization

In this section the mathematical model and MOPSO implementation is presented.

A. Mathematical model

The ERM problem is a hard combinatorial Mixed-Integer Non-Linear Programming (MINLP) problem due to high number of continuous, discrete variables and network non-linear equations. The problem complexity exponential rises when the number of controllable units also increases, such as DR, DG and V2G resources.

The two conflicting objectives of the VPP are to maximize profits and minimize CO_2 emissions, as shown in (1-2) and (3) respectively.

The VPP can receive his income (In) from four sources, as illustrated in (1): the revenue from the consumers demand; the energy sale to the electricity market or other entities; the revenue from the charging process of storage units and the charging of EVs.

$$\text{Maximize} \quad In = \sum_{t=1}^{T}\left[\begin{pmatrix}\sum_{L=1}^{N_L} P_{Load(L,t)} \cdot MP_{Load(L,t)} + \sum_{M=1}^{N_M} P_{Sell(M,t)} \cdot MP_{Sell(M,t)} + \\ \sum_{E=1}^{N_E} P_{Discharge(E,t)} \cdot MP_{Discharge(E,t)} + \sum_{V=1}^{N_V} P_{Discharge(V,t)} \cdot MP_{Discharge(V,t)}\end{pmatrix} \cdot \Delta t\right] \qquad (1)$$

Function OC (2) represents the operation cost of the resources managed/contracted by the VPP. It considers the cost with DG, external suppliers, discharge of ESS and EVs, DR, penalization with non-supplied demand and penalization with DG units' generation curtailment.

$$\text{Minimize} \quad OC = \sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum_{I=1}^{N_{DG}} P_{DG(I,t)}\cdot c_{DG(I,t)} + \sum_{S=1}^{N_S} P_{Supplier(S,t)}\cdot c_{Supplier(S,t)} + \\ \sum_{L=1}^{N_L} P_{LoadDR(L,t)}\cdot c_{LoadDR(L,t)} + \sum_{E=1}^{N_E} P_{Discharge(E,t)}\cdot c_{Discharge(E,t)} + \\ \sum_{V=1}^{N_V} P_{Discharge(V,t)}\cdot c_{Discharge(V,t)} + \sum_{L=1}^{N_L} P_{NSD(L,t)}\cdot c_{NSD(L,t)} + \\ \sum_{I=1}^{N_{DG}} P_{GCP(I,t)}\cdot c_{GCP(I,t)}\end{array}\right)\cdot\Delta t\right] \quad (2)$$

The equation (3) show the objective function to minimize the CO_2 emissions:

$$\text{Minimize} \quad E = \sum_{t=1}^{T}\left[\left(\begin{array}{l}\sum_{I=1}^{\Omega_{DG}^{d}} P_{DG(I,t)}\times E_{DG(I,t)} + \\ \sum_{S=1}^{\Omega_{SP}^{c}} P_{Supplier(S,t)}\times E_{Supplier(S,t)}\end{array}\right)\cdot\Delta t\right] \quad (3)$$

The problem constraints are similar to [9]. The problem is mainly constrained by the network equations, namely active and reactive powers, voltage and angle limits, DG generation and supplier limits in each period, ESS capacity, charge and discharge rate limits, EVs capacity, EVs' trips requirements, charge and discharge rate limits.

B. Multi-Objective Particle Swarm Optimization

PSO is recognized for its high speed of convergence, while being easily adapted to multi-objective problems. Its analogy with evolutionary algorithms makes it suitable for using a Pareto ranking scheme. The individual best solutions can be used to store non-dominated solutions which is analog to the elitism mechanism found in evolutionary algorithms [10]. MOPSO is an advanced optimization algorithm to solve multi-objective problems [10] used in this work to handle the optimization problem. It is demonstrated to outperform other important multi-objective evolutionary algorithms such as Non-dominated Sorting Genetic Algorithms (NSGA-II), Pareto Archive Evolutionary Strategy (PAES), and microGA in several benchmark functions [10], [11] MOPSO adopts an external repository similar to the adaptive grid of PAES and uses a mutation operator aiming to explore the remote region of the search space and the full range of each decision variable. We also employ mutation of the strategic parameters used in Evolutionary PSO [12] instead of the usual fixed parameters as in the original MOPSO. 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 flowchart of MOPSO is presented in Fig. 1.The flowchart represents the implemented algorithm to solve the ERM problem in this work. Two types of mutation occur during the search loop, namely mutation of the parameters of the velocity equation and mutation in the position of some particles (randomly selected). The algorithm stops after the defined number of iterations is reached; this setup is widely used in other multi-objective metaheuristic-based algorithms.

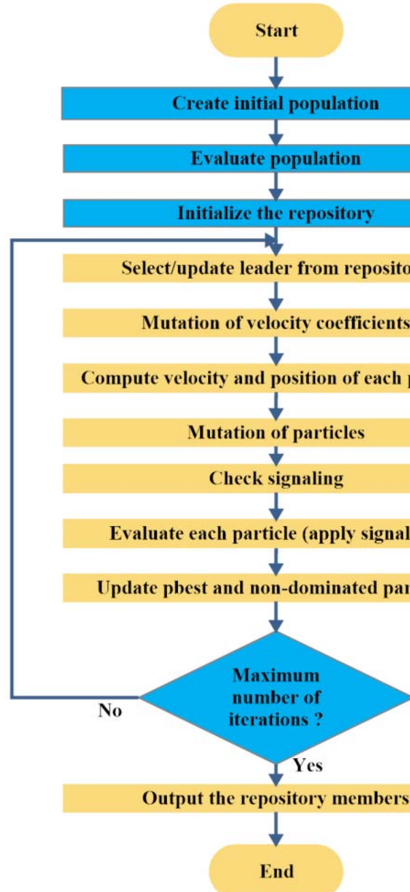

Figure 1. Flowchart of the developed MOPSO.

1) Fitness function implemented in MOPSO

The fitness function (4) in MOPSO considers the total profit and the emission of CO_2. The total profit is obtained by subtracting operation costs (2) to the income (1). The fitness function (4) minimizes emissions and maximizes profit.

$$\text{fitness} = \left[-(In - OC) + E\right] + \text{penalties} \quad (4)$$

where

penalties denotes the sum of penalties found (violations).

A full AC power flow is used [13] to check the network conditions. The penalties configured in MOPSO are the following: 100 for voltage limits violations, 1000 for line limits violations and 1000 for the solutions with insufficient generation.

A modified PSO methodology is developed in [14], [15] to solve the problem of ERM with high penetration of DG and EVs with V2G with the aim to improve the performance of PSO. However, the reported work has a single objective function, i.e. minimize the operation cost. Hence, the previous signaling method for PSO [14], [15] is adapted and used in the current paper to help MOPSO to escape violations and improve fitness function.

IV. CASE STUDY

The proposed methodology was tested using a case study implemented on a Medium-Voltage (MV) 30 kV distribution network with 233 buses. This is a part of a real network from Vila Real in Portugal. A reconfiguration was performed to the original mostly meshed network using the software developed in [16] to obtain the radial configuration presented in Fig. 2. This single-line diagram does not represent the actual geographical location.

A. Scenarios description

1) Demand forecast

The regular demand (without EVs) was forecasted for 2020, 2030 and 2050 taken into account the published results. According to [3] the consumption will rise by 4%, 12% and 29% for 2020, 2030 and 2050, respectively, in comparison with 2010. Hence, three scenarios with an updated consumption curve for 2020, 2030 and 2050 were obtained from the base scenario.

2) Electric vehicles forecast

Taken into account the actual population (21,000) in Vila Real city, the total number of regular vehicles was estimated using the expected growth/decay rate and the vehicle rate per person. According to the penetration rate of EVs provided by [17], the total number of EVs was obtained, namely 1540, 3090, and 5080 for 2020, 2030 and 2050 respectively. The EVs' scenarios were created using EVeSSi tool [18]. The charging and discharging efficiency considered was 80% for 2020 and 90% for 2030 and 2050.

3) Distributed generation capacity

According to [3] the forecasted penetration of renewable generation in Portugal will amount to 49%, 72% and 77% in 2020, 2030 and 2050, respectively. Photovoltaic capacity installation is expected to be larger than wind installation in the future. Moreover, it was considered that the capacity of the Combined Heat and Power (CHP) increased by two-fold after 2020.

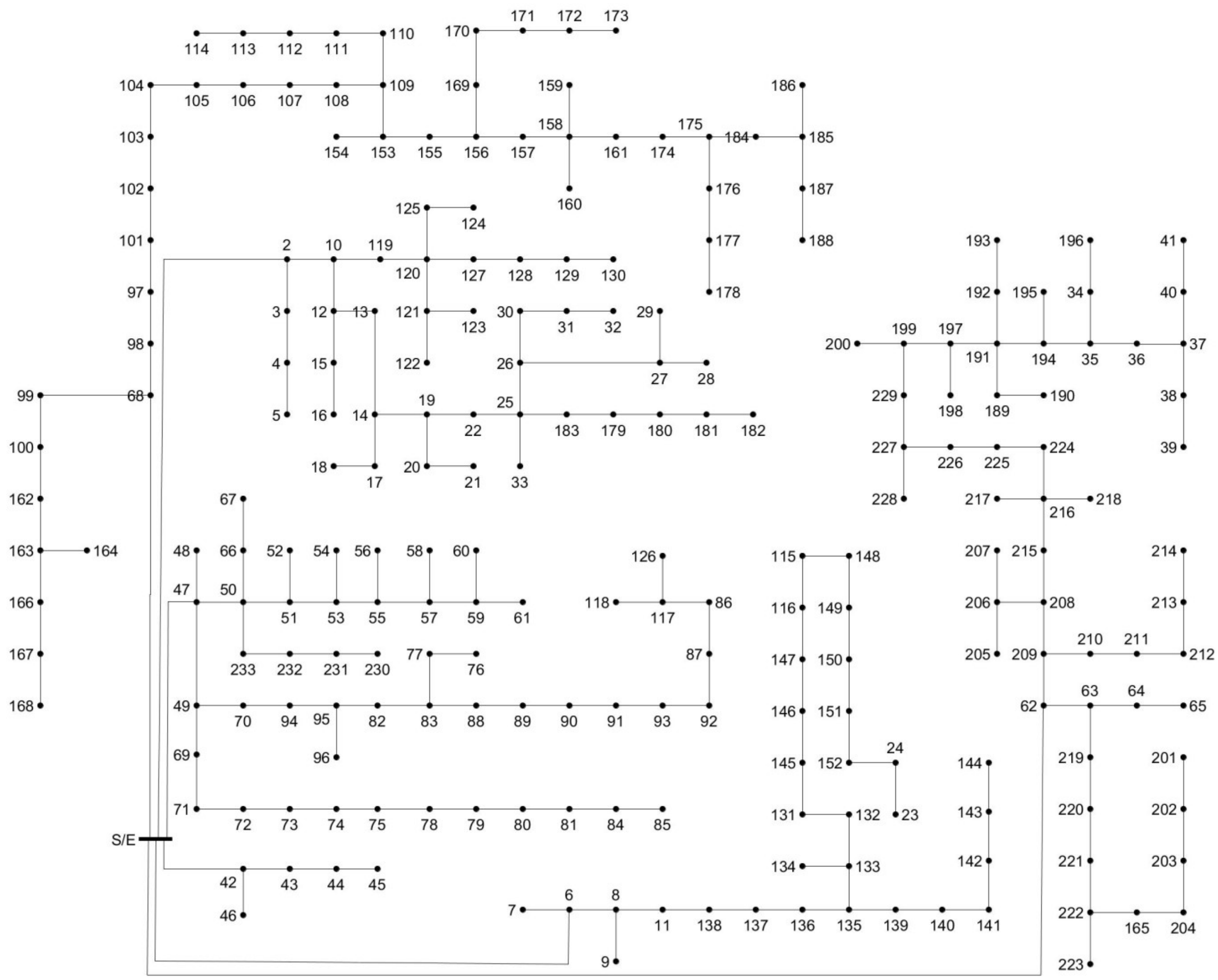

Figure 2. Vila Real 233-bus 30 kV MV network.

TABLE I. ENERGY RESOURCE DATA

Energy resources		Availability (MW) min – max 2020	2030	2050	Prices (m.u./kWh) min – max 2020	2030	2050	Units 2020	2030	2050
Biomass		0 – 0.20	0 – 0.25	0 – 0.50	0.15 – 0.15	0.15 – 0.15	0.15 – 0.15	1	1	1
CHP		0 – 1.80	0 – 4.00	0 – 4.00	0.10 – 0.10	0.10 – 0.10	0.10 – 0.10	3	3	3
Small Hydro		0 – 1.83	0 – 1.83	0 – 2.52	0.13 – 0.13	0.13 – 0.13	0.13 – 0.13	1	1	1
Photovoltaic		0 – 1.04	0 – 2.6	0 – 3.75	0.20 – 0.20	0.20 – 0.20	0.20 – 0.20	81	81	81
Wind		0.20 – 1.15	0 .30– 1.69	0.38 – 2.22	0.12 – 0.12	0.12 – 0.12	0.12 – 0.12	48	48	48
External Supplier		0 – 10.00	0 – 10.00	0 – 15.00	0.11 – 0.11	0.11 – 0.11	0.11 – 0.11	1	1	1
Storage	Charge	0 –0.25	0 – 1.50	0 – 2.00	0.12 – 0.12	0.12 – 0.12	0.12 – 0.12	4	6	8
	Discharge	0 – 0.25	0 – 1.50	0 – 2.00	0.18 – 0.18	0.18 – 0.18	0.18 – 0.18			
Electric Vehicle	Charge	0 – 8.33	0 –16.32	0 – 31.29	0.14 – 0.14	0.14 – 0.14	0.14 – 0.14	1540	3090	5080
	Discharge	0 – 7.31	0 – 14.65	0 – 29.21	0.19 – 0.19	0.19 – 0.19	0.19 – 0.19			
Demand Response	Red	0 – 1.06	0 – 1.14	0 – 1.31	0.11 –0.17	0.11 – 0.17	0.11 – 0.17	89	89	89
Load		6.59 – 14.76	7.12 -15.91	8.20-18.34	0.09 – 0.15	0.09 - 0.15	0.09 – 0.15	162	162	162
Market		0 – 4.00	0 – 4.00	0 – 4.00	0.08 – 0.10	0.08 – 0.10	0.08 – 0.10	1	1	1

Table I shows the data for each of the developed scenarios taken into account the mentioned forecasts. The considered prices were maintained the same for each of the three scenarios and took into account the levelized generation costs for 2019 presented in [19]. The same prices were maintained for easier comparison of the results, however it is expected that the cost of photovoltaics will reduce considerably compared to the reference year. Hence, the reproduced scenarios were more pessimistic than optimistic regarding the considered prices. In reality the prices correspond to the cost that the VPP has to pay to buy energy from the respective DER's owner, except from the charge of storage (ESS) and EVs, where the owners pay to the VPP instead, therefore contributing to the income (1). The loads also pay to the VPP and the price varies as can be seen in Table I depending on the contract (consumer type).

It was assumed that the VPP is responsible to manage the distribution network aiming to maximize profit and minimize CO2. It is expected that the solutions with higher profits are also those with higher CO2 emissions.

The circa 14,000 consumers of the network were aggregated by bus totaling 162 aggregated bus-loads. 89 bus of the 162 aggregated loads offered DR possibility. The capacity of the DR was changed according to the scenario. The DG units were also aggregated by bus and by type as can be seen in Table I. The capacity was changed according to the scenario once again. The external supplier located in the substation represented the energy imported from the main grid and was modeled with a permanent 10 MW contract for 2020 and 2030 and 15 MW for 2050. The EVs were considered individually for each scenario. The maximum energy that VPP can export remained equal among the scenarios, and is depicted in the table as the market.

Table II presents the energy supplier (main grid) and the CHP CO_2 emission rate taken into account the values presented in [3], [20]. It was assumed a considerable reduction of CHP's emission rate in 2050 scenario compared with previous ones.

TABLE II. CO_2 PARAMETERS OF THE SCENARIOS

Scenario	Supplier CO_2 emissions ($kgCO_2/MWh$)	CHP CO_2 emissions ($kgCO_2/MWh$)
2020	190	444-963
2030	50	444
2050	20	230

B. MOPSO simulations

The parameters of the MOPSO algorithm used in the simulations are depicted in Table III.

TABLE III. PARAMETERS OF MOPSO

Parameter		Description
Number of particles		50
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 bounds
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})		$-v_{max}$

These depicted parameters in Table III were obtained by extensive experimental tests and by previous recommendations made in the literature [10]. The repository size was set to 100, as suggested in the literature, in order to obtain a very high quality of the Pareto front.

Figs. 3, 4 and 5 present the Pareto front achieved in MOPSO metaheuristic for each scenario. The marker represents each obtained Non-Dominated Solution (NDS) in MOPSO's repository. NDS-L, NDS-M and NDS-R, represent the non-dominated solutions with lower emissions, average profit and higher profit, respectively. There are some regions of the Pareto front with more markers, thus representing higher density of NDS. The final repository contained 100, 85 and 81 solutions for 2020, 2030 and 2050 scenarios, respectively. In the 2020 scenario the profit ranged between 9006 m.u. and 10023 m.u.; in the 2030 scenario the profit ranged between 11133 m.u. and 12194 m.u. whereas in the 2050 scenario the profit ranged between 12079 m.u. and 14014 m.u. In terms of CO_2 emissions the range varies between 64.31 and 69.71 tonCO_2 in the 2020 scenario; in the 2030 scenario the total emissions ranged between 51.02 and 52.95 tonCO_2; whereas in the 2050 scenario ranged between 25.38 and 27.43 tonCO_2. Analyzing the obtained fronts it can be seen that the profit varied identically around 1000 m.u. in 2020 and 2030 scenario but it was higher in 2050. The maximum profit obtained was 14014 m.u. in 2050 scenario, i.e. 40% higher than 2020 and 15% higher than 2030. This increase in profit is highly related with the increase of DERs, i.e. EVs, DGs, ESSs and regular load demand. Regarding the CO_2 emissions, a significant decrease was also achieved (60% reduction in 2050 compared to 2020 and 50% compared to 2030).

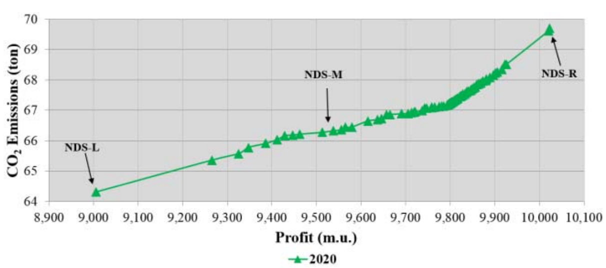

Figure 3. Pareto front for the 2020 scenario.

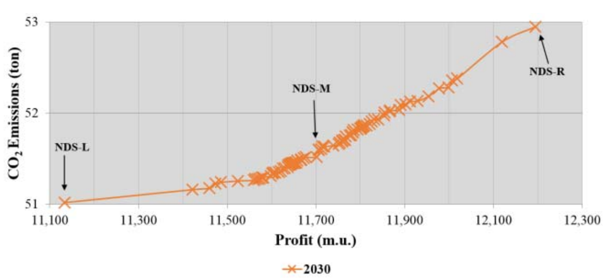

Figure 4. Pareto front for the 2030 scenario.

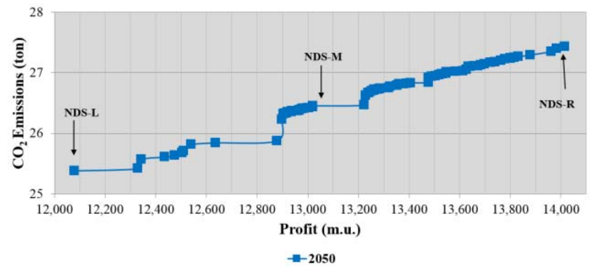

Figure 5. Pareto front for the 2050 scenario.

Figs. 3, 4 and 5 present the total generation and consumption for three solutions of the Pareto front, namely NDS-L, NDS-M and NDS-R for 2020, 2030 and 2050 scenario.

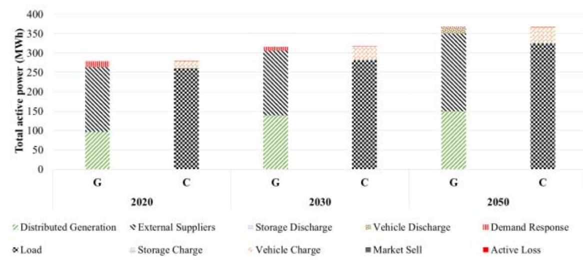

Figure 6. Total generation and consumption: NDS-L (lower emissions)

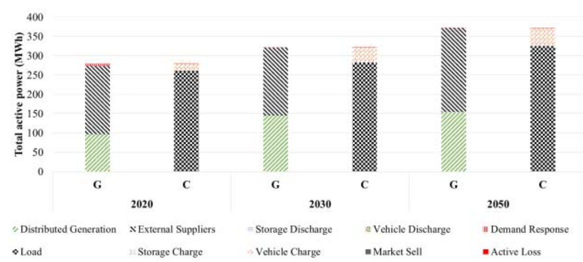

Figure 7. Total generation and consumption: NDS-M (average profit)

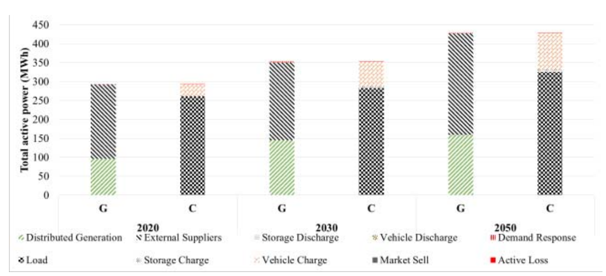

Figure 8. Total generation and consumption: NDS-R (higher profit)

The consumption increased by 32%, 33%, 46% from 2020 to 2050 in NDS-L, NDS-M and NDS-R, respectively. This indicated that to achieve more profit the VPP increased the sales and purchases of energy, while to achieve solutions with lower emissions, the VPP seems to reduce these transactions. The load share of EVs was 6%, 10% and 11% in 2020, 2030, and 2050 scenario for NDS-L, respectively. In the case of NDS-R, the load share of EVs was 11%, 19%

and 23% in 2020, 2030, and 2050 scenario, respectively. Clearly, to achieve higher profit the VPP sold more energy to charge EVs, thus leading to an increase in the energy consumption. EVs discharge was significant in 2050 scenario for NDS-L with a total energy amount of 16 MWh but not significant in any other scenario. Storage discharge amounted to 1 MWh in this case. This apparently helped the VPP to achieve solutions with lower emissions. The amount of storage charge was less significant than EVs charge but it was higher in NDS-R (7 MWh) than NDS-L (2 MWh) concerning the 2050 scenario. In fact, storage charge was less significant in 2020 and 2030 scenario compared to 2050. It seems that EVs and ESS (storage) can contribute to improve profits or reduce emissions as demonstrated by the Pareto solutions. DR played a significant role in 2020 and 2030 scenario in the NDS-L, with a total amount of 15 MWh and 10 MWh, respectively. In the 2050 scenario for NDS-L this amount was less than 2 MWh.

Table IV depicts the profit and emissions for each scenario. The profit increased by 34%, 36% and 40% from 2020 to 2050 in NDS-L, NDS-M and NDS-R, respectively. The higher difference in CO_2 emissions between NDS-L and NDS-R was achievable in 2020 scenario with 6 tonCO_2. In 2030 and 2050 scenario, this difference was only 2 tonCO_2. Hence, the average profit loss to reduce one ton of CO_2 was 170 m.u., 531 m.u. and 968 m.u. in 2020, 2030 and 2050 scenario, respectively. This indicates that it was much more expensive to reduce CO_2 emissions in the latter scenarios than in 2020 scenario. However, the emissions in 2030 and 2050 scenario were already much lower than in 2020 scenario. This further indicates that in long-term due to the increase of renewables, ESS and EVs, the opportunity to reduce CO_2 emissions in SG will come at a higher cost and perhaps irrelevant in the future.

TABLE IV. SCENARIOS RESULTS: TOTAL PROFITS AND EMISSIONS

Scenario: Indicator	NDS	2020	2030	2050
Income (m.u.)	**R**	40,695	48,483	58,899
	M	38,265	44,766	51,797
	L	36,880	42,618	51,041
Cost (m.u.)	**R**	30,673	36,288	44,885
	M	28,752	33,065	38,777
	L	27,874	31,485	38,962
Profit (m.u.)	**R**	10,023	12,194	14,014
	M	9513	11,702	13,020
	L	9006	11,133	12,079
Emissions (tonCO_2)	**R**	70	53	27
	M	66	52	26
	L	64	51	25

The developed ERM MOPSO algorithm took an average execution time of 45 minutes using single core mode. This time could be reduced to about 2 minutes using GECAD's computing cluster with 6 machines, 42 workers (cores) configured with MATLAB distributed computing environment. Each worker can execute code independently and simultaneously. The parallel code can independently execute velocity and update equations, mutation, signaling and evaluation instead of serially execution this steps for each particle.

V. CONCLUSIONS

This paper presented a study regarding Energy Resource Management (ERM) in SGs with multi-objective goals, namely the VPP's profit and CO_2 emissions. The repository-based Multi-objective PSO was used to tackle the ERM large-scale optimization problem.

A realistic case study was developed using as basis a real distribution grid from Vila Real in Portugal. Several DERs managed by a VPP were considered in the grid. Three scenarios were evaluated for the profit seeking VPP in 2020, 2030 and 2050 perspectives.

The results indicate a relevant increase of the consumption until 2050 in the studied region. Moreover, EVs, ESS and DR can help VPP not only to achieve higher profits but also to reduce emissions. Nevertheless, it seems that the opportunity to reduce emissions in the future will come at a higher cost as the grid evolves towards a green, and sustainable system, with negligible carbon emissions.

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