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A communitarian microgrid storage planning system inside the scope of a smart city

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HIGHLIGHTS

- Energy scheduling in mini/microgrids systems considering plug-in electric vehicles and drones.
- Sets of non-dominated solutions opening possibilities for smart cities managers.
- Smart cities citizens awareness for investing in alternatives energy based vehicles.
- Energy storage systems contributing for renewable energy integration with mini/microgrids.

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ABSTRACT

In this paper (a substantial extension of the short version presented at REM2016 on April 19–21, Maldives [1]), multi-objective power dispatching is discussed in the scope of microgrids located in smart cities. The proposed system considers the use of Plug-in Electric Vehicle (PEV) and Unmanned Aerial Vehicle (UAV) as storage units. The problem involves distinct types of vehicles and a community, composed of small houses, residential areas and different Renewable Energy Resources. In order to highlight possibilities for power dispatching, the optimization of three distinct goals is considered in the analysis: mini/microgrid total costs; usage of vehicles batteries; and maximum grid peak load. Sets of non-dominated solutions are obtained using a mathematical programming based heuristic (Matheuristic). By analyzing cases of study composed with up to 70 vehicles, we emphasize that PEVs and UAVs can effectively contribute for renewable energy integration into mini/microgrid systems. Smart cities policy makers and citizens are suggested to consider the proposed tool for supporting decision making for cities under development, guiding their choices for future investments on renewable energy resources.

1. Introduction

The field of research involving community energy planning is rising attention from Scholars and urban planners [2]. In particular, MicroGrid (MG) will be part of the heart of the Smart Cities (SC) [3,4]. This paper addresses a Microgrid Storage Planning Problem (MSPP), which involves Plug-in Electric Vehicle (PEV) [5,6] and Unmanned Aerial Vehicle (UAV) [7], also known as Drones, or Unmanned Aircraft System (UAS), as storage units. Despite the fact that batteries are high cost equipment, they play an important role for Renewable Energy Resources (RER) integration [8,9]. Adding that conventional vehicles are being highly taxed for parking in the central areas of a city business district [10,11], in order to encourage people to use collective transports and share vehicles, such as: PEVs and Plug-in Electric Bicycles (PEB). Out from the peak

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Fig. 1. UAVs charging station in New York, a special type of drones V2G interaction – extracted from eVolo Magazine 2016 Skyscraper Competition, Mohammad, Zhao and Zhu [20].

time, these vehicles may not be used. On the other hand, batteries are important components that should be efficiently used, when available. The main purpose of the current analysis is to motivate and show novel opportunities for promoting batteries use during their idle time. It is expected that, by discussing this topic, citizens will become aware about the open opportunities and importance of investing in PEVs.

Naturally a Multi-Objective (MO) problem arises from this complex decision making scenario [12], in which PEVs and UAVs might be used as storage units, interacting with the grid in what have been called vehicle-to-grid (V2G) [13–16]. Power dispatching schedule is then planned to meet vehicles operational requirements, settled by its users, and trying to charge them in the most suitable time (such as when energy price is cheaper).

There are several motivations for considering vehicles interaction with microgrid, such as the "boom" that many companies are investing in UAVs delivery system [17–19]. In addition, it is expected that the sky will be full of drones, providing agility, convenience with a potential of improving humanity life quality. A huge drone tower is illustrated in the awarded-winning draw depicted in Fig. 1.

The scenario envisioned by Coelho et al. [12] can be exemplified as a university. In this case, a Mini/Microgrid community interacts with professors, students and the infrastructure. Professors could park their cars at the SmartParks and, instead of paying for parking, they would receive an amount of money if their vehicle is used by the energy management system. Since the cost of the PEV battery represents a significant part of its total price [21], the idea of using it in idle time is acceptable. In a general view, the owners of the PEV would be seen as holders of important MG equipments [22], able to enhance electricity efficiency, quality and to reduce energy costs.

The Multi-Objective Microgrid Storage Planning Problem (MOMSPP) considered here is composed of: small and medium MG users, which may be composed of small houses, residential areas or commercial building; different RER; and several vehicle storage units. The main goals of the MOSPP are the minimization of: MG total costs; usage of PEVs and UAVs batteries; and maximum grid peak load. Meanwhile, other operational requirements should be respected. A possible contribution of discussing these objectives is related to assist policy makers and urban planners decision making, as well as enhancing citizens awareness about possible ESS applications.

Added to the multi-criteria analysis, we propose the consideration of different energy powered vehicles, and consequently, different battery types, provides several strategic opportunities for power dispatching systems. Combining two or more energy storage technologies can yield various advantages [6]. However, this task is packed with uncertainties. In this sense, a previous work [12] handled additional criteria, by considering probabilistic forecasts: volatility behavior in extreme scenarios and two different criteria based on the Sharpe Ratio index.

Fig. 2 shows the conceptual model that represents the MSPP. This causal diagram was developed based on System Dynamics modeling approach. The systemic causal relationship has a set of negative feedback loops that superstabilizes the system, featuring it as a hyperstable system [23]. Thus, the system remains dynamically dominated by a negative feedback loop.

In this diagram, vehicles batteries maximum capacity (PEVs and UAVs Batteries Maximum Power) limits ESS maximum power, an important microgrid when intermittent renewables are being dealt, defined as ESS Maximum Power. While batteries charges require energy from the RER or the ESS, discharges can dispatch power to the final MG demand response or assist the MG itself. Forecasts feed historical demand profile, which can be used for guiding MG user actions, affecting the current demand. On the other hand, wind speed and solar radiation historical data can be used for realizing RER production. Smart sensors and meters are being integrated with Internet of Things [24] capabilities and will support the forecasting and decision making tasks. In our proposal, MG demand response is controlled and managed, considering a centralized microgrid component. The latter can be adapted to the policy makers and SC citizens' wishes and requirements. In particular, in our current study, this demand response is analyzed according the three objectives to be minimized, balancing: costs, batteries uses and microgrid system energy quality.

In order to solve the MOMSPP and to find near efficient Pareto fronts, a Branch-and-Bound Pool Search Algorithm (BBPSA) was designed by them [12]. The strategy generates different sets of weights for each objective function, solving various Mixed-Integer Linear Programming problems (MILP). Furthermore, we improve this previously developed MILP model (Section 2) and design a novel mechanism for the BBPSA, updating the name of the procedure to Multi-Objective Smart Pool Search (MOSPOOLS). In our case, the optimization of sub-problems is performed by the state-of-the-art IBM CPLEX MILP solver, using its advanced

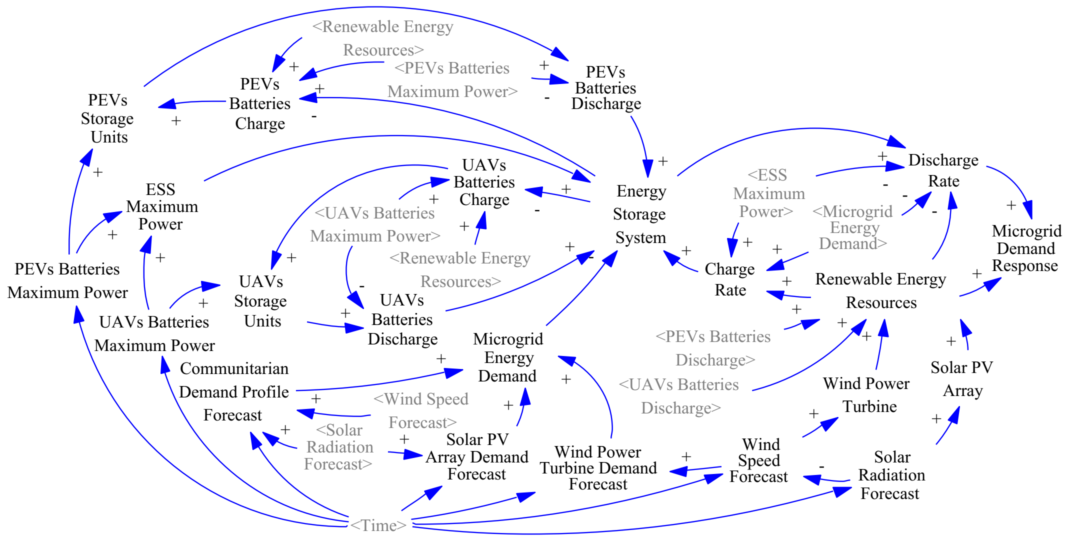


Fig. 2. Causal diagram of the MSPP.

features such as dynamic search, cutting planes and heuristics to quickly provide optimal non-dominated solutions. Thus, the more iterations are performed with a diverse set of weights, the better is the quality of the Pareto Front. However, specially when complex and large problems are being handled, finding feasible solutions might request a considerable computational effort. Thus, the main improvement in this work is to supply each MILP with the best known Mixed-Integer Programming (MIP) solution for that specific combination of objective function weights, together with an improved generation of solutions.

In this current work, we also highlight the importance of the proposal for the urban future generations, taking into account the role that cities will play in the global sustainable development. Smart cities terminology is recently being a target academic papers [25], since its first insight around the beginning of the 90' and has been used according specific agendas [26]. Indeed there is a wave in order to reduce the use of noisy and pollutant car. Therefore by studying the benefits of carless cities [27], the size of shared PEVs is becoming smaller and merging with the so-called PEB. Considering that those who supports carless environments also support PEB, this work contributes to a transition to the urban model of SC with less conventional vehicles. However, as mentioned by Shuai et al. [28], the inclusion of electric based vehicles requires a careful and complex design. By promoting and making parking profitable, which demands a strategic economic policy, this paper aims to enhance users motivation to buy this kind of batteries based equipment. Consequently, it also contributes to SC urban planning and management in accordance to efficiency through PEB and small PEVs.

This work is organized as follows. Section 2 describes improvements made to the MILP model of the problem, while Section 3 presents the proposed Smart Pool Search Matheuristic. Computational experiments include novel larger microgrid scenarios, generated in Section 4.1 and discussed in Section 4.2. Finally, Section 5 draws some final considerations and future works for this current research.

2. Microgrid energy storage planning MILP model

The presented model is an extension of the MILP proposed by Coelho et al. [12], including practical constraints related to PEVs and UAVs integration into mini/microgrids. The complete model is described in Appendix A.

The three objective functions, that should be minimized, are described bellow:

- **Total cost:** this function checks energy exchanged with the grid, namely MG demand response, and calculates the price that is being payed or received during the analyzed period.
- **Batteries costs:** this term tries to minimize the use of vehicles batteries, in particular, in costly cycles. In this sense, if this cost is sufficiently higher than the other ones then vehicles will be only charged when necessary.
- **Grid max load:** this parcel check MG demand response peak rate. This objective function is a motivation for dealing with energy quality, in the sense that MG should not request high loads from the main grid (as well as not delivering unexpected RER production).

While performing previous simulations, we observed that if the vehicle arrives at the first interval and immediately leaves in the consecutive one, the previously developed model was not capable of charging the vehicle. Thus, Eq. (A.15) improves the MILP (described as Eq. A.15 in [12]), adding the term $\sum_{c \in C}(y^{d}_{vci} pev^{dRate}_{vc} - y^{c}_{vci} pev^{cRate}_{vc})$ to the right hand side of the equation.

A slightly change is also suggested to the objective function, that was measuring batteries' wear and tear. The total capacity of the vehicles battery, namely pev^{Power}_{v}, is now being multiplied by the rate of discharge or charge, as well as the discharging/charging price (given the desired rate of discharge). Thus, as can be seen in Eq. (A.3), minimizing batteries total costs sounded more reasonable than minimizing only battery rates.

When we applied the model for dispatching energy in a small microgrids (such as the Reference Energy Disaggregation Data Set (REDD) [29], we detected that energy was being sold and bought at the same time due to rounding errors. Thus, a set of M_i values, for each interval i, is now calculated according to the maximum possible grid rates. This modification improve the big values of M, used in Eqs. (A.5) and (A.6) of the previous model. For calculating each M_i, the maximum rate of charge/discharge was summed to the expected grid rate. Furthermore, these changes improved the accuracy of our model, since an extremely large M number can reduce solver performance [30], even for medium sized problems.

3. Proposed Smart Pool Search Matheuristic

In order to find near efficient Pareto solutions for the MOMSPP in short computational time, we improve the Multi-Objective Smart Pool Search (MOSPOOLS) Matheuristic [12]. The core of the MOSPOOLS is to solve the mathematical model by using a commercial Black-Box solver for MILP problems with different weights for the three objective functions. This strategy is capable of providing a good balance between each of the objectives, by ensuring that different weighted MILP problems are solved.

Algorithm 1 presents the procedure used to generate the weights of each MILP problem, solve them, and filter the obtained solutions in order to create a Pareto front. Several different MILP problems are generated by the linear combination of the weights λ_1, λ_2 and λ_3 (for each objective function). Since the handled MILP is convex, mainly due to several discretizations over batteries charge and discharge rates, any Pareto-optimal solution regarding the objectives can be achieved by a specific combination of weights. However, the problem could also involve nonconvex functions which would change the nature of the system.

Algorithm 1. Smart Pool Search Matheuristic.

Input: solver time limit $sTLimit$ and
vector of MILP weights $\Lambda = \{v\lambda_1 \times \times v\lambda_2 \times v\lambda_3\}$
Output: Set of non-dominated solutions Xe

1 $mipPop \leftarrow \emptyset$
2 **forall** $\lambda_i \in \Lambda \mid \forall i = \{1, ..., 3\}$ **do**
3     $model \leftarrow$ MILP model with weights λ_i
4     $mipSol^* \leftarrow$ best solution $\in mipPop$ regarding current $model$ weights
5     $poolSol, poolEval_{[1...3]} \leftarrow$ Black-Box Solver($model$,$sTLimit$,$mipSol^*$)
6     $mipPop \leftarrow mipPop +$ news solutions from the current $poolSol$
7   **for** $nS \leftarrow 0$ ***to*** $|poolSol|$ **do**
8         $addSolution(Xe, poolSol_{nS}, poolEval_{nS})$
9   **end**
10 **end**
11 **return** Xe

The Black-Box solver solves an instance of the MILP problem by exploring a tree formed by linear programming relaxation nodes. In this process, different feasible (integer) solutions are usually achieved during the searching procedure. Those solutions are returned at the end of the search, which can be finished when optimal values has been reached or due to other stopping criteria, such as computational time (*sTLimit*). It is worth mentioning that an optimal value regards to the best solution that minimizes a that weighted single objective function that is being solved. In this regard, it is usually necessary to solve multiple problems with different weights, in order to satisfy the multi-objective nature of the problem. The obtained set of solutions is hereafter called Pool of Solutions (variable *poolSol*, obtained in line 5).

In the case of study analyzed in Section 4.1, we tackled problems with up to 70 vehicles. It was verified that the solver was expending considerable efforts in finding a first feasible solution. Thus, a new a smart strategy for using previous founded MIP solutions was designed. The proposed strategy picks the best MIP starting solution, for the current set of weights (line 4 of Algorithm 1), from the pool of feasible solutions at the beginning of the search done by the Black-Box solver. Finally, the procedure addSolution (extracted from Lust and Tehrem [31]) filters the non-dominated ones from the obtained population of feasible solutions. This latter mechanism (line 8) efficiently tries to add each obtained solution $s \in$ *poolSol* in the set of non-dominated solutions *Xe*.

4. Computational experiments

The proposed MOSPOOLS was implemented in C++, with assistance of the OptFrame 2.2[1] [32–34]. Experiments were carried out on a OPTIPLEX 9010 Intel Core i7-3770, 3.40 $\times$ 8 GHZ with 32 GB of RAM, with operating system Ubuntu 14.04, and compiled by g++ 4.8.4, using the Eclipse Kepler Release, which runs on the Black-Box solver CPLEX 12.5.1 (calling its Dynamic Search procedure).

In the proposed approach, only the binary variables from the original MILP are stored, as well as the objective function values. Thus, the CPLEX solver starts its search from a previous known feasible solution.

4.1. Generating microgrid scenarios composed of UAVs and PEVs

Load time series from a small microgrid residential area (with maximum load of 243 kW), in a city of Zhejiang Province of China, provided by Liu et al. [35], was considered here, as well as a house with high load fluctuation (with maximum load of 2.13 kW), extracted from the REDD dataset.

A scenario regarding the MG residential area was considered by Coelho et al. [12]. The cases of study described here comprise time series from a wind power farm, adapted to be used as a Wind Power Turbine (WPT), and Solar PV array. They have been adapted from time series of a WPT with 1.6 kW capacity and PV array with a total capacity of 1 kW. Two scenarios are described:

1. Profile 1 (Fig. 3a):
   - load is composed only with demand from a household of REDD;
   - adapted WPT production;
   - original solar array historical data is considered.
2. Profile 2 (Fig. 3b):
   - load from a residential area in China;
   - adapted WPT production multiplied by 100;
   - original solar array is multiplied by 100.

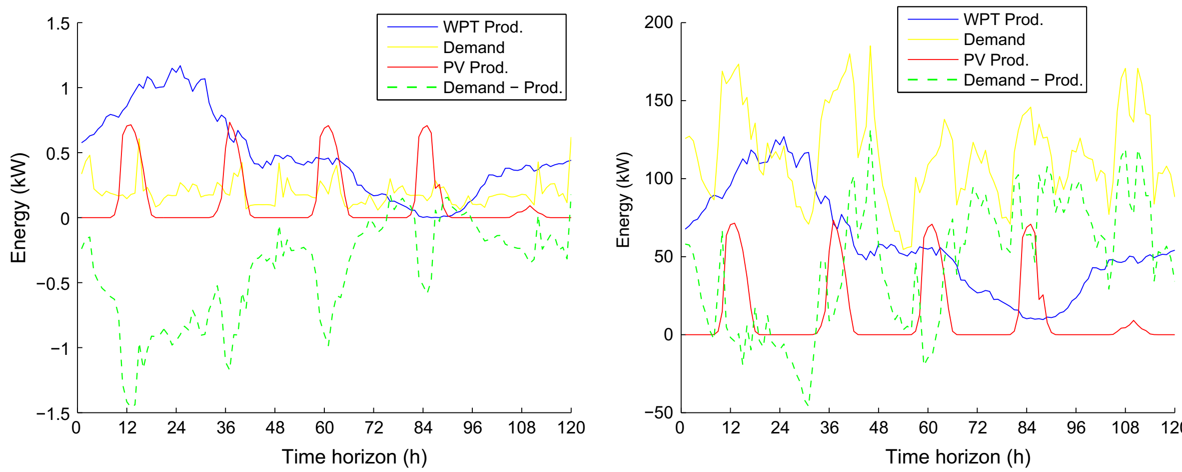
Profit or costs are calculated according to the price time series depicted in Fig. 4. Selling price was set to be 70% of the buying price. Energy prices were extracted from a typical day from the benchmark prices time series dataset of the GEFCOM 2014 [36].

Table 1 indicates vehicles composition of the designed cases of study.

Fig. 5 depicts the discharging prices that we assigned to the vehicles' batteries. Four different energy storage systems were considered: Compressed Air Energy Storage (CAES), Superconducting Magnetic Energy Storage (SMES), Flywheels and Lithium-ion. Some studies in the literature have been discussing if rapid charging is really a point to be damaging batteries. Researchers have been discussing what are the real factors that promote batteries degradation. Results in a particle accelerator, performed by Li et al. [37], at the Department of Energy of the SLAC National Accelerator Laboratory in Menlo Park, showed that more uniform charging, whether fast or slow, were the main causes of battery degradation. Even considering Flywheels and SMES systems, with linear discharge behavior, we defined ascending curves of costs regarding higher discharging/charging rates. Basically, we analyzed the balance of available energy, considering that higher discharges may let the system unable to attend unexpected faults (reducing system overall protection).

They found evidences that rapid charging and draining don't damage Lithium Ion Electrode as much as the literature used to present. In any case, our model is robust enough to be adjusted

[1] Available at http://sourceforge.net/projects/optframe/.



(a) Profile 1 – maximum peak load of 1,46 kW and profit of $16,05

(b) Profile 2 – maximum peak load of 131,60 kW and cost of $2961,15

Fig. 3. Microgrid energy consumption and RER production profile during the analyzed period of 120 h.

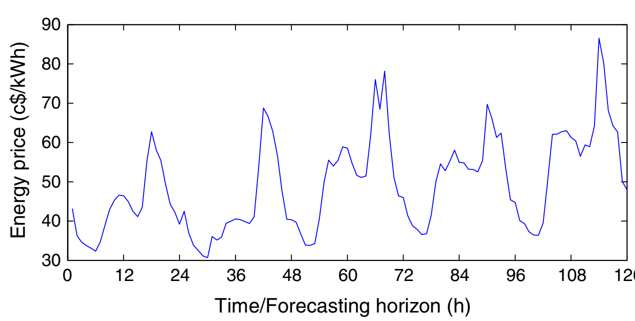


Fig. 4. Energy price, when buying from the main grid, for the analyzed period of 5 days.

to any new information found by researchers. Since it is based on a discrete set of values associated to each charge or discharge cycle, the only thing that might be needed is to updated those values, keeping the consistency of our approach.

Vehicles battery maximum power, measured by the maximum amount of energy it could release in one hour (kWh), are randomly generated, picking values from following set of possibilities:

- PEVs: {20; 30; 60; 70}.
- UAVs: {0.5; 1; 3; 5}.

Considering current battery technologies, UAVs with a energy capacity from 0.5 to 1 kWh are already feasible [38]. It is reasonable to declare that the energy content of these components can grow up to 5 kWh in the near future, for medium size UAVs. In particular, when SMES, flywheel and other novel disruptive technologies in the batteries and ESS are taken into account.

At least, 100 discretized points were considered as possible rates for charging and discharging the PEVs batteries. They were uniformly generated from 0 until the maximum rate for each vehicle. Uncertainties over maximum rates of charge and discharge were premeditated, promoting diversity over the vehicles.

4.2. Obtained results

The proposed multi-objective math-heuristic black-box has been set to proceed with its search with the maximum time of 10, 30 and 60 s per MILP problem. The number of weighted MILP was fixed to 27, combining the following weights: {0, 0.5, 1}, for objective 1; {0, 0.5, 1}, for objective 2; {0.0001, 1, 10}, for objective 3. It should be noticed that the first MILP problem solving time limit could be increased up to 100 times, in order to provide a greater opportunity for finding a first feasible solution and feed the next models. As mentioned in Section 3, any feasible solution can be used for solve the next weighted MILP.

Obtained sets of non-dominated solutions were analyzed according to the following quality indicators: Hypervolume (HV) [39]; coverage [39]; Spacing [40]; Diversity metric Δ [41]; and Cardinality Coverage and Cardinality were calculated regarding a Pareto Front Reference (REF), composed with all obtained solutions for each case. Hypervolumes were calculated using the computational tool provided by Beume et al. [42], the reference point was set {100, 2000, 100}, for cases 1–4, and {10,000, 2000, 500}, for cases

Table 1
Characteristics of the cases of study.

	#PEVs	#UAVs	$\text{maxLoad}^{vehicles}$ (kW)	Average cost/profit ($)	Profile
Case 1	1	3	1.86	−5.77	1
Case 2	1	5	6.30	45.12	1
Case 3	2	3	3.45	14.04	1
Case 4	2	5	9.41	57.60	1
Case 5	5	20	138.73	3181.17	2
Case 6	5	50	132.97	3206.03	2
Case 7	20	20	141.30	3428.21	2
Case 8	20	50	142.26	3598.90	2

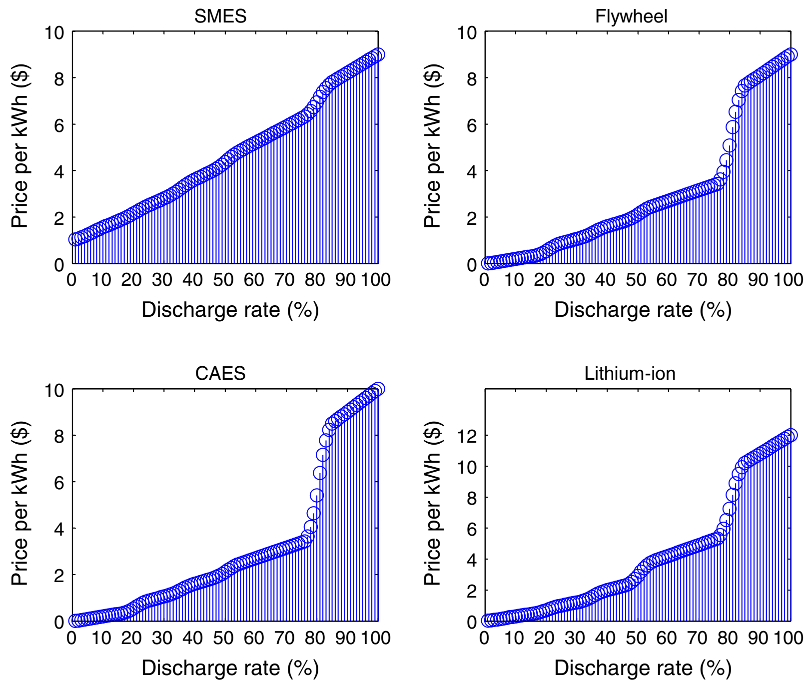


Fig. 5. Batteries discharge prices according to the rate of discharge.

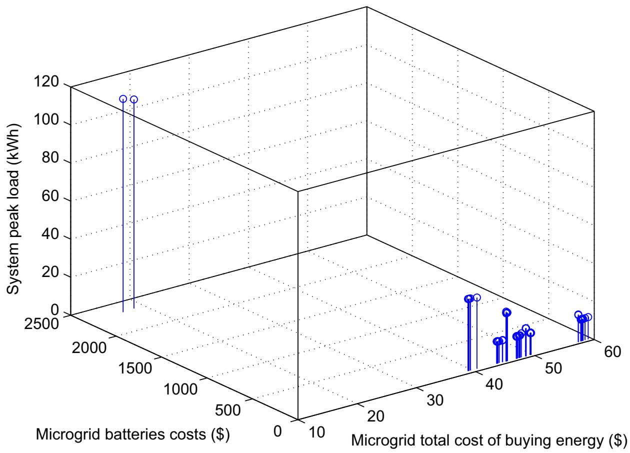
5–8. The Utopian Solution for the Δ metric was defined as $\{-100, 0, 0\}$.

As it can be seen, in Table 2, the coverage and cardinality increased as the solving time growth. Any feasible solution was found within time limits of 1000 s for the cases of study with more than 25 vehicles. Specially in problems with more than 25 vehicles the proposed model is not able to find any solution in five seconds execution. Then to be added to the final Pareto Front. In tis sense, the idea of initializing the model with initial feasible solutions is useful and is able to enhance the quality of the final set of non-dominated solutions.

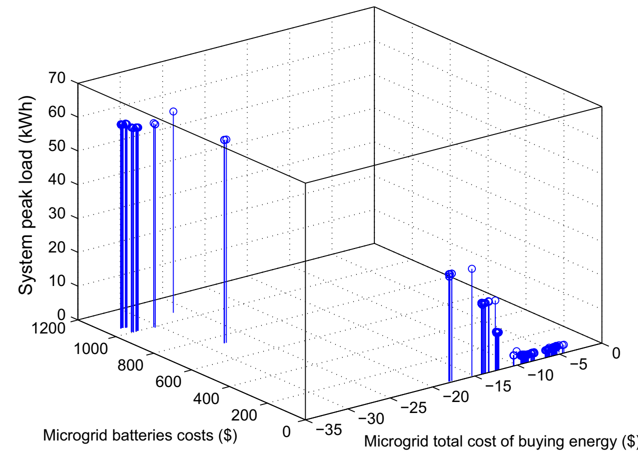
Some Pareto fronts examples are depicted in Fig. 6, while different possible power dispatching schedules are depicted in Fig. 7 The solution with lowest cost found for case 4, Fig. 6a, is $16.27, with maximum peak load of 12.15 kWh and around $1000 for the vehicles' wear and tear. On the other hand, a maximum peak load of 15 kWh can be designed, if the expected microgrid cost is $59.23 and only $16 for playing the vehicles. Fig. 6b depicts the sets of non-dominated solution from the Pareto reference of case 1. As can be noticed, a maximum profit of $32.63 can be achieved. On the other hand, the costs of batteries, due to quick discharges, would be enormous. However, the potential of the microgrid in

Table 2
Average indicators of quality values for different solver time limit and case of study.

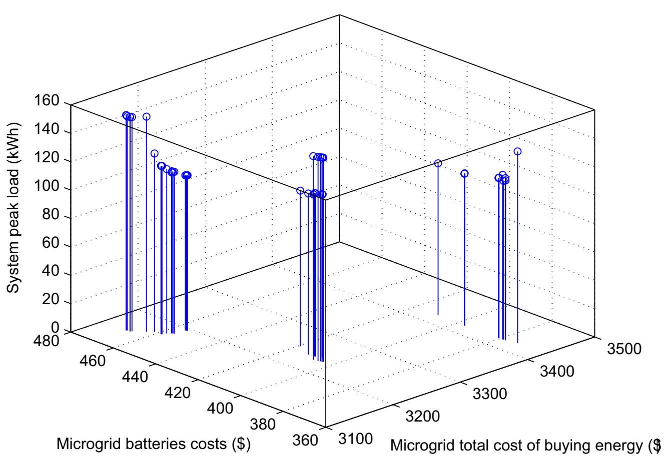
Case	*sTLimit*	PF size	Card	SC	Spacing	Δ metric	HV (10^6)
1	10	125	88	0.15	1.03	0.77	23.08
1	30	154	103	0.17	1.43	0.71	23.04
1	60	206	168	0.28	1.65	0.71	23.03
2	10	121	76	0.17	0.58	0.88	13.27
2	30	171	128	0.28	0.49	0.89	13.28
2	60	193	142	0.31	1.62	0.76	13.31
3	10	134	66	0.10	0.27	0.94	19.03
3	30	186	129	0.20	2.95	0.73	19.31
3	60	229	179	0.28	1.28	0.81	19.21
4	10	100	60	0.13	1.76	0.82	10.38
4	30	137	96	0.22	0.67	0.90	10.38
4	60	174	144	0.33	0.58	0.90	10.39
5	10	21	15	0.06	18.80	0.95	5143.51
5	30	48	31	0.14	6.86	0.97	5179.76
5	60	87	82	0.36	6.19	0.96	5204.16
6	10	–	–	–	–	–	–
6	30	12	10	0.15	14.72	0.98	4928.50
6	60	32	29	0.45	8.48	0.98	4984.75
7	10	–	–	–	–	–	–
7	30	26	16	0.12	10.56	0.97	4350.85
7	60	58	52	0.38	4.18	0.98	4371.86
8	10	–	–	–	–	–	–
8	30	10	8	0.21	10.97	0.99	4185.30
8	60	13	12	0.33	9.42	0.98	4244.62



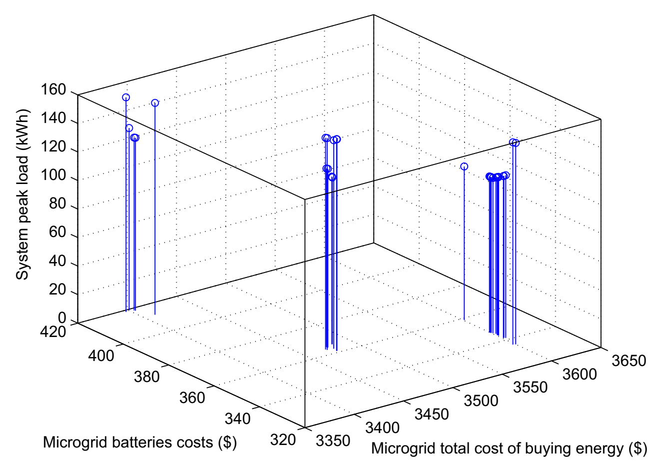
(a) Set of non-dominated solution for case 4 with *sTLimit* of 10 seconds



(b) Obtained Pareto reference set for case

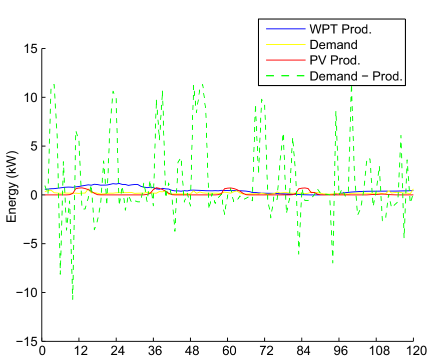


(c) Set of non-dominated solution for case 7 with *sTLimit* of 60 seconds

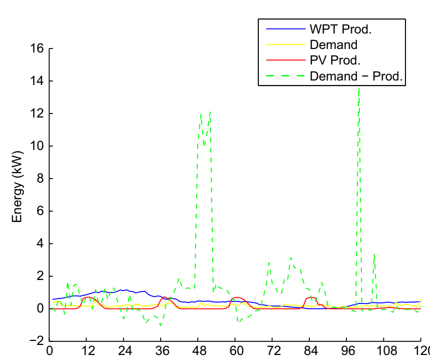


(d) Obtained Pareto reference set for case

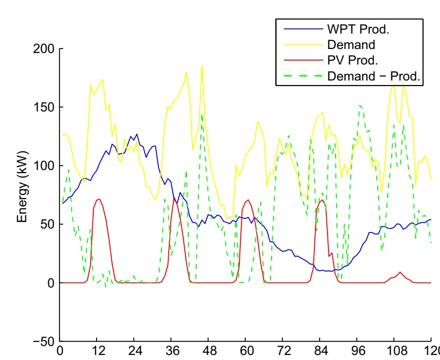
Fig. 6. Pareto fronts examples.



(a) Power dispatching scheduling with lowest cost for case 4



(b) Power dispatching scheduling with maximum cost for case 4



(c) Power dispatching scheduling with lowest cost for case 7

Fig. 7. Energy power dispatching and expected grid rates.

delivering high peak loads can be explored when RER production is higher than demand, as the example of case 1, in particular, for assisting unexpected demand.

5. Final considerations, possible real applications and extensions

5.1. Real applications

The current study deals with several concepts of energy storage, in particular, considering microgrid scenarios with PEVs and UAVs, which may be the new wave of focus for integrating RER. In this sense, use this vehicles in their idle time can assist faults and unexpected events of the energy system. This work may guide the SC evolution and design for urban planners and policy makers, who may now consider the power and flexibility of AI tools for management the future of our cities.

The purpose of car sharing [43] is already reality in several cities in the developed world (as showed in Fig. 8).

The tendency of the SC is to reduce the use of conventional vehicles [44], allowing these new technologies, including electric bicycles, to be used in the cities. The establishment of the SmartParks, in the surroundings of the business district, would not only encourage car sharing and alternative means of transport from that point, but would also work as an energy supply station. Thus, during the day, those SmartParks may supply Business microgrid systems, meanwhile users are on work, for example. Conversely, at night, PEVs would assist their specific neighborhood while the car sharing system would supply the center of the city.

UAVs regulation are under prospection and several conferences are measuring the impact of this flexible and powerful energy based systems. The eminent insertion of these equipment into the hearth of the cities may happen by several reasons, such as: cheaper transportation systems, security and vigilance in public areas (beaches and public events), as well as a possible short distance human transportation system. Undoubtedly, at the beginning, these vehicles will not be fully activated during the whole day, letting opportunity for the design of efficient power dispatching systems.

5.2. Conclusions

In this current paper, a multi-objective energy storage planning problem was addressed, the Microgrid Storage Planning Problem (MSPP). Due to the high complexity of this problem, which involves several non-linear variables and requires real time multi-criteria decision making, a matheuristic optimization technique was used. Smart cities will face high penetration of renewable energy resources and several benefits might occur, if the intermittent exceeding energy is smartly used. In this sense, the objective functions considered in this current paper showed the range of possibilities for using PEVs and UAVs integrated into microgrid systems.

We improved a recently proposed MILP including practical constraints related to the charge/discharge of PEV and UAVs. The previously developed algorithm was also embedded with new mechanisms, improving its ability of efficiently extracting good quality non-dominated solution when solving MILP problems. Different possible power dispatching schedules were found and highlighted the potential of integrating energy based vehicles with SC mini/microgrids. An efficient approach for applying such technologies is paramount for the society, taking into account the natural intermittency from the resources integration for demand response. Batteries, in its idle time, can be used as important equipment, improving microgrid capacity of achieving higher profits and delivering/requesting high amount of well balanced energy.

5.3. Extensions

Future works should include other RER and higher discretization levels, which would allow a more precise power dispatching, improving the proposed model and designing novel optimizing strategies. As could be noticed, the proposed model exponentially increase its size by increasing the number of vehicles and desired discretization level. The problem could be threatened with very low discretization time intervals, which would allow the optimization to be performed in real time (even in terms of ms). For tackling this last proposal, metaheuristics algorithms could be applied. Possible extensions may include a new set of parameters for controlling energy efficiency according to the way the battery is discharged. Some points were still not considered in our model, such as strategies for handling vehicles that do not reach the charging stations (SmartParks), as predicted. A computer model based on the causal diagram conceptualized in this work could be developed for performing dynamic simulation of real scenarios.

Since the use of vehicles in central areas is also a topic under discussion [45], the use of alternative transportation systems (such as small Self Balancing 2-Wheel transportation system, PEB, Smart Electric Scooter, Hoverboards), continuously plugged into the grid, will be reality and might be further investigated.

(a) Reserved parking slot in the main square of Padova.

(b) A car in a idle moment during the day in the city of Padova.

(c) An electric car connected to the grid in the city of Oslo.

Fig. 8. Char sharing and charging stations.

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Appendix A. Mini/microgrid storage planning MILP model

The mathematical model detailed here, adapted from Coelho et al. [12], can be seen from Eqs. (A.1)–(A.17). Model parameters are described bellow:

I	storage schedule planning horizon, from 1 to k
q_i^d	mini/microgrid demand of all customers together at the interval $i \in I$
q_i^{rG}	indicates the RER production at time horizon $i \in I$
q_i^{sell}	energy selling price at $i \in I$
q_i^{buy}	energy buying price at $i \in I$
PEV	set of plug-in electric vehicles
$pev_v^{SOC_{min}}$	indicates the minimum DoD of the vehicle v
pev_v^{Power}	indicates PEV battery maximum capacity
pev_{vi}^{a}	indicates if the vehicle v is available at the time horizon $i \in I$
pev_{vi}^{arr}	indicates if the vehicle v is arriving at the time horizon $i \in I$
$pev_{vi}^{SOC_{arr}}$	indicates the battery percentage of the vehicle v at its arrival at time $i \in I$, it is positive only if $pev_{vi}^{arr} = 1$, otherwise it does not need to be attended
pev_{vi}^{dep}	indicates if the vehicle v is departing from at $i \in I$
$pev_{vi}^{SOC_{dep}}$	shows desired battery percentage demanded by the vehicle v at its departure time $i \in I$
C	set of different battery cycles
pev_{vc}^{dRate}	battery discharging rate (% from its total capacity) of the vehicle v with cycle of discharge c
pev_{vc}^{dPrice}	price for discharging the battery of the plug-in vehicle v with rate pev_{vc}^{dRate}
pev_{vc}^{cRate}	indicates the charge rate of the vehicle v
pev_{vc}^{cPrice}	analogous to pev_{vc}^{dPrice}

The following decision variables were defined:

e_i^{sell}	indicates the amount of energy that will be sold at time horizon $i \in I$
e_i^{buy}	analogous to e_i^{sell}, indicating amount of energy to be bought
$e_i^{sellActive}$	binary variable which indicates if any energy being sold at the interval $i \in I$
$e_i^{buyActive}$	analogous to $e_i^{sellActive}$
y_{vi}^{bR}	variable, with real values, which indicates the battery rate of the vehicle v at time horizon $i \in I$
y_{vci}^{c}	binary variable which indicates if the vehicle v is charging with power cycle c at time $i \in I$
y_{vci}^{d}	binary variable which indicates if the vehicle v is discharging with power cycle c at the interval $i \in I$
tC	indicates the total amount of energy being charged into all batteries (kWh)
tD	analogous to tC, indicating total amount of energy being discharged (kWh)
$f_{objTotalCost}$	mini/microgrid profit or costs by interacting with the main grid
$f_{objBatteriesPrice}$	total price to be payed to the vehicles, due to its charges and discharges
$f_{objMaxPeakLoad}$	objective function that measures maximum peak expected throughout the storage planning

The global objective function to be minimized (Eq. (A.1)) is composed of the linear combination of three different objective functions, described in Eqs. (A.2)–(A.4). Total MG cost (Eq. (A.2)) is measured by the total amount of energy that is being bought or sold at each interval $i \in I$; Batteries use (Eq. (A.3)) is figured by the cost associated with vehicles charges and discharges, paid to vehicles owners. Eq. (A.4) attributes the maximum peak load of the MG system to the value of the third objective function.

Eqs. (A.5)–(A.7) force the system to only buy or sell energy at each interval. Eq. (A.10) forces the PEVs to only charge or discharge while Eqs. (A.11) and (A.12) make them charge or discharge only when PEVs are available at the SmartPark. Battery SOC limits is specific in Eq. (A.13). Eq. (A.14) ensures that PEVs' batteries will attend a minimum SOC wished at its departure. PEV's battery rate is updated according to Eqs. (A.15) and (A.16). Eq. (A.15) attends the special case of the first interval while Eq. (A.16) takes the rate of the last battery, if the vehicle is not arriving, and add or subtract energy from charges or discharges. Finally, in Eq. (A.17), the amount of energy that is being sold or bought, at each interval $i \in I$, is determined.

Minimize:

$$\lambda_1 f_{objTotalCost} + \lambda_2 f_{objBatteriesUse} + \lambda_3 f_{objMaxPeakLoad} \tag{A.1}$$

S.T.:

$$f_{objTotalCost} = \frac{\sum_{i \in I}\left(e_i^{buy} q_i^{buy} - e_i^{sell} q_i^{sell}\right)}{100} \tag{A.2}$$

$$f_{objBatteriesUse} = \sum_{i \in I} \sum_{v \in PEV} \sum_{c \in C} \left(y_{vci}^{d} \frac{pev_{vc}^{dRate}}{100} pev_v^{Power} pev_{vc}^{dPrice} + y_{vci}^{c} \frac{pev_{vc}^{cRate}}{100} pev_v^{Power} pev_{vc}^{dPrice} \right) \tag{A.3}$$

$$f_{objMaxPeakLoad} \geqslant e^{buy} + e^{sell} \quad \forall i \in I \tag{A.4}$$

$$e_i^{sellActive} M_i \geqslant e^{sell} \quad \forall i \in I \tag{A.5}$$

$$e_i^{buyActive} M_i \geqslant e^{buy} \quad \forall i \in I \tag{A.6}$$

$$e^{sellActive} + e^{buyActive} \leqslant 1 \quad \forall i \in I \tag{A.7}$$

$$tC = \sum_{i \in I} \sum_{v \in PEV} \sum_{c \in C} \left(y_{vci}^{c} \frac{pev_{vc}^{cRate}}{100} pev_v^{Power} \right) \tag{A.8}$$

$$tD = \sum_{i \in I} \sum_{v \in PEV} \sum_{c \in C} \left(y^{d}_{vci} \frac{pev^{dRate}_{vc}}{100} pev^{Power}_{v} \right) \tag{A.9}$$

$$\sum_{c \in C} (y^{d}_{vci} + y^{c}_{vi}) \leqslant 1 \quad \forall v \in PEV,\ i \in I \tag{A.10}$$

$$\sum_{c \in C} y^{d}_{vci} \leqslant pev^{a}_{vi} \quad \forall v \in PEV,\ i \in I \tag{A.11}$$

$$\sum_{c \in C} y^{c}_{vci} \leqslant pev^{a}_{vi} \quad \forall v \in PEV,\ i \in I \tag{A.12}$$

$$pev^{SOC_{min}}_{v} pev^{a}_{vi} \leqslant y^{bR}_{vi} \leqslant 100 \quad \forall v \in PEV,\ i \in I \tag{A.13}$$

$$y^{bR}_{vi} \geqslant pev^{SOC_{dep}}_{vi} pev^{dep}_{vi} \quad \forall v \in PEV,\ i \in I \tag{A.14}$$

$$\sum_{c \in C} y^{bR}_{v1} = pev^{SOC_{arr}}_{v1} pev^{arr}_{v1} + \sum_{c \in C} (y^{d}_{vci} pev^{dRate}_{vc} - y^{c}_{vci} pev^{cRate}_{vc}) \quad \forall v \in PEV \tag{A.15}$$

$$\begin{aligned} \sum_{c \in C} y^{bR}_{vi} = & \Big\{ (1 - pev^{arr}_{vi}) y^{bR}_{v(i-1)} + pev^{arr}_{vi} pev^{SOC_{arr}}_{vi} \\ & + \sum_{c \in C} (y^{d}_{vci} pev^{dRate}_{vc} - y^{c}_{vci} pev^{cRate}_{vc}) \Big\} \left(pev^{arr}_{vi} + pev^{dep}_{vi} \right) \\ & \forall v \in PEV,\ i \geqslant 2 \in I \end{aligned} \tag{A.16}$$

$$\begin{aligned} e^{sell}_{i} - e^{buy}_{i} = & \sum_{v \in PEV} \sum_{c \in C} \left(y^{d}_{vci} \frac{pev^{dRate}_{vc}}{100} pev^{Power}_{v} - y^{c}_{vci} \frac{pev^{cRate}_{vc}}{100} pev^{Power}_{v} \right) \\ & + q^{rG}_{i} - q^{d}_{i} \quad \forall i \in I \end{aligned} \tag{A.17}$$

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