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A smart pool search matheuristic for solving a multi-objective microgrid storage planning problem

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Abstract

In this paper, a multi-objective power dispatching problem that uses Plug-in Electric Vehicle (PEV) as storage units is considered. The problem involves several PEVs and a microgrid community, composed of small houses, residential areas, and different Renewable Energy Resources. Three different objectives are considered: microgrid total costs; usage of PEV batteries and maximum grid peak load. In order to find sets of non-dominated solutions, a matheuristic black box solves several Mixed Integer Linear Programming (MILP) subproblems. We improve a previously developed MILP model and design a new multi-objective matheuristic including new problem initialization mechanisms.

Keywords: Microgrids, Power dispatching, Energy storage management, Matheuristic, Mixed-Integer Linear Programming, Multi-objetive optimization

1. Introduction

This paper addresses a multi-objective power dispatching problem called the Microgrid Storage Planning Problem (MOMSPP), which involves Plug-in Electric Vehicles (PEV) as storage units. The

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MOMSPP considers a small Microgrid (MG) community, which may be composed of small houses, residential areas, and different Renewable Energy Resources (RER). In this scenario, the PEVs are used as main storage units, located at SmartParks. Power dispatching schedule is then planned to meet PEV operational requirements, settled by its users, and trying to charge PEV batteries when energy price is cheaper. The main goal of the MOSPP is the minimization of three different objective functions: the microgrid total costs; usage of PEV batteries and maximum grid peak load.

A scenario envisioned as a Mini/Microgrid community was proposed by Coelho et al. [1], such as a University. Professors could park their car 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, 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 microgrid equipments [2], able to enhance electricity efficiency, quality and to reduce energy costs.

The idea of considering a SmartPark with different vehicles and different battery types provides several strategic opportunities for power dispatching systems. Combining two or more energy storage technologies can yield various advantages [3]. However, this task is packed with uncertainties. In this sense, a previous work [1] handled three additional criteria: volatility behavior in extreme scenarios and two different criteria based on the Sharpe Ratio index. In order to evaluate suitable schedules to be applied in extreme scenarios, probabilistic forecasts were used for generating different scenarios. Some points were still not considered in the model, such as strategies for handling the PEV that do not reach the electric parking as predicted. In order to solve the MOMSPP and to find near efficient Pareto fronts, a Branch-and-Bound Pool Search Algorithm (BBPSA) was designed. The proposed algorithm generates sets of weights for each of the objective functions and solves several Mixed Integer Linear Programming (MILP) problems.

In this current study we improve a previously developed MILP model (Section 2) and design a novel mechanism for the BBPSA (detailed in Section 3), updating the name of the procedure as Smart Solution Pool Based Matheuristic, since optimization is done by the CPLEX solver, as a black box tool, described as dynamic search. The latter consists of the same building blocks as branch & cut: LP relaxation, branching, cuts, and specific heuristics to accelerate the search.

Obtaining solutions from each MILP optimization model is an efficient way of achieving good quality solutions for composing 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 proposed in this work is to feed each MILP with the best known MIP solution for that specific combination of objective function weights, together with an improved generation of solutions.

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. Energy storage planning MILP model improvement

The presented model is an extension of the MILP proposed by Coelho et al. [1], including practical constraints related to the PEV and the energy grid. When several PEVs were generated, it was noticed 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. 1 improves the MILP (in [1], described as Eq. 15), adding the term $\sum_{c\in C} \left(y_{vci}^{d} pev_{vc}^{dRate} - y_{vci}^{c} pev_{vc}^{cRate}\right)$ to the right hand side of the equation.

$$\sum_{c\in C} y_{v1}^{bR} \leq pev_{v1}^{SOC_{arr}} pev_{v1}^{arr} + \sum_{c\in C}\left(y_{vci}^{d} pev_{vc}^{dRate} - y_{vci}^{c} pev_{vc}^{cRate}\right) \forall \in PEV \; (1)$$

Another practical characteristic of the PEV was added to the objective function that measures batteries wear and tear, as can be seen in Eq. (2). The total capacity of the PEV battery is now being multiplied by the rate of discharge or charge. As will be verified in Section 4.1, batteries with different total capacity (kWh) were generated. Thus, minimizing the total energy charged or discharged from the batteries sounded more reasonable than minimizing only the battery rates.

$$f_{objBatteriesUse} = \sum_{i \in I} \sum_{v \in PEV} \sum_{c \in C} \left(y_{vci}^{d} pev_{vc}^{dRate} + y_{vci}^{c} pev_{vc}^{cRate} \right) pev_{v}^{Power} \quad (2)$$

Finally, the big values of M on Eqs. 5 and 6 of the previous model were also improved (a huge number was being assigned to parameter M). This improvement was made since the model was applied for dispatching energy in a small microgrids generated with data from the Reference Energy Disaggregation Data Set (REDD) [4], thus, we detected that energy was being sold and bought at the same time due to rounding errors. In this sense, a new set of M_i values was introduced, for each interval i, and is now calculated according to the maximum possible grid rates. The maximum rate of charge/discharge is considered and 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 [5], even for medium sized problems.

3. Proposed Smart Solution Pool Matheuristic

In order to solve find near efficient Pareto solutions for the MOMSPP in short computational time, we present the Smart Pool Search Matheuristic (SPSMH). The idea of SPSMH 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 a large number of weighted problems are solved.

Algorithm 1, presented in Figure 1, presents the procedure used to generate weighted sum MILP problems, solve them, and filter the obtained solutions in order to create a Pareto front. The main improvement regarding to the previous Pool Search Algorithm [1] is the inclusion of a MIP starting solution (line 5) in the beginning of the search done by the Black-Box solver. Several different MILP problems are generated by the linear combination of the weights λ1, λ2 and λ3 (for each objective function). Since the handled MILP is convex, any Pareto-optimal solution regarding the objectives can be achieved by a specific combination of weights.

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. It is worth mentioning that the optimal values regards to the best solution that minimizes a specific weighted-sum single objective function. So, it is 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 (line 6). The procedure addSolution (extracted from Lust &Tehrem [6]) filters the dominated solutions in the obtained population. This latter mechanism (line 9) efficiently tries to add each obtained solution s ∈poolSol in the set of non-dominated solutions Xe.

Algorithm 1: Smart Pool Search Matheuristic

Input: Number of linear combination intervals $nIntervals$
Output: Set of non-dominated solutions Xe

$\Lambda = [0, \frac{1}{nIntervals}, ..., \frac{nIntervals-1}{nIntervals}, 1]$
$mipPop \leftarrow \emptyset$
for *each possible combination of* $\lambda_1, \lambda_2, \lambda_3 \in \Lambda$ **do**
  $model \leftarrow$ MILP model with weights $\lambda_1, \lambda_2, \lambda_3$
  $mipSol^* \leftarrow$ best solution $\in mipPop$ regarding current $model$ weights
  $poolSol, poolEval_{[1...3]} \leftarrow$ Black-Box Solver($model$,$mipSol^*$)
  $mipPop \leftarrow mipPop +$ news solutions from the current $poolSol$
  for $nS \leftarrow 0$ ***to*** $|poolSol|$ **do**
    $addSolution(Xe, poolSol_{nS}, poolEval_{nS})$
  end
end
return Xe

Figure 1 Smart Pool Search Matheuristic Algorithm

4. Computational experiments

The proposed SPSMH with assistance of the OptFrame 2.2 [7]. Experiments were carried out on Intel i7-4790K 4.00GHz, running with the Black-Box solver CPLEX 12.5.1.

In the proposed approach, only the binary variables from the original MILP are stored, as well as the objective function values. Thus, the CPLEX restores each solution and starts its search.

4.1. Generating microgrid scenarios with PEVs

Load time series from two different small microgrid residential areas and one commercial building, in a city of Zhejiang Province of China, provided by Nian Liu et al. [8], were considered here, as well as a microgrid house with high load fluctuation, extracted from the REDD dataset.

A scenario regarding the microgrid residential area was already tackled by the BBPSA dataset. The cases of study described here comprise a small Wind Power Turbine (WPT) and Solar PV array. The last two have been adapted from time series of a WPT with 160 kW capacity and PV array with a total capacity of 80 kW. We design three scenarios: the case 1 is composed only with the REDD microgrid house (Figure 2); the second one combined two different residential areas and loads from the house (right side of Figure 2); finally, case 3 combines the demand profiles from the commercial building and the microgrid household.

We included some uncertainties over the batteries maximum rates of charge and discharge. They were generated at random according to the PEV maximum battery (20, 30, 60 or 70 kWh), also chosen at random. However, 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. Scenarios were composed of different number of PEVs: 3, 10, 20, and 50. Forecasting horizons of 24 hours ahead were considered.

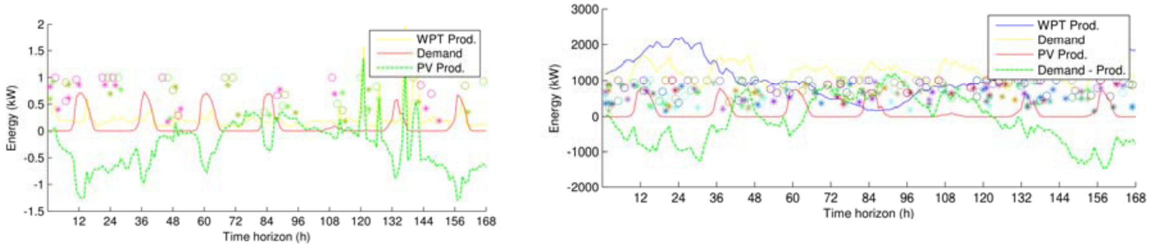

Figure 2 On left side a microgrid household with two small sources of RER generation and 3 PEVs. The right side shows a residential microgrid area with two sources of RER generation and 10 PEVs.

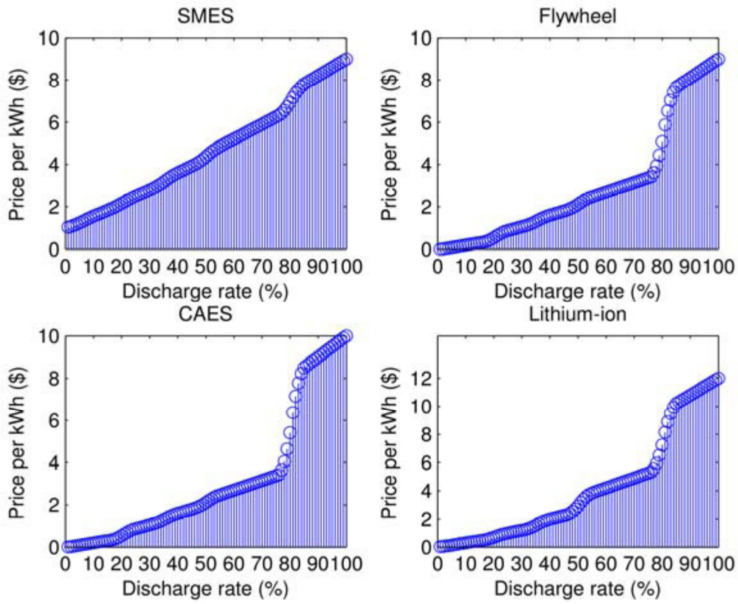

Figure 3 Batteries discharge prices according to the rate of discharge.

4.2. Obtained results

The CPLEX math-heuristic black-box has been set to proceed with its search with the maximum time of 5 seconds. Different numbers of MILP were generated for each scenario: 27, 64 and 125. Two variants were analyzed, the first one solves the weighted-sum MILP problems in sequential order, while the second, denominated SPSMH-R, generates MILP and, then, shuffle them. Thus, in each execution the MILP problems might be initialized with different solutions.

Obtained sets of non-dominated solutions were analyzed according to the Hypervolume (HV) quality indicator, Diversity metric Δ [10] and cardinality. As can be seen in Table 1, the lower Δ metric values indicates better quality of the Pareto Fronts obtained by the SPSMH. The other quality indicators also reported higher results when using the proposed initialization mechanisms. Specially in problems with 20 and 50 PEVS, the BBPSA has difficulty in finding feasible solutions, in five seconds execution, to be add to the final Pareto Front. The idea of initializing the model with initial feasible solutions was very useful and was able to enhance the quality of the non-dominated solutions. Further experiments should analyze the behavior of the method with higher computational times.

Table 1. Pareto fronts comparisons

Indicator of Quality	BBPSA	SPSMH	SPSMH-R
Cardinality	53,1	62,7	64,5
Coverage	0,1498	0,2525	0,2346
Δ metric	0,0236	0,0025	0,0026
HV (10^9)	217,10	224,65	227,93

5. Conclusions and extensions

In this current study, a multi-objective energy storage planning problem was addressed, called the Microgrid Storage Planning Problem. The importance of the problem tackled here can be highlighted by the fact it minimizes three objectives: the total system cost considering a community of owners of the equipments; grid maximum peak load; the use of batteries.

A larger benchmark set of instances can be carefully addressed in future works, following the strategies described in this paper. Unmanned Aerial Vehicle (UAV) should also be considered for the future scenarios, since high quantities of UAVs together might represent a significant storage system. Those scenarios should include other RER and higher discretization levels, which would allow a more precise power dispatching. Possible extensions may include a new set of parameters for controlling energy efficiency according to the way the battery is discharged.

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Biography

Control and Automation Engineering obtained at UFOP and PhD in Electrical Engineering with the PPGEE/UFMG. He has been investigating different fields of computational intelligence applied for a more sustainable world. Vitor received several teachings about high level programming from his brother Igor and Bruno, as well as advised by the masters, Marcone, Fred and Haroldo.