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To cite this version:

Rémy Rigo-Mariani, Vincenzo Roccuzzo, Bruno Sareni, Maurizio Repetto, Xavier Roboam. Power flow optimization in a microgrid with two kinds of energy storage. COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering, 2016, 35 (3), pp.860-870. 10.1108/COMPEL-11-2015-0409 . hal-01323624

HAL Id: hal-01323624

https://hal.science/hal-01323624v1

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To link to this article : DOI:10.1108/COMPEL-11-2015-0409
URL : http://dx.doi.org/10.1108/COMPEL-11-2015-0409

To cite this version : Rigo-Mariani, Rémy and Roccuzzo, Vincenzo and Sareni, Bruno and Repetto, Maurizio and Roboam, Xavier *Power flow optimization in a microgrid with two kinds of energy storage.* (2016) COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering, vol. 35 (n° 3). pp. 860-870. ISSN 0332-1649

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Power flow optimization in a microgrid with two kinds of energy storage

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Abstract

Purpose – The purpose of this paper is to present the optimization of the power flows inside a microgrid with renewable sources and two kinds of storage. The considered microgrid consists in commercial buildings with maximum daily peak value of 50 kW, photovoltaic arrays with total capacity of 175 kW, a 50 kW/50 kWh high speed flywheel storage and a 50 kW/50 kWh set of Li-ion accumulators.

Design/methodology/approach – The power flows in the microgrid are optimized the day ahead at one hour discretization in order to minimize the electric bill. Several scheduling strategies are proposed for solving the corresponding optimization problem including standard deterministic methods, stochastic algorithms and hybrid heuristics.

Findings – All scheduling strategies investigated in the paper are compared with regard to their accuracy and computational time.

Originality/value – Beyond the comparison of different algorithms devoted to the power flow optimization problem, the authors approach also addresses the integration of battery ageing in the scheduling strategy.

Keywords Battery ageing, Mixed integer linear programming, Niching evolutionary algorithms, Power flow optimization, Smart grid

1. Introduction

With the growing number of renewable energy sources, major changes have occurred in electrical grid architecture in the past ten years. In the near future, the grid could be described as an aggregation of several microgrids both consumer and producer (Celli *et al.*, 2004). A microgrid is a portion of the electrical distribution system, containing distributed generation (DG) and local electrical loads, which can exchange power with the main electrical network through a point of delivery. The management of the microgrid requires choosing the most appropriate mix of power production and power purchase from the grid in order to minimize the overall energy cost fulfilling both user needs and technical constraints at the same time. This optimal scheduling is often performed

considering price policy and forecasts for both consumption and production. If DG is controllable, as in the case of internal combustion engines gen-sets, it can be a variable of the optimization. On the contrary, if it is based on a renewable energy source like photovoltaics (PV), it is taken as an assigned power production profile. If energy storage is present, another degree of freedom is available and allows decoupling the time instant of power production to make it comply with the peak consumption hours. In this paper, the power flow optimization in a microgrid with PV production and two kinds of energy storage (i.e. Li-ion accumulators and flywheel units) is studied. All power flows in the microgrid are determined the day ahead from PV production and load consumption forecasts in order to minimize the electric bill. Several scheduling strategies are investigated and compared in terms of accuracy and computational time.

The remainder of the paper is organized as follows. In Section 2, the microgrid topology and the models of its components are presented. Section 3 is devoted to the formulation of the power flow optimization problem. Section 4 introduces several optimization approaches for solving the scheduling problem. Those approaches are tested on a typical test day and are discussed in Section 5. A particular attention is paid to the integration of battery ageing in the power flow optimization. Finally, conclusions are drawn in Section 6.

2. Model of the microgrid

2.1 Microgrid topology

The microgrid considered in the paper is composed of industrial buildings with a subscribed power 156 kW and a PV generator with peak power of 175 kW. Two kinds of storage including a 50 kW/50 kWh flywheel storage (FW) and a 50 kW/50 kWh battery (BT) set of Li-ion accumulators. The power flow model of the microgrid is given in Figure 1. All the microgrid components are connected though a common DC bus. Voltages and currents are not represented and only active power flows are considered. In the rest of the paper the instantaneous values are denoted as $p_i(t)$ while the profiles over the periods of simulation are written in vectors $\mathbf{p_i}$. Due to the grid policy, three constraints have to be fulfilled at each time step t:

(1) $p_1(t) \geqslant 0$: the power flowing through the consumption meter is strictly mono-directional.

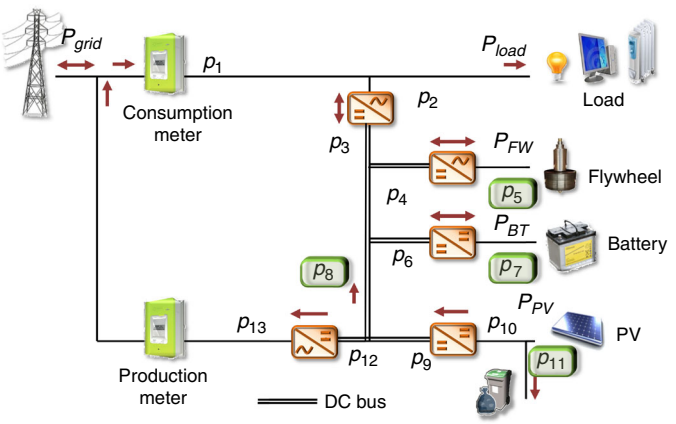


Figure 1. Topology of the microgrid

(2) p_{13} $(t) \geqslant 0$: the power flowing through the production meter is strictly mono-directional.

(3) p_8 $(t) \geqslant 0$: in order to avoid illegal use of the storage. FW and BT accumulators cannot be discharged through the production meter.

The equations between all power flows are generated using the graph theory and the incidence matrix similarly to Bolognani *et al.* (2011). As illustrated in Figure 1, four degrees of freedom are required to manage the whole system from the power production P_{PV} (t) and load consumption P_{load} (t):

(1) p_5 (t): the power flowing from/to the FW storage (defined as positive for discharge power).

(2) p_7 (t): the power flowing from/to the BT storage (defined as positive for discharge power).

(3) p_8 (t): the power flowing from the PV arrays to the common DC bus.

(4) p_{11} $(t) = \Delta P_{PV}$ (t) denotes the possibility to decrease the PV production (MPPT degradation) in order to fulfill grid constraints. In particular when the power supplier does not allow (or limits) the injection of the PV production into the main grid while the consumption remains low and the storage fully loaded the production would have to be reduced.

2.2 Models of the microgrid components

In this load flow model, all components are described by their efficiency which expresses the different power losses:

- *Power converters.* The converter efficiencies are supposed to be constant (typically $\eta_{CVS} = 98$ percent).
- *FW model.* The losses in the high speed FW are computed from the FW state of charge (SOC_{FW} in percent) and the FW power using a function P_{loss} (SOC_{FW}) and calculating the efficiency with a fourth degree polynomial η_{FW} (P_{FW}). Both P_{loss} and η_{FW} functions are extracted from measurements provided by the manufacturer. Another coefficient K_{FW} (in kW) is also introduced to estimate the self-discharge of the flywheel (see (2)). Once the overall efficiency is computed, the true power P_{FW} associated with the FW is calculated as well as the SOC_{FW} evolution using the maximum stored energy E_{FW} (here 50 kWh), the time step Δt (i.e. the scheduling period of one hour) and the control reference p_5:

$$\begin{cases} p_5(t) < 0 \rightarrow P_{FW}(t) = P_{loss}(SOC_{FW}(t)) + p_5(t) \times \eta_{FW}(-p_5(t)) \\ p_5(t) > 0 \rightarrow P_{FW}(t) = P_{loss}(SOC_{FW}(t)) + p_5(t)/\eta_{FW}(p_5(t)) \end{cases} \tag{1}$$

$$\begin{cases} p_5(t) \neq 0 \rightarrow SOC_{FW}(t+\Delta t) = SOC_{FW}(t) - \frac{P_{FW}(t) \times \Delta t}{E_{FW}} \times 100 \\ p_5(t) = 0 \rightarrow SOC_{FW}(t+\Delta t) = SOC_{FW}(t) - \frac{K_{FW} \times \Delta t}{E_{FW}} \times 100 \end{cases} \tag{2}$$

The FW storage is supposed to ensure a significant number of cycles (typically up to 100,000 cycles). Therefore, the ageing effects are neglected.

- *BT model.* The Li-ion accumulator is represented by the Shepherd model (Tremblay and Dessaint, 2009) which predicts the voltage of the storage element V (see Figure 2) as follows:

$$\begin{cases} I > 0 \rightarrow V = E_0 - R.I - K(Q + I.\Delta t)\frac{Q_{nom}}{Q_{nom} - Q} + Ae^{-BQ} \\ I < 0 \rightarrow V = E_0 - R.I - K.Q\frac{Q_{nom}}{Q_{nom} - Q} - K.I.\Delta t.\frac{Q_{nom}}{Q_{nom} - 0.1Q} + Ae^{-BQ} \end{cases} \tag{3}$$

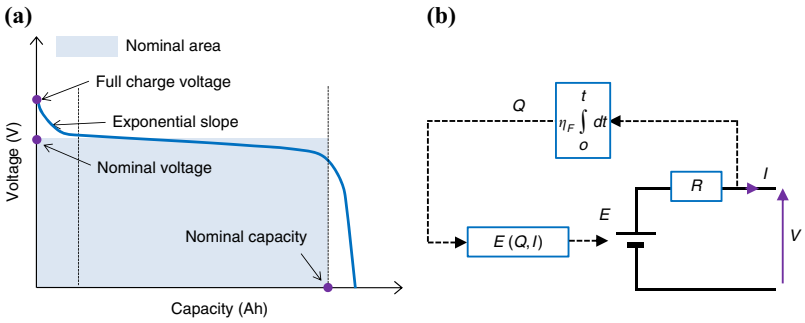
where I denotes the BT current; E_0 the open circuit voltage (or nominal voltage); R the internal resistance; K the polarization voltage; Q the BT capacity; Q_{nom} the nominal BT capacity; A the exponential zone amplitude; and B the inverse time constant of the exponential zone. The values of the main BT parameters are determined by fitting the data provided by the manufacturer data in the case of a saft 48 V Intensium-3.

The BT capacity Q is obtained from the BT current integration including the Faraday efficiency η_F typically defined as:

$$\begin{cases} I > 0 \rightarrow \eta_F = \frac{1}{99.7\%} \\ I < 0 \rightarrow \eta_F = 99.7\% \end{cases} \tag{4}$$

Self-discharge and memory phenomena are neglected in our model but ageing effects are considered through the analysis of BT SOC cycles during the microgrid exploitation with regard to the BT number of cycles to failure curve (see Figure 3(a)). In practice, the cycle counting method known as "rainflow" based on Downing's algorithm (Downing and Socie, 1982) is applied for determining the number of cycles N_{cycle} corresponding to different intervals of depth of discharge (DOD). Typically, the whole DOD range is divided into 100 equally spaced intervals. Finally, the "equivalent" number of full cycles $< N_{cycle} >$ is calculated as follows:

$$< N_{cycle} > = \sum_{DOD} \omega_{cycle}(DOD) \times N_{cycle}(DOD) \tag{5}$$



Notes: (a) Typical discharge curve; (b) Shepherd model

Figure 2.
Li-ion accumulator

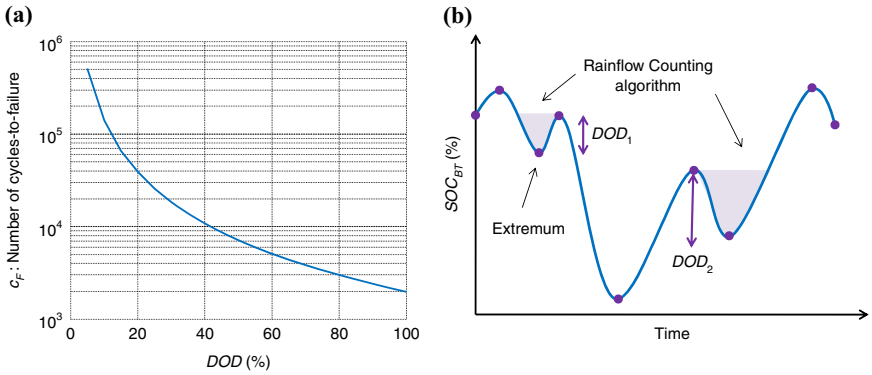


Figure 3.
Li-ion BT ageing indicator

Notes: (a) Typical number of cycles to failure; (b) illustration of the rainflow counting

where the weight ω_{cycle} evaluates the effect of a cycle at a given DOD with regard to a cycle at full DOD, i.e.:

$$\omega_{cycle}(DOD) = \frac{c_F(100\%)}{c_F(DOD)} \tag{6}$$

The number of expected battery replacement N_{rep} in the system over a given period can be deduced from the corresponding equivalent number of full cycles:

$$N_{rep} = \frac{< N_{cycle} >}{c_F(100\%)} \tag{7}$$

3. The power flow optimization in the microgrid

The power dispatching strategy aims at minimizing the electrical bill for the day ahead. Prices of purchased and sold electricity are assumed to be time dependent with instantaneous values, respectively denoted as C_p (t) and C_s (t). The time scheduling period is one day discretized on a one hour basis within which the variables are considered to be constant. References of the power flows associated with the degrees of freedom over this period are computed in a vector $\mathbf{P_{ref}} = [\mathbf{p_5}\ \mathbf{p_7}\ \mathbf{p_8}\ \mathbf{p_{11}}]$ of 96 elements (i.e. the total number of unknowns in the corresponding optimization problem). Once $\mathbf{P_{ref}}$ is determined, all the other power flows in the microgrid can be computed from the PV production and load consumption. Then, $\mathbf{p_1}$ and $\mathbf{p_{13}}$ are known allowing the computation of the balance between the purchased and sold energy expressed by the following cost function C $(\mathbf{P_{ref}})$:

$$C(\mathbf{P_{ref}}) = \sum_{t=0}^{24\ \mathrm{h}} C_p(t) \times p_1(t) - C_s(t) \times p_{13}(t) \tag{8}$$

Three constraints are included into the power flow optimization problem in order to ensure the unidirectional flows outlined in Section 2, i.e.:

$$g_i(p_i) = \sum_{t=0}^{24\ \mathrm{h}} \max(0, -p_i(t))^2 = 0 \quad i = 1,\ 8,\ 13 \tag{9}$$

The limits for the SOC levels (between 0 and 100 percent) are also introduced with adapted constraints. At last two additional constraints are considered with the aim of

ensuring for both storage devices a SOC level of 50 percent at the beginning and at the end of the scheduling period.

4. Optimal scheduling strategies of power flows in the microgrid

Due the non-linear relations in the microgrid model and the presence of constraints in the power flow scheduling problem, non-linear and constrained optimization methods should be preferred. In particular, several approaches have been used for solving that kind of problem:

- Classical non-linear programming methods, especially gradient-based algorithms such as SQP (Whitefoot *et al.*, 2011). Those deterministic methods quickly provide a feasible solution to the scheduling problem but its quality usually depends on the starting point (i.e. initial values of the $\mathbf{P_{ref}}$ vector).
- Stochastic optimization methods such as genetic algorithms (Lai *et al.*, 1997) or particle swarm optimization algorithms (Abido, 2002). Such approaches are well suited in the case of multimodal problems but are more expensive than deterministic techniques in terms of CPU time.

Several approaches have been investigated in our work in order to perform the power flow scheduling in the considered microgrid:

- The trust-region-reflective (TRR) algorithm (Coleman and Li, 1996) with multiple starting points randomly sampled in the decision variable space.
- Two niching evolutionary algorithms: the clearing (CL) algorithm (Pétrowski, 1996) and the dynamic archive niching differential evolution (DANDE) (Epitropakis *et al.*, 2013).
- Two hybrid heuristics combining advantages of deterministic and stochastic approaches. The first named as CL-TRR couples CL with TRR as follows: after each generation, TRR is applied with a probability p_l to an individual randomly chosen in the population. This probability controls the balance between CL and TRR (i.e. between exploration and exploitation of the search space solutions). The second hybrid method uses a mixed integer linear programming (MILP) approach with the CL. MILP has been already used for the power flow optimization of electrical networks and small microgrids (Canova *et al.*, 2009; Warkozek *et al.*, 2012; Trodden *et al.*, 2012). It has been shown (Rigo-Mariani *et al.*, 2013) in a similar study case with a single FW storage that linear programming can be applied on a simplified linear model of the microgrid by neglecting the "non-linear" features (i.e. FW efficiency and self-discharge). MILP provides the optimal solution of the linear problem in a significantly reduced computational time but the obtained solution has to be repaired with a correction procedure in order to take the non-linear phenomena into account. In the considered microgrid with two storage devices and higher level of non-linearity resulting from the battery model characteristics, the MILP solution of the simplified linear problem is introduced in the initial population of the CL with the aim of boosting the convergence speed. This second hybrid algorithm is called MILP-CL.

5. Test case, results and discussion

5.1 Typical test day

The scheduling methods presented in the previous section are evaluated on a particular day whose characteristics are given in Figure 4. The consumption profile is extracted from data provided by the microgrid owner while the production estimation is based on

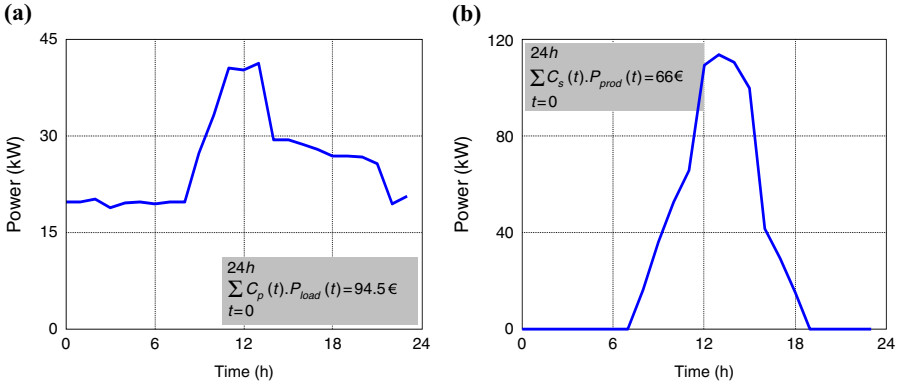


Figure 4.
Typical forecasts

Notes: (a) Load consumption; (b) PV production

solar radiation forecasts computed with a model of PV arrays (Darras *et al.*, 2010). Energy prices result from one of the fares proposed by the French main power supplier increased by 30 percent. Thus, the purchase cost C_p has night and daily values with 0.10€/kWh from 10 p.m. to 6 a.m. and 0.17€/kWh otherwise. C_s is set to 0.1€/kWh which corresponds to the price for such PV plants. In a situation with no storage device, all the production is sold (66.0€) while all loads are supplied through the consumption meter (94.5€). In that case, this leads to an overall cost equal to 28.5€ for the considered day. It should also be noted that no grid constraints are introduced in the investigated tests.

5.2 Power flow optimization without taking the battery ageing into account

Power flows in the considered microgrid are optimized with the scheduling algorithms introduced in Section 4 for the particular test day and with respect of the electricity cost minimization presented in section. The TRR algorithm is applied with 100 independent starting points randomly sampled in the decision variable space. CL and DANDE niching evolutionary algorithms are used with a population of 100 individuals and a number of generations of 50,000. The first hybrid heuristic CL-TRR is run on 500 generations only and with a probability associated with TRR of $p_l = 5$ percent. Finally, the second hybrid heuristic MILP-CL is also tested with a reduced number of generations set to 500. Ten runs are performed for all evolutionary-based approaches in order to take the stochastic features into account. Table I provides the optimal electricity cost of the test day obtained with the different scheduling algorithms. Best, worst and mean results are underlined. Best values are indicated in italic type. It should be noted that negative values indicate a benefit of the scheduling strategy on the particular day. All data should be compared with the reference and non-optimized cost of 28.5€ which corresponds to the electricity cost of the day for the microgrid without storage.

Table I.
Results of the scheduling algorithms on the particular test day (energy cost optimization)

Scheduling algorithm	Best value	Mean value	Worst value	SD	CPU time
TRR	−2.6€	4.5€	57€	15€	*3* min
DANDE	−2.7€	4.9€	6.8€	1.2€	14.7 h
CL	−2.6€	0.6€	2€	1.2€	11.9 h
CL-TRR	*−3.2€*	*−2.3€*	*−0.3€*	*0.8€*	2.1 h
MILP-CL	0.9€	4.8€	9.8€	3.8€	13.8 min

It can be seen from this table that TRR significantly outperform all other scheduling methods with regard to the CPU time leading to a benefit of 2.6€. This solution is quite good compared to those obtained with the other algorithms. As expected CL and DANDE niching evolutionary algorithms require a higher CPU time to find a good solution but there are less sensitive to initial conditions. Best results are obtained with the hybrid heuristic CA-TRR which can be considered as the most robust (due to the minimum standard deviation) and accurate. In addition, the convergence speed is better than DANDE and CL. The introduction of MILP solution in the CL algorithm does not improve the convergence speed as indicated by the poor performance of MILP-CL with a reduced number of generations.

5.3 Power flow optimization taking the battery ageing into account

The second power flow optimization approach consists in taking the BT ageing into account. For that purpose, a battery cost C_{BT} is added into the electricity cost balance. C_{BT} is considered as the cost of ownership for one day if the profile is run for the whole lifetime of the system (typically 20 years). The required number of batteries N_{bat} is determined by considering the ageing on 20 years. Then C_{BT} is computed with a cost per kilowatt-hour C_{kWh} (typically 1,000€/kWh) and the nominal energy E_{BT} in kWh in the following equations:

$$N_{bat} = 1 + N_{rep} \times 20 \times 365 \tag{10}$$

$$C_{BT} = \frac{N_{bat} \times C_{kWh} \times E_{BT}}{20 \times 365} \tag{11}$$

With this new formulation of the cost, the optimal solution found in the previous section leads to an overall cost of 45.3€ which is higher than the reference solution (without storage). All scheduling algorithms are applied to this formulation including the battery costs. The control parameters and the number of runs are identical to those defined in the previous section. Results are given in Table II.

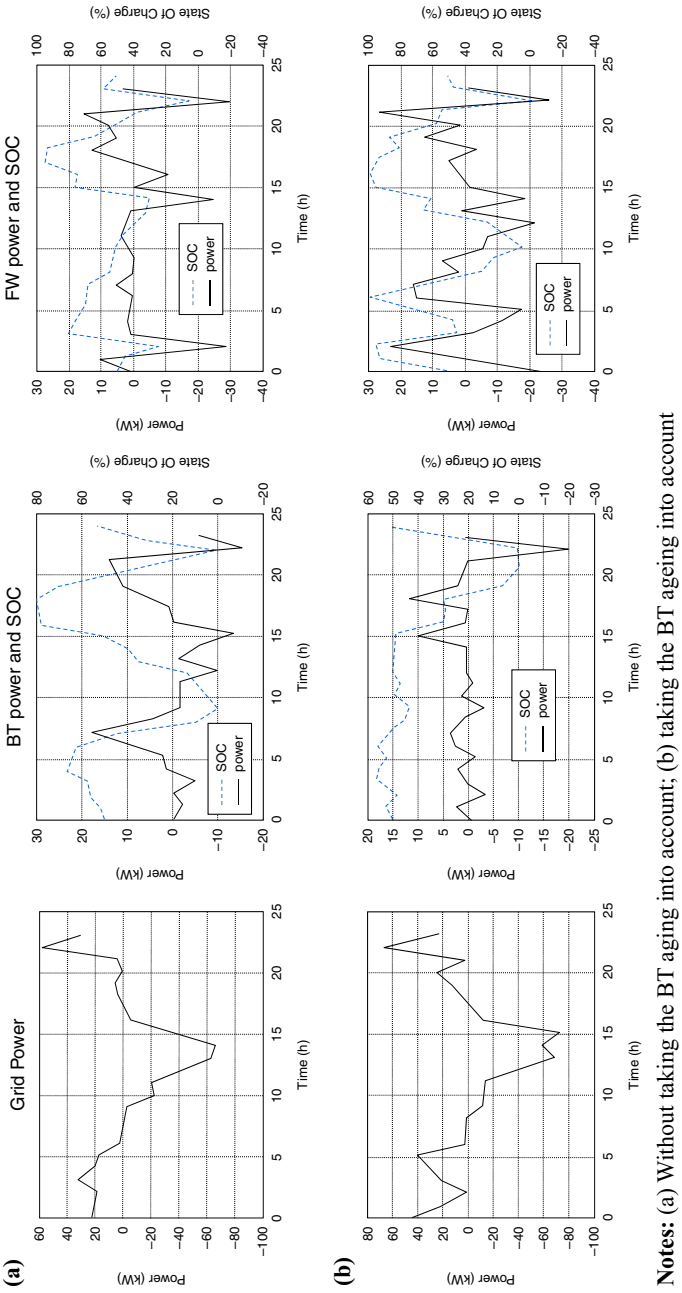
Unlike the previous case, TRR algorithm was unable to converge with this formulation. This is not surprising if we consider the non-linear and multimodal features of the BT cost related to the number of cycles to failure. Indeed, equivalent values of this ageing indicator can be found for different shapes of SOC. This can also explain the low efficiency of CL-TRR compared with the previous case. Nevertheless, all stochastic approaches succeeded in finding a better cost value than the reference solution. It should also be noted that the CPU time is increased for all algorithms due to the use of the rainflow counting method.

Finally, Figure 5 illustrates the main power flows in the microgrid and the FW and BT SOC's corresponding to the optimal solutions found with both formulations (i.e. with and

Table II. Results of the scheduling algorithms integrating battery ageing

Scheduling algorithm	Best value	Mean value	Worst value	SD	CPU time
TRR	43.7€	72.3€	156€	25.7€	*12* min
DANDE	13.3€	15.5€	17.1€	1.4€	19.7 h
CL	*9.2€*	*9.7€*	*10.6€*	*0.5€*	17.2 h
CL-TRR	12.0€	15.0€	21.1€	2.4€	10.5 h
MILP-CL	10.7€	14.2€	20.4€	3.5€	34 min

Note: Results of the scheduling algorithms on the particular test day (electricity cost optimization including battery ageing cost)



Notes: (a) Without taking the BT aging into account; (b) taking the BT ageing into account

Figure 5.
Power flows associated with the optimal solutions

without taking the BT ageing into account). It can be seen from this figure that the number and deepness of the BT cycles are strongly reduced with the second formulation including the BT ageing cost. Conversely, the FW storage is more exploited while the power exchanged with the grid remains quite similar for both formulations.

6. Conclusions

In this paper, several scheduling algorithms have been applied in order to solve the optimal day ahead scheduling of power flows in a microgrid with two storage devices including Li-ion BT accumulators and a high speed FW. Two formulations of the power flow optimization problem have been investigated based on the electricity cost and on the BT ageing cost. Results show that the accuracy of the scheduling algorithms and the optimal solutions found strongly depend on the problem formulation, especially when the BT ageing cost is included in the cost balance. This can be easily justified by the nature of the rainflow counting algorithm combined with the number of cycles to failure curve used to estimate the BT lifetime from SOC variations. Such criterion makes the scheduling problem more difficult by increasing the multimodality features. All stochastic algorithms investigated in the paper were able to provide a good solution in a few hours of CPU time consistent with a day ahead scheduling. However, this CPU time should be further reduced in the context of the power flow optimization with smaller time scheduling periods or if the optimal sizing of the microgrid components is investigated over long periods of time (typically one year of simulation) similarly to Rigo-Mariani *et al.* (2014). Such context will certainly require the use of a MILP approach combined with a linear mircogrid model and a simpler and linearizable BT lifetime criterion in order to reach convergence speeds of a few seconds. This will be investigated in the perspectives of this work.

References

Abido, M.A. (2002), "Optimal power flow using particle swarm optimization", *International Journal of Electrical Power & Energy Systems*, Vol. 24 No. 7, pp. 563-571.

Bolognani, S., Cavraro, G., Cerruti, F. and Costabeber, A. (2011), "A linear dynamic model for microgrid voltages in presence of distributed generations", *Proceedings of the First IEEE International Workshop on Smart Grid Modeling and Simulation (SGMS)*, pp. 31-36.

Canova, A., Cavallero, C., Freschi, F., Giaccone, L., Repetto, M. and Tartaglia, M. (2009), "Optimal energy management", *IEEE Industry Applications Magazine*, Vol. 15 No. 2, pp. 62-65.

Celli, G., Pilo, F., Pisano, G., Allegranza, V., Cicoria, R. and Iaria, A. (2004), "Meshed vs radial MV distribution network in presence of large amount of DG", *Proceedings of the 2004 IEEE PES Power Systems Conference*, Vol. 2, pp. 709-714.

Coleman, T.F. and Li, Y. (1996), "An interior trust region approach for nonlinear minimization subject to bounds", *SIAM Journal on Optimization*, Vol. 6 No. 2, pp. 418-445.

Darras, C., Sailler, S., Thibault, C., Muselli, M., Poggi, P., Hoguet, J.C., Melsco, S., Pinton, E., Grehant, S., Gailly, F., Turpin, C., Astier, S. and Fontès, G. (2010), "Sizing of photovoltaic system coupled with hydrogen/oxygen storage based on the ORIENTE model", *International Journal of Hydrogen Energy*, Vol. 35 No. 8, pp. 3322-3332.

Downing, S.D. and Socie, D.F. (1982), "Simple rainflow counting algorithms", *International Journal of Fatigue*, Vol. 4 No. 1, pp. 31-40.

Epitropakis, M.G., Li, X. and Burke, E.K. (2013), "A dynamic archive niching differential evolution algorithm for multimodal optimization", *IEEE Congress on Evolutionary Computation, Cancun*, pp. 79-86.

Lai, L.L., Ma, J.T., Yokoyama, R. and Zhao, M. (1997), "Improved genetic algorithms for optimal power flow under both normal and contingent operation states", *International Journal of Electrical Power & Energy Systems*, Vol. 19 No. 5, pp. 287-292.

Pétrowski, A. (1996), "A clearing procedure as a niching method for genetic algorithms", *Proceedings of 1996 IEEE International Conference on Evolutionary Computation*, *Nagoya*, pp. 798-803.

Rigo-Mariani, R., Sareni, B. and Roboam, B. (2014), "Fast power flow scheduling and sensitivity analysis for sizing a microgrid with storage", paper presented at the 11th International Conference on Modeling and Simulation of Electric Machines, Converters and Systems (ELECTRIMACS'2014), Valencia, May 19-22.

Rigo-Mariani, R., Sareni, B. and Roboam, X. (2013), "A fast optimization strategy for power dispatching in a microgrid with storage", *39th Annual Conference of the IEEE Industrial Electronics Society (IECON'13)*, pp. 7902-7907.

Tremblay, O. and Dessaint, L.A. (2009), "Experimental validation of a battery dynamic model for EV applications", *World Electric Vehicle Journal*, Vol. 3 No. 1, pp. 289-298.

Trodden, P.A., Bukhsh, W.A., Grothey, A. and McKinnon, K.I.M. (2012), "MILP islanding of power networks by bus splitting", IEEE Power and Energy Society Meeting, pp. 1-8.

Warkozek, G., Ploix, S., Wurtz, F., Jacomino, M. and Delinchant, B. (2012), "Problem formulation and analysis for optimal energy management in multisources systems: W effect", *COMPEL*, Vol. 31 No. 3, pp. 904-919.

Whitefoot, J.W., Mechtenberg, A.R., Peters, D.L. and Papalambros, P.Y. (2011), "Optimal component sizing and forward-looking dispatch of an electrical microgrid for energy storage planning", paper presented at the ASME 2011 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Washington, DC.

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