LONG-TERM PLANNING FOR SMALL-SCALE ENERGY STORAGE UNITS

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ABSTRACT

The number of Distributed Generation (DG) units connected at low and medium voltage is evermore increasing. Due to the mostly non-dispatchable generation profile, grid performance can be ameliorated as well as deteriorated. The integration of small-scale energy units can play an important role in DG planning and distribution system benchmarking. An overview is given of storage systems as well as their major benefits. A robust, multi-objective search algorithm is presented, based on accuracy improving Monte Carlo (MC) simulations nested in an Evolutionary Algorithm (EA). Robustness is essential since load profiles and DG generation patterns have a stochastic nature and storage operation can be non-ideal. Multiple objectives are pursued to assess proper trade-offs regarding imbalance market revenues, ancillary services and energy self-sustainment amongst others.

INTRODUCTION

The old paradigm "electrical energy can not be stored" is making place for a more flexible operation of the grid. Like DG operation can be perceived complementary to connected loads, so can the use of energy units be regarded as the dual of Demand Side Management (DSM) because of the time shifting aspect and the resulting feed-in of a load-DG-storage portfolio. The most commonly used large-scale units are pumped hydro installations and Compressed Air Energy Systems (CAES). Placement of these units depends mostly on finding an adequate geographic location. The use of small-scale energy units in distribution grids is nowadays mostly limited due to high capital costs (€/kW as well as €/kWh) and uncertain return-of-investment.

Uninterruptible Power Supplies (UPS), installed to improve power quality at critical loads, are often based on batteries or flywheel technologies for higher power ratings. In the family of lower power rating units, Li-ion batteries are considered the most promising offspring. When considering the integration of these units, several planning considerations arise. Some are already highlighted in the discussion of non-dispatchable DG planning. How are conflicting objectives analyzed while keeping track of load and generation uncertainties? In case of storage, other relevant topics are which operation of charging/discharging cycles to use and how future technologies can influence the objectives. The concept of a robust multi-objective planning tool is not of interest as a means to act as a central planner since it is quite redundant in the context of a deregulated market. Emphasis lies on gaining insight in the impact of storage placement and on distribution system benchmarking. The planning scheme as proposed in this paper involves inevitably some sort of optimization algorithm. In this paper the acquisition of trade-off sets is envisaged. The final decision taking strategy is not discussed.

STORAGE TECHNOLOGIES

A basic scheme to illustrate distinct classes of storage units is the power-energy diagram (Fig. 1). Location of a storage unit on this diagram characterizes its basic use for

- amelioration of power quality (1);
- levelling of load or generation by renewables (2);
- energy management applications (3).

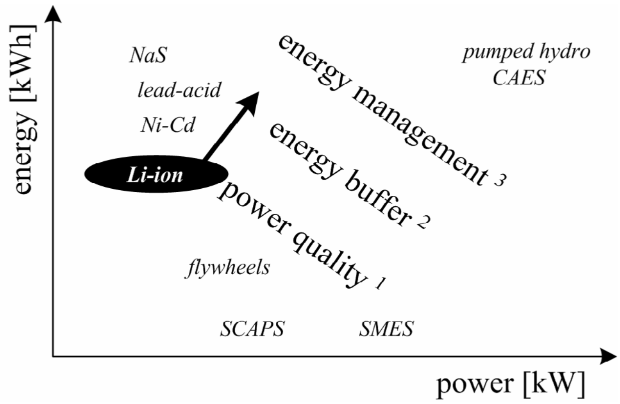

Figure 1: Energy versus power ratings in common storage applications and the predicted shift of Li-ion

The small-scale energy storage units treated in this article are situated in zones 2 and 3. At present low-cost lead-acid batteries are most commonly used, followed by nickel-cadmium based batteries which have a long lifetime. Both have rather low energy densities and are constructed using toxic materials which make them less desirable to use in large-scale energy storage. Sodium-sulphur technology is also considered a good candidate because of its high energy density and high efficiency. No toxic materials are involved but the high operating temperature and the corrosive nature of sodium requires strong safety measurements. Stationary applications however make these easier to handle compared to mobile devices, which were the first target of this type of batteries. Lithium-ion batteries constitute a relatively new technology with main advantages of high energy density and the fact that life time is not influenced by the number of charging/discharging cycles. At the moment only small applications (e.g. cellular phone, notebook) use this type of storage device. It is however considered the most promising technology for use as grid energy storage. A future lithium-ion type battery in terms of cost and efficiency will be used. As mentioned earlier flywheels are considered to be used as very short-term bridging power back-up. Also super-capacitors and SMES, located in zone 1, are not analyzed with regard to bridging power and energy management applications. Fuel cell technology can be regarded as small-scale energy storage, but is not considered in this article.

BENEFITS OF STORAGE

Possible benefits of storage depend upon whether the storage owner coordinates its operation with that of a load or that of a DG unit.

Table 1: Potential benefit of energy storage depending on load and DG in portfolio

	load	no load
DG	avoided feed-in	improved DG reliability
no DG	DSM	arbitrage / ancillary services

1. If storage is combined with one or more loads and DG units, an interesting goal is to locally match energy generation and demand in order to avoid feed-in of DG based energy.
2. When only loads are considered and several price levels exist, storage can be used to shift energy buying in high-price to low-price periods. In Belgium, two price levels exist at residential distribution level, a day tariff and a night/weekend tariff. Whenever a price differentiation exists, storage can act as an integrating element to optimize energy cost in a DSM scheme.
3. Another often quoted benefit of storage is the possible improved dependability of generation by a hybrid storage-renewable plant. For PV panels or wind turbines, it is difficult to assure a power output a priori in a contractual commitment. A buffer element can smooth out stochastic fluctuations and improve output predictions.
4. When neither load, nor DG units are directly involved in storage operation, pure arbitrage is assumed. Energy storage units can play a role in power exchanges, or in local imbalance markets [1]. The shorter the gate closure of a market, the more it may be subject to higher price fluctuations. At present, battery storage can not give a positive economic return on investment in such markets. When the battery technology roadmap substantiates itself however, battery arbitrage could become cost-effective.

Since the operation of the energy storage unit evidently has an impact on grid performance, dispatchability can also be optimized regarding grid operation. This could imply the opening of an ancillary services market, but it can also be regarded in light of capacitor placement deferral. Weighting this objective with purely economic measurable objectives can be delicate.

A ROBUST MULTI-OBJECTIVE SEARCH

Two keywords in a long-term planning scheme of energy storage units are ‘reliability’ and ‘multi-objective’ [2]. Reliability is interpreted in terms of algorithm robustness. In the field of load forecasting, similar basic problems arise. Customer classes have to be identified. Combined with stochastic weather data and heuristics, a time and space pattern can be predicted. In long-term DG planning weather data is crucial regarding renewables such as PV panels and wind turbines. CHP based generation is assumed to be depending upon heat demand, which is also weather linked, whereas micro-turbines are driven by market price incentives. Deterministic optimization algorithms fail to produce a feasible, risk-averted solution.

Another essential question is which goal to aim for. Optimal economic benefit seems evident. In terms of problem formulations several pitfalls appear. A simple translation of all objectives in cost terms is not always very straightforward, e.g. lifetime expectancies, interest rates, voltage profile improvements, etc…

Objectives

Which goals do we want to achieve? Both technical and economic objectives are considered. Technical objectives are e.g. ancillary services like voltage support or power quality enhancement. Economic benefit is aimed for on the imbalance market. Since the conditions under which performance is measured, are stochastic, the concept of reliability is included in each objective. Applying weight factors assumes taking a priori decisions. By performing a true multi-objective optimization, one can gain powerful insight in the planning problem at hand. Correlated and independent objectives are easily identified, revealing crucial trade-offs.

Algorithm

The proposed algorithm is based on an evolutionary algorithm (EA) with nested accuracy improving Monte Carlo (MC) simulations. The use of EAs is justified in case of non-convex optimizations. If a function is convex, an attained local optimum is per definition the global optimum. Many software tools are available dealing with this type of optimization, even when integer variables are involved. A common negligence is to not recognize the convexity of a problem at hand by means of reformulating it (e.g. line loss minimization by connecting undispatchable DG units [2]). In case of true non-convex problems EAs push a population of variable representatives towards fitter solutions by mechanisms mostly inspired by laws of biology, while maintaining diversity to avoid convergence to local optima. The major drawback of EAs is the non-guaranteed convergence. A group of elements with similar performance in the vicinity of the global optimum may be obtained. The search however can in practical problems better be conceived as goal-oriented, rather than globally optimizing.. Tools for convex problems guarantee convergence, but the approach is in most cases too deterministic. Since in EAs no function derivatives are needed, solely function evaluations, a higher flexibility in the search pattern becomes possible. This is exploited to come to a robust, multi-objective planning tool (Fig. 2).

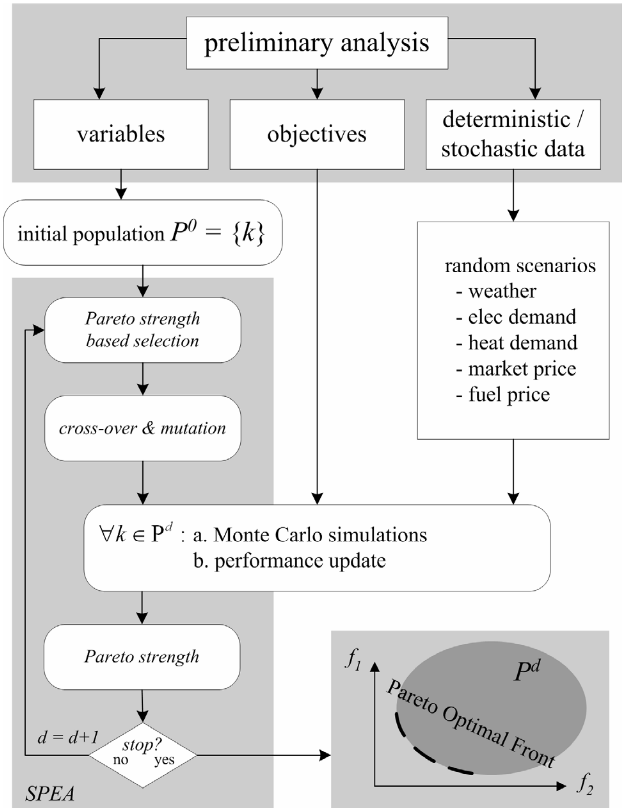

Figure 2: Robust, multi-objective planning method flowchart

As basic scheme, the Strength Pareto Evolutionary Algorithm is taken [3]. Pareto strength comparison of two topologies indicates which dominates or alternatively is dominated more. The group of non-dominated solutions of the final iteration is assumed to constitute a sufficient approximation of the Pareto Optimal Front (POF). This POF can as such be formed in a single run of the algorithm whereas traditional optimization schemes require consecutive changes in weight factors and runs to identify all trade-offs.

The fitness evaluation step is used to perform a fixed number of MC simulations on the entire population. In these MC runs an entire year is generated in terms of weather profile, heat and electricity demand. Performance regarding all relevant objectives is stored for each population member. For members who survived several generations, these additional trials increase the accuracy of statistic performance indicators (e.g. mean value, percentile values,…). How are these random years generated? Classic load forecasting aims at short-term load profiles or at long-term trends. In this planning problem emphasis lies on long-term 'representative' load profiles. Historic weather and load (heat and electrical) data are translated into future time frames. Since both load and renewable generation are weather-dependent, a correlation is taken into account. The SPEA parameters and stop criterion are problem specific; there is no such thing as a free lunch.

TEST CASES

To illustrate the flexibility of the planning procedure Li-ion battery integration is considered in the IEEE 34-node grid, scaled down to a 230V level (Fig. 3) [4]. A number of DG units are assumed to be connected, i.e. PV panels, wind harvesters and micro-CHP units, all in a 1-20kW range. Historic balancing prices, load and DG generation profiles are known [5],[6],[7]. Battery operation is based on optimal threshold prices. Batteries differ in power output and maximum energy content.

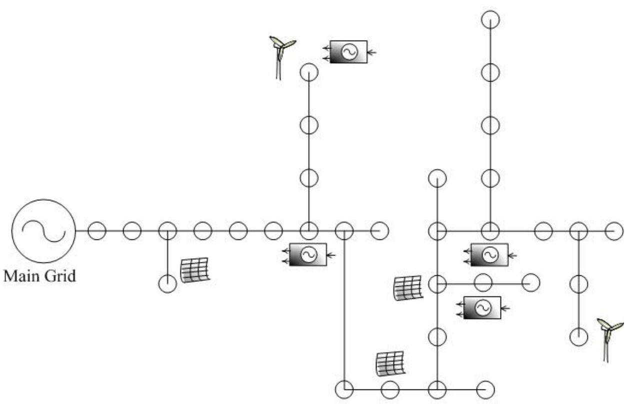

Figure 3: IEEE 34-node radial grid with connected PV panels, CHP units and wind turbines

In a first case a single trade-off is envisaged as an illustration:

- Revenue on balance markets
- Main grid energy dependence

The former assumes a sufficient number of storage units can be aggregated to enter this market. It is assumed to be maximized. Main grid dependability is expressed as the ratio of energy imported in the local grid over the total yearly load. Limits are put on installation budget and number of units. A wide trade-off front is found (Fig. 4), indicating both objectives are clearly conflicting.

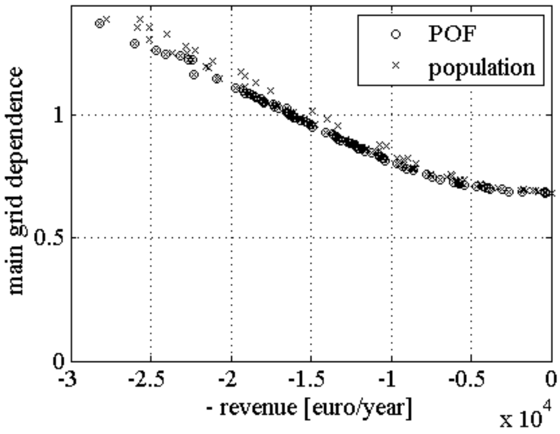

Figure 4: Test case 1 - conflicting objectives

In a second case more correlated objectives are considered

- Voltage profile improvement
- Main grid energy dependence

The first can be perceived as ancillaries from undispatchable sources. It is expressed as the expected 95-percentile maximum voltage deviation in the grid. According to the EN50160 standard, this value has to be within a 10 percent range of the rated voltage. The POF is much smaller (Fig. 5). Note the shift of minimized voltage deviations to higher values in the final generation. This can be explained by the accuracy improvement taking place in each iteration.

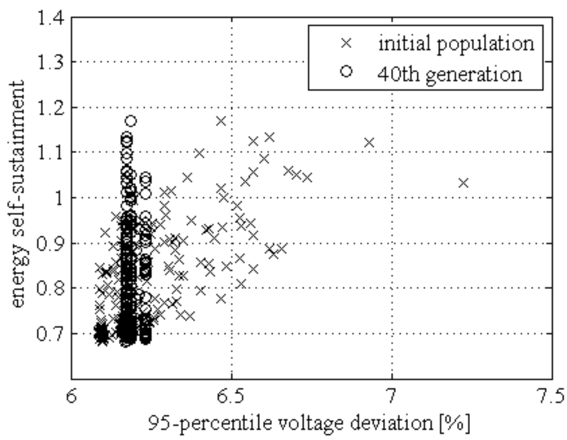

Figure 5: Test case 2 - correlated objectives

In a third case more objectives are taken into account simultaneously. Flexibility of the proposed planning method lies in the adaptability to include multiple objectives as well as the relation it shows between them. No a priori decisions are required. An optimization with six objectives is performed. A (random) subset of the final POF is shown in Fig. 6. Multiple criteria are visualized by petal diagrams. All objectives are translated as minimizations and normalized (dashed circle). The circle segment radius is proportional to the objective value. Since no weighting is assumed, all segment angles are equal.

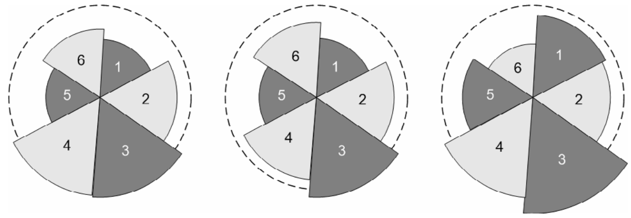

Figure 6: Visualization of three Pareto optimal topologies with criteria: cost (1), revenue (2), line losses (3), conversion losses (4), 95-percentile voltage deviation (5), main grid energy dependence (6)

The final decision out of a given set of Pareto optimal topologies can be made based on e.g. fuzzy logic or game theory. In future work the power/energy optimization can be extended to the assignment of energy content to specific purposes (arbitrage, voltage improvement, local energy self-sustainment, …).

CONCLUSIONS

The potential benefits of small-scale energy storage units in distribution grids are discussed. A robust, multi-objective planning method is presented to obtain a set of Pareto optimal integration topologies. Results have accurate performance data given adequate input. The multi-objective approach offers flexibility in terms of decision making and better insight in the impact of energy storage on profitability and ancillary services.

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