Multi-Objective Valuation Of Electricity Storage Services

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Abstract

Electricity storage services can bring benefit to multiple stakeholders in the grid, in various ways. Local integration planning from a single stakeholder's point of view depends upon the available storage technology, load and generation characteristics which are present in its portfolio. Since storage services have a potential large electricity grid impact as well (both positive and negative), an overall valuation is needed to assess the potential of a significant introduction of storage units in the grid. A method is presented that searches for the optimal integration of storage services in a grid taking into account the technological parameters, dynamic and stochastic interaction of present loads, renewable energy production and market prices based on multiple objectives. This reveals crucial trade-offs which have to be made. It can serve as benchmark in policy making as or as aid in decision making tools for grid investment.

I. Introduction

The number of electricity storage applications is becoming almost as comprehensive as the number of technologies [1]. Unfortunately there exists a lack of understanding as to how several applications can be combined and optimally dimensioned. The fact that load, renewable energy generation and market prices interact in a stochastic pattern and have to be evaluated in terms of nominal values (power) and aggregated benefits (energy) does not simplify this at all. The planning optimization of a single investor has to take all these considerations into account. A global optimization goes even a step further. In a liberalized, unbundled market attaining a global optimum assumes correct incentives are given to all market players, e.g. in case of grid investment deferral, ancillary services, CO_2 reduction etc… It comes down to the basic question: what is the potential of storage in a specific grid and how can this be achieved? A bottom-up deduction of the method is presented starting with that of the operation of a single storage unit.

II. Arbitrage

A simple example of storage operation optimization is based on profit maximization for a given deterministic market price curve. Taking into account power rating, energy content and charging/conversion inefficiencies the problem can be translated straightforward into an LP formulation. This shows the impact of price volatility and energy losses on profitability, but results are too optimistic to use in an investment analysis. Forecasting uncertainties are crucial. The two main techniques used to deal with the stochastic nature of market prices are multi-stage Stochastic Programming (SP) and Dynamic Programming (DP), both having pros and cons [4] (Figure 1).

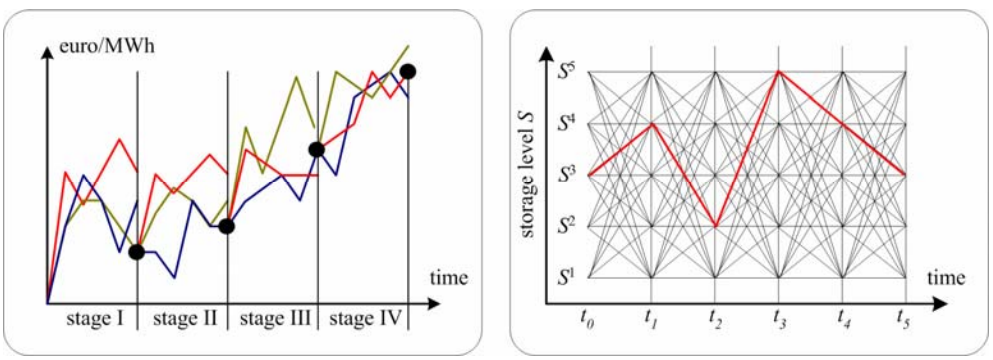

Figure 1: Optimal operation of a storage unit through multi-stage Stochastic Programming (left) or Dynamic Programming (right)

SP divides the time horizon in several stages. At each stage operation is optimized based on several price expectation trends (as illustrated in Figure 1) and the expected optimal value for future time stages, introducing recourse in the problem formulation (a scenario tree) [2]. The more stages are introduced, the more profit can be captured at the cost of higher computational requirements. DP on the other hand has no limitation on the number of stages, but does need to limit the number of operation possibilities (actions) at each stage to overcome the 'curse of dimensionality' [3]. A basic prerequisite for DP optimality is that optimization of future

actions is not depending on information of the past, i.e. choosing the optimal operation is purely forward looking. This principle rules out the use of regression models in e.g. price volatility. Nevertheless since DP works in a smaller forward looking frame, it can achieve higher profits as shown in [4]. It may however not be compatible with power exchange rules in which day-ahead bids are placed. For small-scale customers highly volatile balancing markets could be more attractive and if prices drop and efficiencies increase even become cost-effective [7]. Several elaborations can be made in this stochastic operation planning scheme.

a. Combined local resources optimization

Local storage operation is often determined by present local resources of the storage owner. The pure storage versus external market approach can be broadened by considering loads and local generation. Consumers can increase reliability or improve their time-of-use energy cost management as an alternative for dispatchable loads. The owner of a production unit based on renewable resources can virtually shift the time of production with respect to committed short and long term agreements and in strategies on power exchanges and balancing markets. An often cited example of a storage application is that in coordination with PV plants or wind farms (e.g.[8], [9]) to match local loads or decrease imbalance penalties. Although a storage unit is no true source of energy, it has a non-negligible storage service value.

b. Multiple markets

A single large and fast responding unit or even an aggregation of multiple smaller units has the potential to optimize its revenues over multiple markets (e.g. power exchange and balancing market), possibly in conjunction with load and generation specific objectives. As pointed out in [6] the optimal operation policy across multiple markets, each with its own volatility and uncertainties, is based on uniformity of expected revenues across all commodities.

c. T&D investment deferral

Storage can be installed at grid substations as an alternative to grid investment because of occasional overload. These units need to be highly reliable and fast responding. From an electricity market unbundling perspective and in view of developments in distribution systems this approach can appear questionable.

d. Distributed Energy Resources Planning

The previous paragraph does not give an exhaustive list of all storage service applications, but highlights several aspects that need consideration in storage valuation. An optimal integration of storage is pursued. This search is formulated in terms of a planning problem that is truly multi-objective and as such identifies all trade-offs and considers the grid system as a whole

Even when an unbundled energy market eliminates the viewpoint of that of a ‘central planner’, the global optimization approach still has significant relevance.

- Studies of micro-grid systems acknowledge the need to come to an optimal placement of Distributed Energy Resources (DER) to fully exploit all potential advantages in energy efficiency and grid operation [10].
- The European Electricity Directive concerning common rules for an internal market 2003/54/EC clearly states energy efficiency/demand-side management measures and/or distributed generation need to be considered by the Distribution System Operator (DSO) in the development planning of the grid [11]. A DER stakeholder and a DSO have potentially conflicting objectives. Whereas a DER operator sees revenues in terms of aggregated energy, the DSO analyzes grid operation and grid investment in terms of power flows. Incentives can be given directly by means of demand charges or in a balancing market, but specific localized signals are missing.
- The directive also urges regulators to put forward a policy in which full account of costs and benefits of DER connection is reflected in connection tariffs and terms. The global optimum can serve as a benchmark.

III. Multi-objective Valuation of Electricity Storage Services

The global storage service planning method consists of a two-stage iterative optimization. In a first outer cycle storage size and operation strategies are optimized in a multi-objective evolutionary algorithm (EA). The use of EAs is justified and the sole option 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 non-dispatchable DG units [12]). 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. A large advantage of EAs, especially in this planning problem, is that the entire population can be directed to cover the Pareto front and as such constitute a diverse set of trade-off solutions. The method used in this article is based on the Strength Pareto Evolutionary Algorithm (SPEA2) in which the concept of Pareto Strength is used to classify topologies without the need to address weight factors to all partial objectives [13].

An inner optimization cycle is needed to assess performance evaluations of all population members. In this inner optimization each storage unit maximizes its profit based on an SP scheme for an entire synthetic year. This year comprises load profiles, renewable based production profiles and market price curves for a limited number of days on an hourly basis. This synthetic year can be based on samples of historic data or known models. To improve robustness every topology in each generation undergoes several synthetic year evaluations. This allows the outer optimization cycle to take risk-averse positions by e.g. not just considering the average voltage deviation at a given bus in the system but instead trying to optimize the 90-percentile value of voltage deviations. The lay-out of the algorithm and its two cycles is depicted in Figure 2.

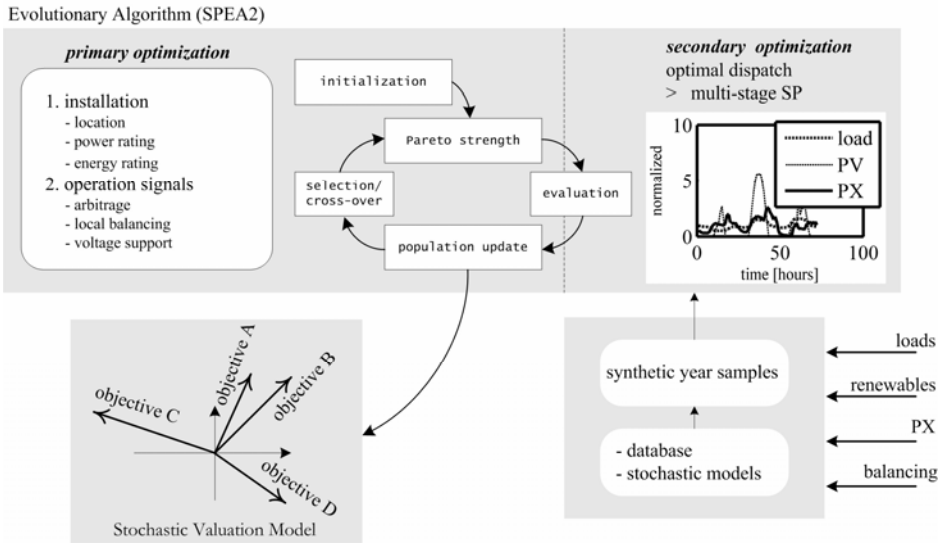

Figure 2: Multi-objective optimization scheme

a. Synthetic years

A prerequisite to obtain reliable results is clearly the correct handling of accurate input data. As stated before, to understand and ameliorate the way in which load, power generation and market prices interact and influence grid operation the dynamic interaction is crucial. Therefore the method is based on scenario evaluations. To take the probabilistic nature into account, numerous new scenarios are created during the search pattern. When dynamic and stochastic data is not available, storage valuation assessment becomes quasi-impossible. In case of numerous measurements synthetic (short) years could be based on data base samples. In this article a generic model is used for loads, renewable power generation and market prices which are sampled a number of times to synthesize these shortened years. Some basic elements to formulate these models are only briefly described as they are a topic of research on its own. Generating long-term customer load profiles can be based on summation of customer appliance cycles in which probabilities on start times and duration together with cyclic hourly, daily, seasonally behavior are integrated [14]. In a higher level grid connection point downstream loads are

known to have a smoothing effect. Therefore load profiles at a transformer connection point can be based on capturing measurement data by adequate probability density functions, e.g. Pearson generalized functions. Concerning the two most common types of undispatchable renewable energy generation, i.e. solar and wind energy, measurements on solar illumination and wind speed at specific locations are often widely available. A common way to generate synthetic profiles is the use of first or second order Markov chain Monte Carlo methods added to average daily and seasonal cycles. Various ways exist to model power exchange price curves. Daily and weekly patterns are clearly visible and can be put forward as a basic curve by isolating the most prominent components in the frequency domain. The residuals represent the volatility which is inherent to electricity prices due to mostly inelastic demand. This residual can be described by a GARCH model in which instances of high volatility appear clustered in time. An improvement of the GARCH(1,1) model, based on parameterized probability density functions, is applied to the log difference of the weekly price residual [15]. An illustration is given in Figure 3. Balancing markets show much less price periodicity and can be modeled as standard Gaussian movements.

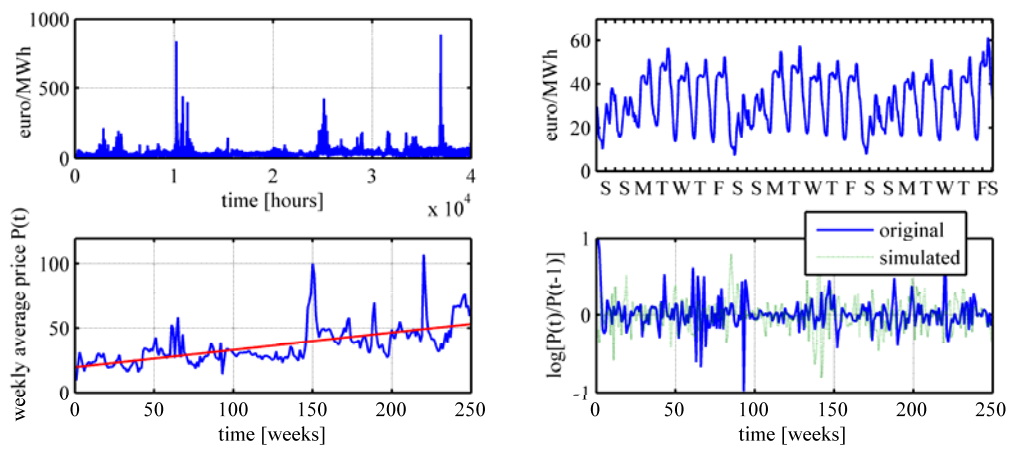

Figure 3: Spot market analysis (upper left) [18]. Weekly patterns are clearly visible (upper right). After surpressing these patterns and the trend (down left), the remaining volatility in the logdifference is estimated as a GARCH(1,1) model (down right)

b. Outer optimization

Optimal placement of storage units and assignment of operation preferences is pursued by the SPEA2 method. Benefits and drawbacks are highlighted before. The choice is based on the flexibility to include controllable units in the placement optimization and the advantage that an entire trade-off front can be pursued in one run of the algorithm. The non-linearity of the power flow equations and the numerous integer variables would make convex optimization computational almost infeasible. Still it must be stressed that proper encoding of variables and adequate adapted heuristics are needed [12]. Chromosomes are coded as a concatenation of selected grid busses with connected power rating, energy content, incentive towards global grid balance and incentive towards local voltage control. The possible power/energy combinations of storage units are restricted to a shortened list, each characterized by installation and O&M cost and lifetime.

c. Inner optimization

In the inner optimization step each storage topology is evaluated by an individual SP cycle for each unit given a synthetic year profile. A four-stage cycle is used with each stage taking six hours. Every storage unit pursues revenue maximization by bidding in a power exchange (external market). As ancillary services are local grid balancing (internal market) and voltage deviation minimization (location-specific) considered. Imbalance and voltage deviation are translated to additional market curves by multiplication with the storage unit incentive values. This system is similar to the idea of price 'droop' signals, which lead to a decentralized control of storage ancillary services [16], although in this case it is simplified to lower computational burden. Forecasted global and local imbalances are translated as market price corrections. The resulting energy storage operation results in missed arbitrage opportunities which are a measure for the value of ancillary services delivered by the storage unit. Figure 4 shows a market price sample with normalized imbalance and voltage deviation curves $P_{imb}(t)$ and $V_{dev}(t,k)$. The storage unit at bus k optimizes its operation P_{stor} based on $P_{imb}(t)$ and $V_{dev}(t,k)$

$$\max \sum_{t} P_{stor} \left[P_{PX}(t) - bP_{imb}(t) - vP_{dev}(t,k) \right] \tag{1.1}$$

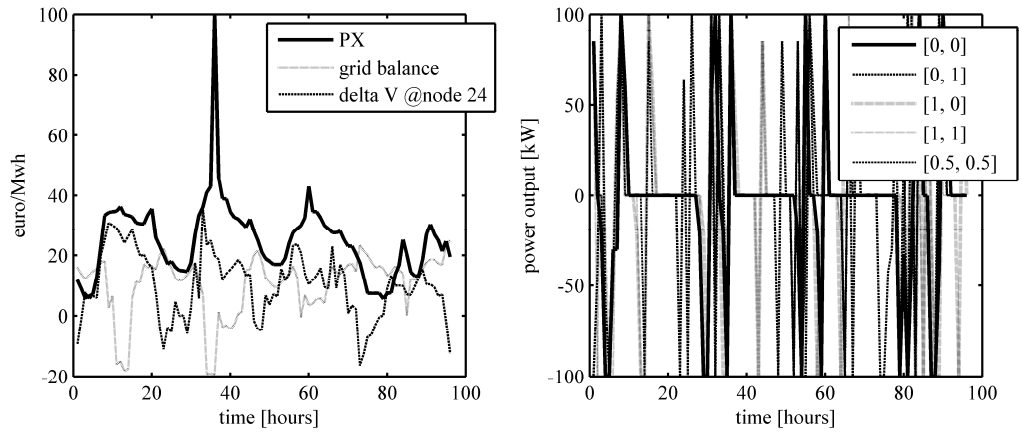

Figure 4: Each storage unit optimizes its output given PX curve and ancillary service incentives. The effect of some ancillary service incentives [*b*, *v*] is given.

IV. Test Cases

The basic blocks are with the following test case. A radial 34-bus system at 24 kV is considered [17] (Figure 5). The grid comprises a diversity of loads and a number of renewable power generators [19], [20]. The system is characterized by occasional high voltage deviations. Load growth would necessitate a transformer upgrade. What impact can storage have in the system under the assumption these units will be integrated by private investors but adequate price signals will be given?

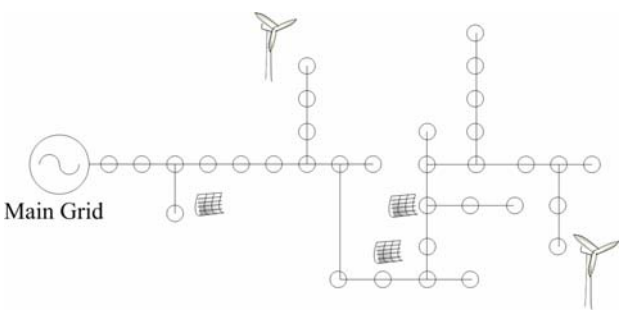

Figure 5: IEEE 34 bus system [17]

The valuation method is illustrated in four test scenarios each with its own level of renewable energy production, i.e. no renewable production (I), PV (II), wind (III) and a combination of both (IV). The outcome of the optimization procedure is a set of storage topologies and ancillary service incentives that are all Pareto optimal in the four described objectives. Visualizing this trade-off set can be done by taking the two principal components of the set, i.e. projection along two orthogonal axes of the set that exhibit the largest (normalized) variance. Some information is evidently lost by this reduction of dimensions, although in most cases the two principal components account for 80% or more of the variability as found in these scenarios as well. Figure 6 depicts the trade-off sets in all cases (dots) as well as the directions of all objective improvements. Case I shows the simple 'more storage equals more revenue' situation with little impact on voltage profile improvement. In Case III for example objectives can be more correlated to one another. Stronger correlation between objectives results in smaller angles in the PCA plots. The result of Case I resembles that of pure arbitrage on a power exchange. It must be stressed that objectives are normalized in these plots, i.e. average equals zero and variance one, so in comparing two situations the absolute values must be considered as well.

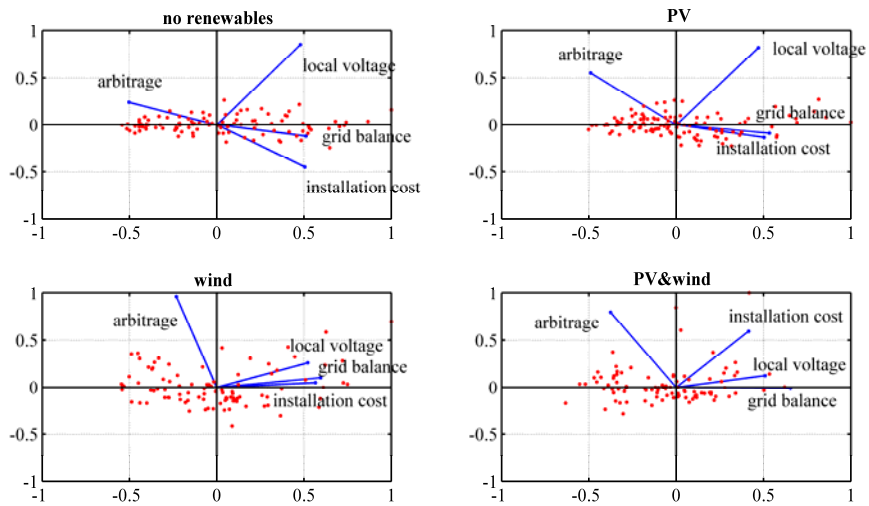

Figure 6: The correlation of four objectives in four test cases

V. Future work

An acknowledged benefit of electricity storage is the increase in reliability at the customer connection point. Reliability assessment in grids is mostly done by time sequential Monte Carlo simulations, often combined with variance reduction techniques to lower computational burden and have a faster convergence of power quality indices. It appears therefore straightforward to include reliability enhancement in the proposed optimization scheme by quantifying it in terms of a global index, e.g. SAIDI, SAIFI, EEN, etc…. The largest obstacles remain essentially the choice of reliability quantification and obtaining 'reliable' data of failure rates.
The method as proposed for now evaluates the impact of storage in the grid as it is, by introducing sufficient degrees of freedom in integration and operation. Interpretation of the objective correlations can give valuable information for storage investors and DSOs to come to a mutually beneficial situation when costs and benefits are correctly reimbursed. Future work will highlight this further.

VI. Conclusions

The list of potential benefits of electricity storage is widely known. A lack of knowledge however remains as to how these benefits are related to one another and what the global grid impact could be. A multi-objective optimization scheme is proposed in which both local optimal operation as global integration are analyzed. It is almost impossible to give general comments or rules of thumb for this optimal integration. For a specific case however the method gives insight in mutual beneficial trade-offs that can be achieved between storage operators and DSOs and in the potential impact of new policies.

References

[1] J. M. Eyer, J. J. Iannucci, G.P. Corey, "Energy Storage Benefits and Market Analysis Handbook," *Sandia Laboratories*, Report SAND 2004-6177, 2004
[2] B.G. Gorenstin, N.M. Campodonico, J.P. da Costa, M.V.F. Pereira, "Stochastic optimization of a hydro-thermal system including network constraints," *IEEE Transactions on Power Systems*, Vol. 7, Issue 2, May 1992
[3] D.K. Maly, K.S. Kwan,"Optimal battery energy storage system (BESS) charge scheduling with dynamic programming," IEE Proceedings on Science, Measurement and Technology, Vol. 142, Issue 6, November 1995.
[4] Pedram Mokrian, Moff Stephen, "A Stochastic Programming Framework for the Valuation of Electricity Storage," *26th USAEE/IAEE North American Conference*, September 24-27, 2006
[5] Rahul Walawalkara, Jay Apta, Rick Mancinib, "Economics of electric energy storage for energy arbitrage and regulation in New York," *Energy Policy*, Vol. 35, Issue 4, April 2007.
[6] R. Deb, "Operating Hydroelectric Plants and Pumped Storage Units in a Competitive Environment," *The Electricity Journal*, Vol. 13, Issue 3, April, 2000.
[7] F.D.J. Nieuwenhout, K. Visscher, G.J. Schaeffer, M.P.F. Hommelberg, J.C.P. Kester, "Feasibility of distributed electricity storage," *International Journal of Distributed Energy Resources*, Vol. 2, Issue 4, October - December 2006.
[8] Jukka V. Paatero, Peter D. Lund, "Impacts of Energy Storage in Distribution Grids with High Penetration of Photovoltaic Power," *International Journal of Distributed Energy Resources*, Vol. 3, Issue 1, January – March 2007.

[9] G.N. Bathurst , G. Strbac, "Value of combining energy storage and wind in short-term energy and balancing markets," *Electric Power Systems Research*, Vol. 67, No. 1, October 2003.
[10] Robert H. Lasseter, Paolo Piagi, "Extended Microgrid Using (DER) Distributed Energy Resources," *IEEE Power Engineering Society General Meeting*, Tampa, USA, 24-28 June 2007.
[11] Directive 2003/54/EC of the European Parliament and of the Council, "Concerning common rules for the internal market in electricity and repealing Directive 96/92/EC," 26 June 2003, http://eur-lex.europa.eu/en/repert/1230.htm
[12] E. Haesen, J. Driesen, R. Belmans, "Robust planning methodology for integration of stochastic generators in distribution grids", *IET Journal on Renewable Power Generation*, Vol. 1, No. 1, March 2007 , p. 25-32.
[13] E. Zitzler, M. Laumanns, L. Thiele, "SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization," *Evolutionary Methods for Design, Optimisation and Control with Application to Industrial Problems*, EUROGEN 2001.
[14] Jukka V. Paatero, Peter D. Lundmarkov, "A model for generating household electricity load profiles," *International Journal of Energy Research*, Volume 30, Issue 5, April 2006.
[15] Shi-Jie Deng, Wenjiang Jiang, "Quantile-Based Probabilistic Models for Electricity Prices," *Modelling Prices in Competitive Electricity Markets, Chapter 7*, Derek W. Bunn, John Wiley, 2004.
[16] J. Cardell, "Integrating Small Scale Distributed Generation into a Deregulated Market: Control Strategies and Price feedback," PhD dissertation, MIT, September 1997.
[17] W.H. Kersting, "Radial distribution test feeders," *IEEE Power Engineering Society Winter Meeting*, January 28 - February 1, 2001, http://ewh.ieee.org/soc/pes/dsacom/
[18] Energy Exchange Austria (EXAA), Spot Market data, http://www.exaa.at
[19] Royal Netherlands Meteorological Institute (KNMI), Hourly wind data, http://www.knmi.nl/samenw/hydra/
[20] Flemish regulator for electricity and gas (VREG), Synthetic electricity and gas load profiles of domestic and non-domestic users, http://www.vreg.be