Optimization and online decision making approaches to handle uncertainty in the energy sector

Allegra De Filippo

Department of Computer Science and Engineering, University of Bologna, Italy
allegra.defilippo@unibo.it

Abstract. The focus of this work is the development of optimization techniques and machine learning methods applied to the energy sector to address the challenge of online decision making under uncertainty. We propose a Virtual Power Plant (VPP) energy management system under uncertainty, based on a two-step optimization model that decides the minimum-cost energy balance at each point in time by integrating several types of energy sources, loads and storage devices. We are improving the second step of our model by developing a multi-stage online stochastic model able to react to unexpected event and then test it on real data of a large industrial plant. We plan also to apply machine learning techniques for forecasting flexibility and performing the whole range of predictions involved in the activities of a VPP in the industrial sector.

Keywords: online optimization, forecast uncertainty

1 Introduction

Energy networks will be more and more large-scale and interconnected systems requiring complex decision making in all phases. Even minor improvements from design to operational management can have a significant impact in economical aspects and energy efficiency. Optimization techniques have a long tradition in supporting planning and operational decisions in the energy sector; however, the current challenges call for a new generation of systems. This is due to the need of increasing both the scope and the granularity of the decisions including new factors like distributed generation by renewable sources and smart grids. This is extremely challenging because the models will necessarily be of huge size and simultaneously considering many different sources of complexity like nonlinear processes (gas and power flows, fuel energy production, ...), and uncertainty (energy demand, energy cost, renewable sources...). A key difficulty in optimization under uncertainty is in dealing with an uncertainty space for multi-period or multi-stage optimization models in large scale.

We focus on online optimization which requires to make decisions over time as the input is slowly revealed, without (complete) knowledge of the future by also incorporating stochastic uncertainty about the input. This uncertainty reduces over time, but often delaying decisions is either costly or impossible. We assume that the distribution of future uncertainty, or an approximation of it, is available for sampling, as is the case in applications based on historical data and predictive models. We also assume that the distribution of future uncertainty is independent of current decisions, which is also the case in a variety of applications.

The key research topics of this work are:

- Stochastic (and Robust) optimization to make decisions under uncertainty in the energy sector.
- *online* Stochastic optimization to address the challenge of online decision making under uncertainty with the analysis of assumptions by using historical sampling and machine learning techniques. We also focus on the predictive and prescriptive analytics to bridge the gap between the analysis of large-scale data and the making of relevant decisions in operations contexts.

2 Related Work

The progressive shift towards decentralized generation in power distribution networks has made the problem of optimal Distributed Energy Resources (DER) operation increasingly constrained, due to the integration of flexible (deterministic) energy systems combined with the strong penetration of (uncontrollable and stochastic) Renewable Energy Sources (RES). The integration of these resources into power system operation requires a major change in the current network control structure. This challenge can be met by using the VPP concept, which is based on the idea of aggregating the capacity of many DER to create a single operating profile to increase flexibility through the definition of approaches to manage uncertainty.

The integration of RES must be adequately addressed so as to manage uncertainty and to avoid affecting the operational reliability of a power system. Unit commitment (UC) is a critical decision process, which can be formalized as the problem of deciding the outputs of all the generators to minimize the system cost. The deterministic formulation of this problem may not adequately account for the impact of uncertainty.

For this reason, different approaches are used to manage UC under uncertainty [7]: 1) *Stochastic UC*, which is based on probabilistic *scenarios*. The basic idea is to find optimal decisions taking into account a large number of scenarios, each representing a possible realization of the uncertain factors. Stochastic UC is generally formulated as a two-stage problem [14] that determines the generation schedule to minimize the expected cost over all of the scenarios, while respecting their probabilities. The approach usually requires high computational cost for simulations. 2) *Robust UC* formulations, which optimize assuming a well-defined range for the uncertain quantities, instead of taking into account their probability distribution. The range of uncertainty is defined by the upper and lower bounds on the net load at each time period. Instead of minimizing the total expected cost as in stochastic UC, robust UC reduces the worst-case costs for all possible results of uncertain parameters [13]. 3) *Hybrid models* have been proposed in recent years to combine the advantages and compensate the disadvantages of pure robust and stochastic approaches [12].

Stochastic optimization [8] means, as explained above, that some random element are involved in the optimization (i.e. the uncertainty). In general, traditional optimization techniques assume complete knowledge of all data of a problem instance, i.e. all data are first collected and the optimization procedure is done offline [10, 11]. It is becoming increasingly clear that there are significant opportunities for optimization algorithms that make optimization decisions online. Decisions may have to be made before complete information is available. These observations have motivated the research on *online stochastic optimization* [5].

3 Model and results

We developed a two-step optimization model to be employed in the Energy Management System (EMS) of a Virtual Power Plant (VPP) to manage renewable sources uncertainty.

We considered that the integration of renewable sources in energy optimization models must be adequately addressed so as to manage uncertainty and to avoid affecting the operational reliability of a power system. In particular we analyze a case study based on a VPP. A typical VPP is a large industrial plant with high (partially shiftable) electric and thermal loads, renewable energy generators and electric and thermal storages. Optimizing the use and the cost of energy could lead to a significant economic impact. We propose a VPP EMS, based on a two-step optimization model that decides the minimum-cost energy balance at each point in time considering the following data: (optimally shifted) electrical load, photovoltaic production, electricity costs, upper and lower limits for generating units and storage units. The EMS minimizes the operational costs while fully covering the electric energy demand, avoiding the loss of energy produced by RES generators. The source of uncertainty (load demand and photovoltaic production) is handled with a robust approach and the system is implemented and tested using real data taken from the Electricity North West datasets[1].

The model is composed by two steps: the first (day-ahead) step is designed to optimize the load demand shift and to estimate the cost, and models the prediction uncertainty using a robust (scenario-based) approach. The second step is an online greedy algorithm implemented within a simulator that uses the optimized shifts from the previous step to minimize the operational real cost, while fully covering the optimally shifted energy demand and avoiding the loss of energy produced by RES generators.

We propose, in this work, the following main contributions: (1) a robust optimization approach for planning power flows to minimize the VPP expected

[1] http://www.enwl.co.uk/

cost and to obtain optimized load shifts in presence of forecast uncertainty; (2) the development of a real case study to test the model; (3) an assessment of the quality of our solutions in terms of the Expected Value of Perfect Information (EVPI), i.e. by comparing the actually obtained costs with the optimal expected costs that would be possible assuming perfect information.

A case study is used to illustrate that the first robust step of our model produces good optimized shifts that do not significantly deviate (in term of costs) from the model with no uncertainty. We compare results conducted over 100 input realizations and we can observe that we have a loss of result quality in the second step developed with a greedy heuristic. We plan to improve this second online step in the coming months.

4 Conclusion and future works

One of the main objectives of this work is to adequately integrate renewable sources so as to manage uncertainty. The assessment of uncertainty in the modeling of distributed energy systems has received considerable attention in recent works that apply machine learning techniques for forecasting flexibility of energy systems. Many studies have been done on the residential sector using support vector regression and neural networks [4,6] and some methods present promising results however it seems unlikely they may be implemented in real life in particular in the industrial sector. We plan to improve these methods in our model for future works.

In particular, we are improving the second online step of our VPP EMS model by developing a multi-stage online stochastic model [9] able to react to unexpected event. We plan to test our model on real data of a large industrial plant. We plan also to apply machine learning techniques for forecasting flexibility and to perform the whole range of predictions involved in the activities of a VPP in the industrial sector.

Our aim is to exploit the interaction between the predictive and prescriptive analysis: optimization systems traditionally have focused on a priori planning and are rarely robust to unexpected events. In recent literature [1–3] there are significant opportunities for optimization algorithms that make optimization decisions online. In practice, not all applications have an accurate predictive model of the future (for example, in some cases, only historical data is available). The research goal of the coming years is to be able to integrate machine learning and historical sampling in on-line advance algorithms to address this difficulty.

Online decision making under uncertainty represents a challenging problem: there is an increasingly need to dynamically adapt intelligent systems to uncertainties in order to produce high-quality decisions. We are working on online decision-making stochastic optimization models with the integration of machine learning and historical sampling to address this challenge.

References

1. Russell Bent and Pascal Van Hentenryck. Online stochastic and robust optimization. In *ASIAN*, pages 286–300. Springer, 2004.
2. Russell Bent and Pascal Van Hentenryck. Regrets only! online stochastic optimization under time constraints. In *AAAI*, volume 4, pages 501–506, 2004.
3. Peter AN Bosman and Han La Poutre. Learning and anticipation in online dynamic optimization with evolutionary algorithms: the stochastic case. In *Proceedings of the 9th annual conference on Genetic and evolutionary computation*, pages 1165–1172. ACM, 2007.
4. Richard E. Edwards, Joshua New, and Lynne E. Parker. Predicting future hourly residential electrical consumption: A machine learning case study. *Energy and Buildings*, 49:591 – 603, 2012.
5. Pascal Van Hentenryck and Russell Bent. *Online stochastic combinatorial optimization*. The MIT Press, 2009.
6. Rishee K. Jain, Kevin M. Smith, Patricia J. Culligan, and John E. Taylor. Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Applied Energy*, 123:168 – 178, 2014.
7. K. Jurkovi, H. Pandi, and I. Kuzle. Review on unit commitment under uncertainty approaches. In *2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pages 1093–1097, May 2015.
8. Kurt Marti. *Stochastic optimization methods*, volume 3. Springer, 2005.
9. Luc Mercier and Pascal Van Hentenryck. Amsaa: A multistep anticipatory algorithm for online stochastic combinatorial optimization. *Integration of AI and OR Techniques in Constraint Programming for Combinatorial Optimization Problems*, pages 173–187, 2008.
10. Mario VF Pereira and Leontina MVG Pinto. Multi-stage stochastic optimization applied to energy planning. *Mathematical programming*, 52(1-3):359–375, 1991.
11. Stein W. Wallace and Stein-Erik Fleten. Stochastic programming models in energy. In *Stochastic Programming*, volume 10 of *Handbooks in Operations Research and Management Science*, pages 637 – 677. Elsevier, 2003.
12. C. Zhao and Y. Guan. Unified stochastic and robust unit commitment. *IEEE Transactions on Power Systems*, 28(3):3353–3361, Aug 2013.
13. Q. P. Zheng, J. Wang, and A. L. Liu. Stochastic optimization for unit commitment, a review. *IEEE Transactions on Power Systems*, 30(4):1913–1924, July 2015.
14. Zhe Zhou, Jianyun Zhang, Pei Liu, Zheng Li, Michael C. Georgiadis, and Efstratios N. Pistikopoulos. A two-stage stochastic programming model for the optimal design of distributed energy systems. *Applied Energy*, 103:135 – 144, 2013.