Modelling of Distributed Energy Resources in Industrial Context Using Service Curves of Network Calculus

Alemayehu Addisu
METRON, UPEM
12-14 rue de l′Eglise
75015 Paris, France
Email: alemayehu.addisu@metronlab.com

Laurent George
UPEM, LIGM/ESIEE,
Cite Descartes, 5 bd Descartes,
77454, Champs sur Marne,
France
Email: lgeorge@ieee.org

Pierre Courbin
Léonard de Vinci Pole Universitaire
Technology Lab,
Paris La Defense, France
Email: pierre.courbin@devinci.fr

Vincent Sciandra
METRON
12-14 rue de l′Eglise
75015 Paris, France
Email: vincent.sciandra@metronlab.com

***Abstract*—In this paper, we consider an optimized consumption of energy produced by distributed energy resources (e.g., wind, solar, storage, ...) to match an energy demand in industrial microgrid context. In order to match the load with the supply, we need to optimize the selection of available resources based on some constraints such as energy costs and weather conditions. When an imbalance occurs, we consider buying energy from the main grid or spot market if there is a shortage. In case of surplus energy, we consider selling the excess on the spot market. To achieve our goal, we utilize a network calculus approach (specifically the concept of service curves) to model the energy resources. In this context, service curves provide a lower bound on the amount of energy production of the resources. Then, we propose different strategies and compare their performances against each other to minimize energy procurement costs. To apply our model, we consider a real case study of an industrial site located in France.**

Keywords - Network calculus, Service Curves, Distributed Energy resources, Microgrid

I. Introduction

Integration of renewable energy resources to an energy supply system is facilitated by the introduction of microgrids. The concept of microgrid was first proposed by Lasseter and Piagi [1]. A microgrid consists of Distributed Energy Resources (DERs), energy markets and energy storage systems (e.g., batteries, hydrogen tanks and Plug-in Hybrid Electric Vehicles (PHEVs)) [2]. The microgrid can be operated as a single system (island mode) with DERs and loads or it can be connected to a larger grid. Due to the introduction of IT to microgrids, a two-way communication of energy data between producers and consumers is made possible. This enhances the operational capability of the system. Su and Wang [3] provided overviews of microgrid technology, including energy management systems and benefits of microgrids.

A challenging aspect of DERs in the microgrid is that the energy produced by the renewable resources is intermittent. For example, the output of solar power systems changes frequently depending on the position of the sun and clouds. And also, wind power is subject to some of the same types of daily and seasonal variations. Due to these characteristics, integration of renewable resources into the grids at utility scale creates new operational needs. These conditions require new operating capabilities as a form of control system and modelling of resources in the microgrid.

In this context, we consider a model of the DERs to find a lower bound on their energy production by using service curves of network calculus. This helps us get the total energy production of each energy resource of the microgrid. Then, we want to satisfy the total demand by selecting an energy resource or combination of resources based on constraints such as energy costs.

Network calculus is an alternative to classical queueing theories. It was initially introduced by Cruz [4] for deterministic framework and then different researchers extended it into stochastic framework. The deterministic network calculus is used to compute deterministic (worst-case) bounds on performance metrics, while the stochastic version is used to additionally capture statistical multiplexing gain when some violations of the deterministic bounds are tolerable. Further contribution to network calculus was done by Le Boudec and Thiran [5]. Network calculus consists of concepts such as arrival, service curves and shapers [5]. They can help to transform a complex non-linear queueing system into an analytically tractable system using mathematical theories including convolution and algebras. The bounds can be conservative or violated with small probability [6]. Most of the applications of network calculus are in the context of computer and communication networks. For example, in [7], the authors used network calculus to analyse multi-hop fading communication channels and in [8], Georges et al. applied network calculus to determine whether a switched network may satisfy the time constraints of a real-time application.

Our motivation to extend network calculus theory to energy

978-1-4673-9795-7/15 $31.00 © 2015 IEEE
DOI 10.1109/CSCI.2015.81

management in a microgrid is that the theory can provide an analytical framework for different scenarios and its applicability to different research domains. Among the concepts of network calculus theory, we rely on the theories of service curves. In our context, we use service curves to model distributed energy resources of the power system. After that, we obtain the total energy production which is used to satisfy the total energy demand. When the demand is greater than the supplies, we can purchase energy from either the spot market or the main grid. Hence, our objective is to propose different strategies to minimize energy procurement costs.

The remainder of this paper is organized as follows. In section II, we provide basic notations on service curves and DER modelling. Then in section III, we detail our service curve model of distributed energy resources and description of our problem. Then in section IV, we provide experimental results and discussions. Finally, concluding remarks are given in section V.

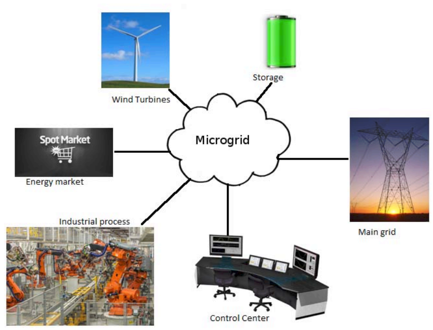


Figure 1. Microgrid components

II. Notations and DER Modelling

Developing clean energy and insuring energy safety have gained much attention from energy industry since the beginning of 21st century. At the center of clean energy, there are DERs. However, DERs impose challenges to integrate them into electricity grid due to their intermittent nature. In order to overcome the negative impact of DERs on power system, and maximize the potential of DERs, a concept of microgrid was proposed by Lasseter and Piagi [1] in 2004. A microgrid is a modern small-scale grid that can operate in "islanded" or grid-connected mode.

In the following section we discuss components of microgrid and modelling of the DER elements using service curves of network calculus.

A. DER modelling using Service curves

We first introduce basic notations of network calculus theory. The theory is based on a (min,+) algebra and it is used to model flows and services in a network with non-decreasing functions [5].

We denote by F a set of non-negative, wide-sense increasing functions, i.e.,

$$F = \{f(\cdot) : \forall 0 \leq x_1 \leq x_2, 0 \leq f(x_1) \leq f(x_2)\}$$

Then for two functions f and g, their (min,+) convolution under (min,+) algebra is defined as:

$$(f \otimes g)(t) = \inf_{0 \leq s \leq t} \{f(s) + g(t-s)\}$$

(min,+) convolution has a number of desirable algebraic properties: it is associative and commutative. Assume that $f(0) = g(0) = 0$, then $f \otimes g \leq min(f, g)$, with equality if both functions are concave. If the functions are convex and piecewise-linear, we can obtain $f \otimes g$ by putting end-to-end the different linear pieces of the individual service curves, sorted by increasing slopes [5].

The concept of service curve is used to abstract the details of packet scheduling [5] which requires a network to offer some guarantees to flows. We say that the network offers a $service\ curve\ \beta$ to flows if and only if: $R^* \geq R \otimes \beta$, where $R^*(t)$ is a cumulative output in number of bits in interval (0,t]. This is equivalent to say $R^*(t) - R^*(t_0) \geq \beta(t - t_0)$ for all $t \geq 0$, $t_0 \geq 0$ and $t \geq t_0$. For constant bit server (e.g., Generalized Process Sharing (GPS) [9]) that serves several flows with rate r, the service curve is $\beta(t) = rt$ [5]. It can be written in (min,+) algebra as: $R^*(t) \geq \inf_{0 \leq s \leq t} [R(s) + r(t-s)]$. More examples and detailed description of service curves are provided in [5], [10].

Before introducing service curves for each DER, we describe how to setup service curve functions. We use Concave Piecewise Linear (CPL) curves to define service curve functions. CPL curves allow us to represent a service curve function using a finite number of parameters. These curves are expressed in the form of affine functions $y = b + a * x$, where x is an independent variable. In [11], Sariowan used CPL curves to define service curves for performance guarantees in integrated service networks. In this paper, we define service curves to model the minimum amount of energy that a DER node provides. We can define a service curve $S_i(t)$ as:

$$S_i(t) = \alpha_i + \beta_i * t \tag{1}$$

where (α_i, β_i) are service curve parameters of energy resource i. This is to say that the DER node provides the amount of energy which is represented by its service curve $S_i(t)$.

In our context, we rely on service curves to model energy provided by DERs. The next section details modelling of wind and solar powers.

1) Wind power: To setup a service curve for wind power generation, we study the characteristics of wind turbines and their power production. Wind turbines generate electrical power by extracting kinetic energy from the air flow using rotors and blades. A typical wind turbine is characterized by its *power curve* [12]. In [13], Slootweg *et. al* described the relationship between wind speed and power extracted from wind speed.

Performing mathematical integration on extracted power over a specific time interval will give us *energy*(in kWh). From these sets of data, we can obtain the service curve parameters $(\alpha_{wind}, \beta_{wind})$ of wind power. Where α_{wind} is in kWh and β_{wind} is in kW.

2) Solar power: Solar photovoltaics (PVs) are arrays of cells containing a material, such as silicon, that converts solar radiation into electricity. Service curve parameters $(\alpha_{solar}, \beta_{solar})$ can be set the same way as wind power case.

3) aggregation: Different DERs can be aggregated to provide a single service curve that represents the total energy production. This can be seen as:

$$(S_1 \otimes S_2 \otimes \cdots \otimes S_N)(t) \tag{2}$$

where $S_i(\cdot)$ is a service curve of resource $i \in [1, .., N]$.

B. Storage

Energy storage devices are the main components of a microgrid which allow the smoothing of renewable energy outputs and the time-shifting of demand away from peak times. Common storage technologies in use today include mechanical, thermo-dynamic, electrochemical and electro-magnetic. Among electrochemical storage technologies, most common battery types are lead-acid and lithium-ion batteries [14].

A battery can be characterized by its maximum capacity C, Depth of Discharge (DoD), charging and discharge times, efficiency, etc. When the energies generated by wind turbines and/or solar panels are greater than the load for a particular time, the surplus energy is stored in the battery. Assume that $b(t)$ represents state of charge at time t, the charging process can be represented as:

$$b(t) = min[C, b(t-1) + [S(t) - D(t)]] \tag{3}$$

where C is the maximum capacity of the battery, $S(t)$ represents a system service curve as shown in equation 2 and $D(t)$ is the energy demand at time t.

In case of discharging the battery to fill the void between supply and demand, if there is enough energy in the battery, we discharge it using:

$$b(t) = min[C, b(t-1) - [D(t) - S(t)]] \tag{4}$$

This consideration assumes perfect batteries as described in [15]. There exist other research papers on modelling of storage systems. For instance, in [6] and [14], the authors used stochastic network calculus to model energy storage systems.

C. Spot market

An electricity spot market can be regarded as a market where the electricity can be sold or purchased at varying prices. There are two types of spot market: day-ahead and real-time markets. In real-time energy markets, the selling or buying of energy is done close to a real-time (e.g., in 15 minutes). However, in day-ahead energy markets, energy prices are announced to buyers and sellers a day before energy transaction. In Europe, EPEX (European Power EXchange) is a marketplace for day-ahead markets of electricity. EPEX calculates the offer and demand curves and their intersection for each hour of the following day (see Figure 2) [16]. It operates in Germany, France, Austria and Switzerland.

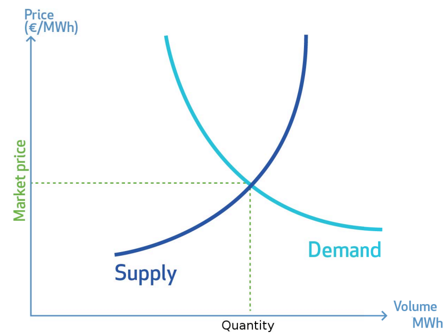


Figure 2. Energy supply and demand curve in the context of spot market

In the EPEX SPOT market, the volume of energy exists in very large amount (in GWh). Hence, there is no limit on amount of purchased energy from the spot market. If energy demand is higher than energy of wind, solar and storage, we buy energy from the spot market or the main electricity grid based on their costs. In case of surplus energy, we have an option of selling the energy on the spot market at market price.

D. Energy net cost

In our work, we consider energy net procurement cost to compare different strategies to be described in the next section. Annual net cost can be given as:

$$\sum_{t \in year} [Pr_{buy}(t) * E_{buy}(t) - Pr_{sell}(t) * E_{sell}(t)] \tag{5}$$

where $Pr(\cdot)$ and $E(\cdot)$ are selling/buying prices in €/MWh and sold/bought energy in MWh. When we consume local energy from wind, solar or battery, we assume that the energy price is zero.

III. Problem formulation

In the above section, we provided our approach of modelling the Distributed Energy Resources using service curves. In this section, we use the models to formulate our problem which is to balance demand and supply.

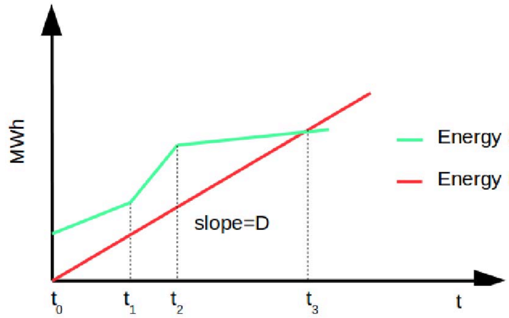


Figure 3. Demand and supply curves

We consider a constant energy demand D for a specific period and N distributed energy resources. Suppose that each resource $i = 1, 2, ..., N$ provides a service curve guarantee $S_i(\cdot)$. Then, the total energy demand is satisfied if

$$\sum_{i=1}^{N} S_i(t) \geq D \cdot t \tag{6}$$

The inequality 6 can be interpreted as the convolution of all the source service curves have to be greater than the demand curve. Using (min,+) convolution, the inequality 6 can be expressed as:

$$(S_1 \otimes S_2 \otimes \cdots \otimes S_N)(t) \geq D \cdot t$$

As shown in Figure 3, the cumulative energy demand is given by straight line $D \cdot t$. When the summation of energy provided by wind and solar is greater than the demand line (Equation 6), we say that the demand is met. Otherwise, we discharge the battery if there is enough energy. If the battery is unable to cover the shortage, we need to buy the energy shortage from either the spot market or the main grid based on the energy costs. We outline different strategies that minimizes energy procurement costs and enables us to use as much as possible local energy.

Our goal is to propose different strategies that minimizes the reliance on external energy sources and make use of local energy more often. In this way, the procurement costs are minimized. We provide three strategies and compare their performance against total net energy procurement cost. We outline the strategies in the following section.

A. Strategy 1: Sell excess energy

In this strategy, we would like to sell the excess energy which is a leftover after a demand is met. According to EPEX Spot, the possibility to sell energy on the spot market depends on the minimum energy volume available to be sold. The minimum is set to 1MWh. Therefore, if we have an excess energy greater than 1MWh for some period, we can sell it on the spot market at the market price. Otherwise, we store it in the battery for future use.

B. Strategy 2: Store excess energy

In this scheme, instead of selling the excess energy, we would like to store it for future use if the battery is not full. If the battery is full, there are two possibilities: either sell the excess energy if it is above 1MWh or otherwise dispose it. For bigger battery size, this condition cannot happen too often. However, for smaller battery sizes, if there are lower energy consumption, the user can opt to sell the excess and this can be another strategy. The strategy 2 also minimizes the net energy cost by providing zero-cost local energy from battery and wind. If the energy from battery and wind cannot meet the load, we buy from either the main grid or spot market that has lower cost.

C. Strategy 3: External energy to charge battery

The cost of energy on the spot market is cheap during some periods of the day. Charging the batteries during these periods can be a good strategy. We assume that the battery can start charging at the beginning of time slot of 1 hour length and can be ready at the end of the slot. We give charging precedence for local energy from wind and if the battery is not full yet, we can buy the energy from the spot market. Furthermore, we set a price limit that we would like to buy from the market. For example, If we set this limit to 20€/MWh, then we buy energy from the market whenever the price is under 20€/MWh. Under this strategy, we store more energy for future use.

IV. Simulation

In this section, we provide descriptions of our datasets and discussions on the results.

A. Description of datasets

1) Wind speed data: We obtained hourly average wind speed for 2014 from *Weather Underground* website [17]. We use the hourly average wind speed data for a wind plant located in France (refer to Figure 4).

2) Solar data: Base on PVWatts Calculator of National Renewable Energy Laboratory (NREL) [18], we retrieved hourly per unit ($25m^2$) solar PV energy generation data.

3) Storage: We consider different battery capacities ranging from [0,100]MWh.

4) Energy demand data: For energy demand (load) data, we obtained hourly energy consumption data from METRONLab servers [19]. These data represent a yearly energy demand of an industrial site located in France (see Figure 5).

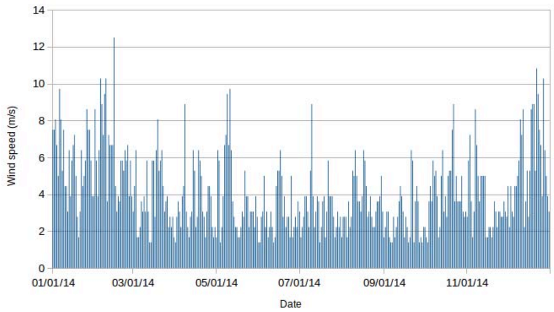


Figure 4. Hourly average wind speed data for 2014

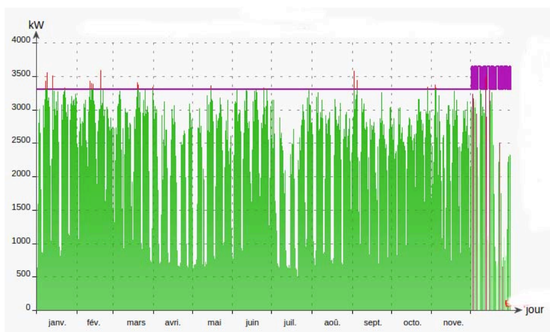


Figure 5. Load profile of the factory

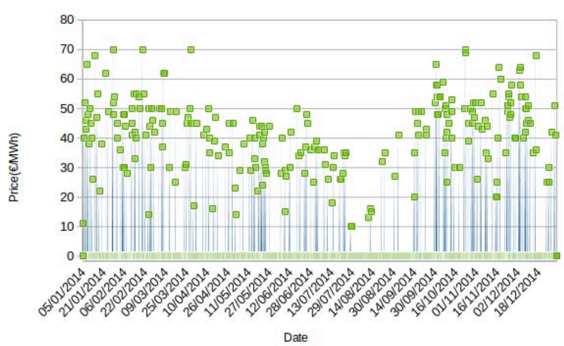


Figure 6. EPEX Day-ahead spot price data for 2014

5) Spot market data: We obtained hourly market price from EPEX Spot website [16]. These prices were published for day-ahead spot market type (see Figure 6).

B. Results and discussions

In this section, we provide different results on the performance of the strategies. First, we compare the strategies against the case of no strategies. From table I, we can see that the net cost is decreased from 621k€ to 396k€ which corresponds to 36% cost saving.

Next, we compare the performance of the strategies against

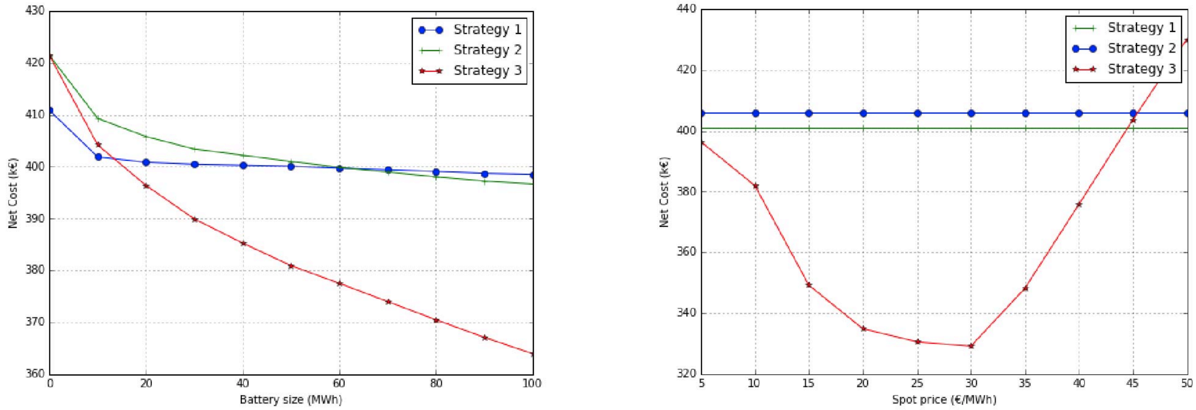
Strategies	Net cost (in k€)
No strategy	621.915
Strategy 1	400.845
Strategy 2	405.815
Strategy 3	396.387

Table I
COST COMPARISON OF DIFFERENT STRATEGIES (TAKING 40€/MWH FOR COST OF MAIN GRID ENERGY, BATTERY SIZE OF 20MWH FOR THE THREE STRATEGIES, AND SPOT MARKET PRICE LIMIT OF 5€/MWH FOR STRATEGY 3)

each other. Referring to Figure 7-a, we can see that for smaller batteries ($\leq$10MWh), strategy 1 is the best among the 3 strategies. This means that it is better to sell energy instead of storing it as the battery capacity is small. However, as the battery size increases, strategy 3 outperforms the others. This shows that for bigger battery sizes, it is good to buy energy from spot market and then store it. The stored energy could be used when the prices are high or load-shedding is required.

Figure 7-b shows the effect of different spot market prices on the performance of the strategies. They affect strategy 3 more than the others. This is because strategies 1 and 2 buy cheaper energy either from the spot market or the main grid. For strategy 3, an optimal point is at [30€/MWh, 329k€] which corresponds to a saving of 47%. These results are based on the assumptions such as perfect batteries and no loss of energy during conversions.

Finally, we would like to say few words on payback periods. One of the major hindering factors of microgrid development is the cost of microgrid components such as batteries, wind turbines, photovoltaic(PV) panels, AC/DC (Alternating current/ direct current) converters, etc [20]. In this paper, we consider the costs of batteries, wind turbines and PV cells. Nowadays, the cost of a lithium-ion battery ranges from \$400 - 600 per kWh [21]. Taking \$400/kWh, the 20MWh battery will cost \$8m which is enormous. However, for smaller battery capacity of 2MWh, the cost is \$800k (approx. 700k€) which is a significant decrease from the previous value. Concerning the cost of a wind turbine, Bolinder and Wiser [23] did a study on trends of wind turbine prices for the past decade (from 2000 to 2010). According to the authors, the trend for wind turbine prices declined an average of 20% from 2002 to 2010. They also pointed out that the price for a wind turbine ranges from \$900 - 1,400 per kW and the average cost is \$1,100/kW. For a wind turbine of 3MW, the average cost could be \$3.1m (approx. 2.72m€). For PV panels, 1W costs \$4.9[24]. For 100 units of 4kW rated PV panels, the cost could be approx. 1.72m€. The payback period for a combination of 3MW wind turbine and 2MWh battery is (2.72m€ + 0.7m€)/(621k€ - 411k€) = 16 years. However, for a combination of wind, solar and battery, the payback would be around 23 years. This shows that due to low irradiation in France, it is better to use a combination of wind turbines and battery.



(a) All strategies with different battery sizes and fixed spot price limit of 5€/MWh for strategy 3

(b) Effect of varying spot price with fixed battery capacity of 20MWh

Figure 7. Performance of the strategies

V. CONCLUSION AND FUTURE WORKS

In this paper, we adopted service curves of network calculus theories to model DERs in industrial context. We relied on service curve concepts for modelling the capacity of DERs. After modelling the resources, we set up three strategies for testing the benefits of our approach. We applied our approach on a use case based on real data of an industrial factory in France. We considered an offline algorithm that uses historical data of wind speed, energy consumption and spot market prices. Based on these data, we compared the performance of different strategies. Our results show that we could gain an energy cost saving upto 47% which can be very interesting to large industries. These results are gained through different simulations considering perfect conditions where energy losses during conversion in AC/DC are ignored. However, in real-world implementation, these factors could affect the results. As a future work, we would like to propose an online algorithm for energy management taking into account energy losses during AC/DC conversion.

REFERENCES

[1] R. Lasseter, and P. Paigi, *Microgrid: a conceptual solution*. Power Electronics Specialists Conference, 2004. PESC 04. 2004 IEEE 35th Annual, VOL. 6, 2004.

[2] C. Villareal, D. Erickson, and M. Zafar, *Microgrids: A Regulatory Perspective*. CPUC Policy & Planning Division, 2014.

[3] W. Su, and J. Wang, *Energy management systems in microgrid operations*. The Electricity Journal, Elsevier, VOL. 25, NO. 6, 2012.

[4] R. Cruz, *A calculus for network delay. I. Network elements in isolation*. Information Theory, IEEE Transactions on, VOL. 37, NO.11, 1991.

[5] J. Le Boudec, and P. Thiran, *Network calculus: a theory of deterministic queuing systems for the internet*. Springer Science & Business Media, 2001.

[6] K. Wang, F. Ciucu, Ch. Lin, and S. Low, *A stochastic power network calculus for integrating renewable energy sources into the power grid*. Selected Areas in Communications, IEEE Journal on, VOL. 30, NO.6, 2012.

[7] H. Al-Zubaidy, J. Liebeherr, and A. Burchard, *A network calculus approach for the analysis of multi-hop fading channels*. arXiv preprint arXiv:1207.6630, 2012.

[8] J. Georges, T. Divoux, and E. Rondeau, *Network calculus: application to switched real-time networking*. Proceedings of the 5th International ICST Conference on Performance Evaluation Methodologies and Tools, 2011.

[9] K. Parekh, and G. Gallager, *A generalized processor sharing approach to flow control in integrated services networks: the single-node case*. IEEE/ACM Transactions on Networking (ToN), VOL. 1, NO. 3, 1993.

[10] A. Bouillard, L. Jouhet, and E. Thierry, *Service curves in Network Calculus: dos and don'ts*. 2009.

[11] H. Sariowan, *A service-curve approach to performance guarantees in integrated-service networks*. 1996.

[12] C. Carrillo, O. Montaño, J. Cidrás, and E. Díaz-Dorado, *Review of power curve modelling for wind turbines*. Renewable and Sustainable Energy Reviews, VOL. 21, 2013.

[13] J. Slootweg, H. Polinder, and W. Kling, *Representing wind turbine electrical generating systems in fundamental frequency simulations*. Energy conversion, ieee transactions on, VOL. 18, 2003.

[14] Y. Ghiassi-Farrokhfal, S. Keshav, and C. LowRosenberg, *Toward a realistic performance analysis of storage systems in smart grids*. Smart Grid, IEEE Transactions on, VOL. 6, NO.1, 2015.

[15] K. Wang, S. Low, and Ch. Lin, *How stochastic network calculus concepts help green the power grid*. Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on, 2011.

[16] EPEX SPOT power exchange, `https://clients.rte-france.com`

[17] Weather Underground website, `http://french.wunderground.com/`

[18] PVWatts Calculator, `http://pvwatts.nrel.gov/pvwatts.php`

[19] METRONLab, `http://www.metronlab.com/`

[20] T. Burr, J. Zimmer, B. Meloy, J. Bertrand, W. Walter, G. Warner, and D. McDonald, *Minnesota Microgrids: Barriers, Opportunities, and Pathways Toward Energy Assurance*. 2013.

[21] L. Wood, J. Li, and C. Daniel, *Prospects for reducing the processing cost of lithium ion batteries*. Journal of Power Sources, VOL. 275, 2015.

[22] K. Wu, Y. Jiang, and D. Marinakis, *A stochastic calculus for network systems with renewable energy sources*. Computer Communications Workshops (INFOCOM WKSHPS), 2012 IEEE Conference on, 2012

[23] M. Bolinder, and R. Wiser, *Understanding trends in wind turbine prices over the past decade*. 2012.

[24] D. Feldman, *Photovoltaic (PV) pricing trends: historical, recent, and near-term projections*. 2014.