Assessing the Impact of Uncertainty of Input Data on the Executed Flexibility of the Residential Load in Smart Electricity Grids

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Large scale integration of distributed energy resources (DERs), with variable, intermittent, and partially dispatchable power output, increases the uncertainty of power systems. The increased uncertainty, in the distribution network imposes new technical challenges to the distribution system operators (DSOs) to operate the grid.

To ensure a reliable electricity supply in a grid with a large share of DER, system operators need to increase the flexibility of the power system [1]. At grid level, this can be done by reinforcing the transmission and distribution grids and/or investing in new energy storage infrastructures [2]. However, such developments involve long development delays (due to various regulatory and economic barriers) and are capital intensive [3], [4]. A more viable and cost effective solution is to utilize the flexibility that exists at the distribution level using demand response (DR) programs [5]. DR enables larger involvement of proactive consumers (i.e., prosumers) in the grid [6].

The DSO analyzes the historical data, to extract necessary information and predict future values, to make sound planning and operational decisions [7]. The ongoing transition in the energy sector casts doubt on the validity of historical data for planning the system of the future; On one hand, the historical data lacks any information about newly emerging actors with new roles, functionalities and financial objectives. On the other hand, the participation of the new actors in the energy system would result in new energy supply and demand patterns that are drastically difficult for the system operator to predict. Moreover, in the context of smart grids, the DSO requires data at building or household level. However, there is substantial uncertainty in the data at such low aggregation levels, because, energy consumption at such levels greatly depends on various uncertain and volatile factors, such as demographic, social and psychological characteristics of the consumers, as well as environmental parameters (e.g., ambient temperature and precipitation). As a result, the DSO needs other means to analyze the power system of the future.

Quantifying the potential flexibility of prosumers is investigated in literature using bottom-up models. These models use detailed information (e.g., physical characteristic of buildings, electricity consumption, consumers' behavior) to study the impact of implementing various DR strategies on flexibility enhancement [8]. When used for studying medium- and large-scale systems the computational time for such simulations becomes prohibitive. Another approach, is to use disaggregation methods [9] to determine the appliance contribution in the total electricity consumption of the households, and further, identify the flexible load of the consumers [10], [11]. Such data-driven models require smart meter data at appliance level for different types of consumers. The problem is, firstly that such data is not always accessible, due to legal (i.e., data privacy) and economic (i.e., smart meters and the ICT infrastructure are costly to install) reasons. Secondly, before installing smart meter infrastructure, it is almost impossible to approximate the potential flexibility that is available to different prosumers.

In the context of our research, we consider two main challenges the DSO has to deal with in this regard: 1) lack of information about the new actors (e.g., flexibility potential of prosumers), and 2) uncertainty of future data (i.e., load and price data). To address these challenges, we develop a data-driven framework, to assess the sensitivity of the DR to various sources of uncertainties. The framework contains a data analytics module, which processes the historical energy consumption and electricity market price data, and identifies the stochastic characteristics of the input data. The data analytics module also defines simulation scenarios to investigate the performance of the DR. The DR module solves an optimization problem that is formulated as a minimization of active power losses, by utilizing the potential flexibility prosumers can provide. We show that under certain assumptions, the active power loss minimization problem is equivalent to standard deviation minimization of the daily net energy consumption of prosumers. The optimization problem is solved subject to physical and economic constraints. It considers the fact that cost of energy for the prosumers after implementing DR remains less than or equal to its value before that.

We identify two sources of uncertainty in our proposed framework; 1) prosumers' preferences for providing flexibility, and 2) uncertainty of input data. To quantify the impact of these uncertainties on the DR, we use Uncertainty Quantifica-

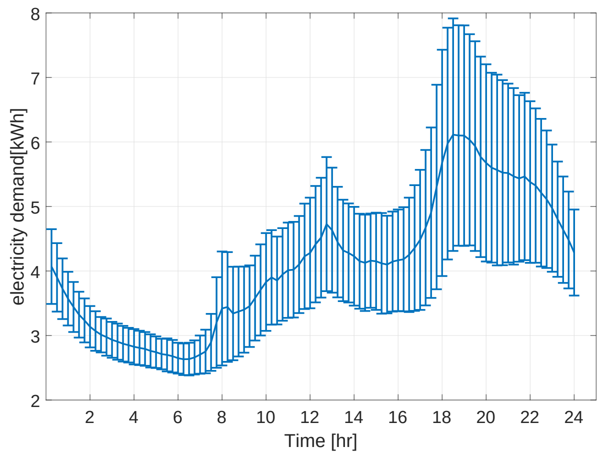

Fig. 1. Mean value and standard deviation of electricity consumption for each PTU for year 2014.

tion (UQ) techniques [12].

In our previous work, we investigated the sensitivity of the DR to different values of prosumers' preferences. We defined two parameters to reflect prosumers' preferences: downward flexibility (α^d), which is the maximum percentage of load that prosumers afford to reduce at each PTU, and load-shifting time window (ω^{tt}), which is the length of time window that prosumers allow the DR to shift their load. We analyzed nine scenarios on different values that reflect prosumers' preferences.

In our current work, we investigate the impact of uncertainty in the input data on the executed flexibility, for a given scenario on the prosumers' preferences. We test our approach for a case study of student housing complex in the city of Wageningen, the Netherlands. In this work, we use the aggregated data for 44 houses in the data set. We combine the consumption data with historical day-ahead (DA) market price data of the Scandinavian electricity market (Nord-Pool spot market). Figure1 presents load variation for every PTU (i.e., 15 min), in a period of one year. The solid line represents the annual average load per PTU. The error bars show the standard deviation of load per PTU in a year. One can observe two types of uncertainty; first the variation of load over a year, which is associated with long-run uncertainty, and second, is the variation of load over the 24 hours of the day (from one PTU to another), which is associated with short-run uncertainty.

In this work, we focus on short-run uncertainty in load, and we investigate its influence on the performance of the DR program. We considered three hypothetical case studies of load profile: mean-load, mean load plus standard deviation (high-load), and mean load minus standard deviation (low-load). For all case studies, we considered a same DA market price profile (i.e., the yearly average profile). The values for prosumers' preferences is set to $\alpha^d = 20\%$ and $\omega^{tt} = 23hr$ (maximum load shifting time window).

Results of this analysis show that, for the three case studies (i.e., high-load, mean-load, and low-load), implementing the DR program reduces the standard deviation of daily energy consumption to 65%, 71%, and 84% of its original value, respectively. It implies that the success rate of the DSO in minimizing active power losses (i.e., minimizing the standard deviation of the daily electricity consumption), strongly depends on the input data, and from there, on the level of uncertainty involved. More research is needed to identify the impact of other sources of uncertainty of the input data (e.g.,price) on the performance of the DR program.

Our proposed framework provides insight to the DSO about the sensitivity of the DR program to various sources of uncertainty, and from there, it helps the DSO improve the success rate of implementing DR in energy systems of the future.

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