Load Sensitivity-Based Demand Control: Impact on Load Forecast Error Reduction

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Abstract

The modern power system has an increasing amount of renewable generation units and modern loads such as e-vehicles. In comparison to the conventional power system with the majority of fossil-fuel power plants, the modern grids have higher intermittency and meanwhile less inertia. Therefore, more power flexibility is required to ensure and maintain the reliable operation of the grid. As a promising solution, the load sensitivity-based demand control utilizes the natural correlation between load power consumption and voltage magnitude, known as the load sensitivity. The control scheme shapes load power by actively modifying the load voltage magnitude within the range grid codes allow. Similar to the conservation voltage reduction, this control scheme can be conducted in substations with tap changers or solid-state transformers. The load sensitivity-based demand control does not rely on the active participation of customers or communication to every single device and thus protects user privacy and reduces communication complicity. This paper provides an initial assessment of how this control can help to reduce the day-ahead load forecast error based on the actual forecast data of Germany and the measured load sensitivity profile from a real apartment.

Index Terms

Load sensitivity, demand-side management, load forecast, power flexibility

I. Introduction

The fossil-fuel power plants dominated conventional power system allows for the scheduling of power generation and has larger system inertia. The modern power system is going “greener” with an increasing share of renewable generation units, which are highly weather-dependent and often connected to the grid through power electronic-based interfaces. Therefore, the modern system is facing challenges of high power intermittency and low system inertia. Meanwhile, the rapid increase of new types of electric loads such as e-vehicles amplifies the challenge. As the generation moves to the distribution level, demand-side management or smart distribution grids have gained more attention. These control schemes seek to provide power flexibility from the distribution grids to support the mains.

Many demand-side management solutions have been proposed, such as price-based schemes and direct load control. These strategies rely on the active participation of customers, and communication to every device and have gained resistance due to user privacy and acceptance. The load sensitivity-based demand control (LSDC) solves the problems by treating the loads as a black box. It does not require communication with each device and active participation of the user. The LSDC uses the correlation between load power and voltage magnitude (load voltage sensitivity) and frequency (load frequency sensitivity) to shape the power consumption by actively controlling the magnitude or/and frequency within a limited range, within which loads under control can operate normally. In [1], household appliances were tested under a large frequency range of 50±10Hz and all the loads can operate normally within a variation of ±5 Hz. Frequency sensitivity values of residential loads are identified experimentally and provided in [2]. A back-to-back converter and a conventional transformer are used as the connection between the Medium Voltage (MV) and Low Voltage (LV) grid [3]. The frequency on the MV side is supported by modifying the LV side power according to the frequency sensitivity. This paper focuses on controlling the voltage magnitude and assumes a frequency very close to the nominal value.

The Voltage Sensitivity-Based Control (VSBC) shapes the load power by controlling the voltage magnitude. This concept is quite similar to the conversation voltage reduction (CVR), a widely applied technique in substations since the 1970s [4]. CVR focuses mainly on energy saving using the correlation between long-time energy and voltage while VSBC focuses on power shaping using the correlation between power and voltage [5]. CVR lowers the magnitude to save energy and VSDC increases or decreases the magnitude to change power. This can be done through tap changers [6] or solid-state transformers (SST) [7], [8].

In the modern power system, load forecasting plays a vital role in ensuring reliable and economical operation. The estimation error is very costly, for instance, increasing the forecast error by 1% can cause an estimated additional 10 million pounds of operating cost for one utility in the UK [9]. Therefore, various estimation approaches have been proposed to improve the accuracy of the power prediction [10], [11], [12], [13]. To further reduce the forecast error, this paper seeks to shape the actual demand towards the forecast power through the VSDC. This can be a cost-efficient solution as no additional equipment is required for the VSDC. The voltage sensitivity can be determined from data recorded by the existing smart meters and the control actions can be conducted with existing tap changers. This paper provides an initial assessment of the effect of LSDC on reducing the day-ahead estimation error. To the authors' best knowledge, such analysis has never been done before. The assessment is based on real day-ahead forecasts and actual power consumption data of Germany in 2023 and 2024. This work focuses on the contribution of applying the VSDC on only residential loads and uses the voltage sensitivity data of a real apartment.

II. Load Sensitivity and Sensitivity-Based Demand Control

A. *Load Sensitivity and Perturbation-Based Identification Method*

Load sensitivity quantifies how the power consumption varies under voltage magnitude or frequency variations. This paper assumes nominal frequency and focuses only on the power-to-voltage sensitivity. The load-to-voltage sensitivities are defined as follows:

$$\mathrm{n_{pv}(t)} = \left.\frac{\mathrm{dP(t)/P_0(t)}}{\mathrm{dV(t)/V_0(t)}}\right|_{\mathrm{V(t)=V_0(t)}} \approx \frac{(P-P_0)/P_0}{(V-V_0)/V_0} \tag{1}$$

$$\mathrm{n}_{qv}(\mathrm{t}) = \left.\frac{\mathrm{dQ(t)}/Q_0(\mathrm{t})}{\mathrm{d}V(\mathrm{t})/V_0(\mathrm{t})}\right|_{V(\mathrm{t})=V_0(\mathrm{t})} \approx \frac{(\mathrm{Q}-Q_0)/Q_0}{(\mathrm{V}-V_0)/V_0} \tag{2}$$

V is the Root Mean Square (RMS) value of voltage. n_{pv} and n_{qv} denotes the active and reactive power-to-voltage sensitivity respectively. The voltage sensitivity quantifies the influence of voltage magnitude changes with ratios of power change (in per unit) to magnitude change (in per unit), where (P_0, V_0) and (Q_0, V_0) are the rated points to compute the per unit (p.u.) values. The rated voltage and frequency can be chosen arbitrarily and are not necessarily the nominal values. As we are interested in controlling the active power here, the rest of the paper will focus only on the active power-to-voltage sensitivity.

As an example, $n_{pv} = 2$ implies that 1% voltage variation will lead to 2% power consumption variation. If a substation has an $n_{pv} = 2$, by reducing the voltage magnitude by 10% through a tap changer, the total power consumption is reduced by 20%.

Apart from describing the relationship between power and voltage magnitude mathematically. The active power-to-voltage sensitivity, referred to as voltage sensitivity in the rest of the paper, also has physical meanings. According to a worldwide systematical survey conducted by the CIGRE Working Group C4.605 in 2010, the exponential load model is one of the most frequently used static load models [14], [15]. The exponential load model with voltage-dependency can be expressed as follows:

$$\mathrm{P} = P_0 \cdot \left(\frac{V}{V_0}\right)^{m_{pv}} \tag{3}$$

The load model has only one unknown parameter m_{pv}. Substituting (3) into (1), we see that the exponent m_{pv} is exactly the voltage sensitivity n_{pv}. Therefore, $n_{pv} = 0$ represents a constant power load, $n_{pv} = 1$ represents a constant current load, and $n_{pv} = 2$ represents a constant impedance load.

This paper analyzes the impact of load sensitivity-based demand control using the voltage sensitivity profiles of an apartment obtained from our previous work. The dataset offers load sensitivity profiles of common residential loads [16]. The load sensitivity is determined using the perturbation-based method. First introduced in [17], the perturbation-based method allows for the identification of load sensitivity experimentally. It introduces tiny artificial variations in voltage and meanwhile records the power response. Assuming that the exponential load model describes the load behavior accurately, and therefore, $P_0/\left(V_0^{n_{pv}}\right) = P_k/\left(f_k^{n_{pv}}\right)$. The load sensitivity can be calculated from measurements as below [2], [17]:

$$n_{pv} \approx \frac{(P_k - P_{k-1})/P_k}{(V_k - V_{k-1})/V_k} \tag{4}$$

where the subscript k denotes the current and $\mathrm{k}-1$ the previous calculation step. [2] provides detailed explanations on how load power-to-frequency sensitivities are identified through sinusoidal artificial variations. The same method is used to determine the voltage sensitivity used here, the only difference is that the artificial variation is applied to voltage magnitude instead of frequency.

B. *Power Forecast Error Compensation with Load Sensitivity-Based Demand Control*

The load forecast is essential for the normal functionality of the modern power system. The estimation error is costly to compensate for. As a cost-efficient solution, here we apply voltage changes to loads to modify the actual power consumption according to the forecast. Usually, loads are designed to operate normally within ±10% voltage magnitude variations to the nominal value without causing significant influence on users[5]. Based on the power estimation error and the identified voltage sensitivity, the voltage variation and the compensated actual power can be calculated as below:

$$\Delta V^* = \left(P_{fcst} - P_{act}\right)/\left(P_{act} \cdot n_{pv} \cdot w\right) \quad \text{with} \quad \Delta V^* \in [-0.1,\ 0.1] \tag{5}$$

$$\mathrm{P_{comp}} = \mathrm{P_{act}} \cdot \left(1 + \mathrm{n_{pv}} \cdot \Delta \mathrm{V}^* \cdot\ \mathrm{w}\right) \tag{6}$$

w represents the percentage of loads applied VSDC. P_{fcst} and P_{act} represents the forecast and actual power respectively. P_{comp} is the actual power with compensation.

An initial verification of the accuracy of the perturbation-based identification method and the feasibility of the sensitivity-based demand control is provided with tests on a microwave oven [18]. A simple proportional controller is used to set the load voltage magnitude according to the desired power and identified voltage sensitivity. An average error of 0.18% was achieved.

III. Assessment of the Effect of VSLC on the Reduction of Load Forecast Error

In this section, we provide an initial assessment of the reduction in day-ahead load forecast estimation error in Germany using voltage sensitivity from residential loads. First, the voltage sensitivity of an apartment over 24 hours is provided, based on which sensitivity profiles of 100 and 10,000 apartments are generated. Based on the sensitivity profiles of apartments and considering different shares of the controllable load, the reductions in the load forecast error Germany in one day of the entire are estimated. In the end, an overview of the day-ahead load forecast error over a year in Germany is provided to show the wide applicability of the compensation results.

C. *Load Voltage Sensitivity Profiles over a Day*

1) Load sensitivity of an apartment over 24 hours: In our previous work, a 5-hour measurement is conducted on a 60m^2 apartment to mimic the high demand and low demand phases of a household over a day. The identified voltage sensitivity and power profiles are provided in [16] in the apartment repository. Here the original 5-hour data is extended to a 24-hour profile: the low-demand phase is extended to the sleeping phase (22:00-06:00), out-of-home phase (07:00-17:00), and rest at home phase (20:00-22:00), by repeating the one-hour measurement data. The two high-demand phases remain the same, one in the morning (06:00-07:00) and one in the late afternoon (17:00-20:00). The obtained 24-hour profiles of the voltage sensitivity n_{pv} and the corresponding rated power P_0 are shown in . The original voltage sensitivity data has a time resolution of 15 seconds. Since the day-ahead load forecast data has a time resolution of 15 minutes, the averaged voltage sensitivity with a 15-minute resolution is calculated and marked in red. The rated power is the total 3-phase power consumption of the apartment. In the low-demand phases, the power consumption and voltage sensitivity change slightly. This is caused by the switch between the cooling and standby mode of the fridge and freezer. In reality, this periodic behavior will take place with lower frequency, e.g. 4-6 hours.

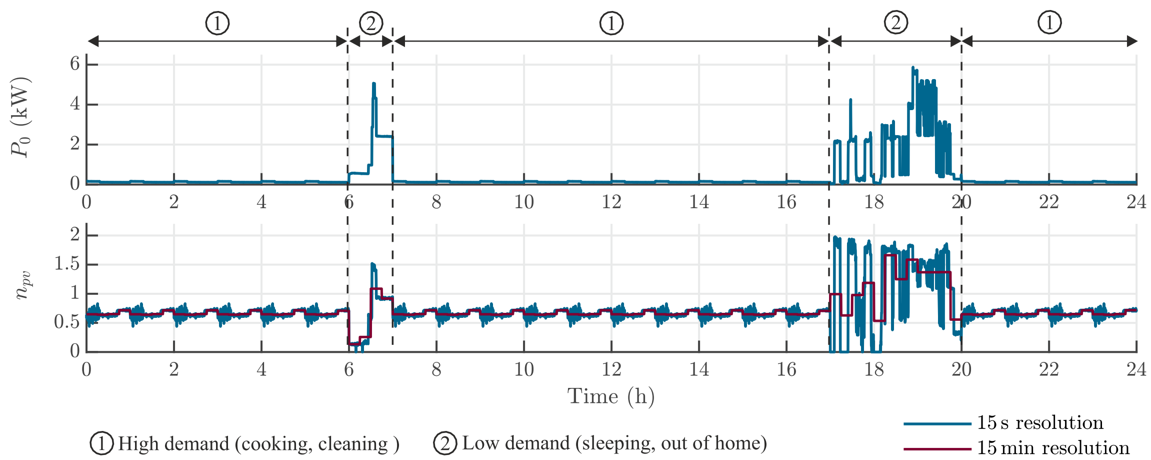

Fig. 1 Power and load sensitivity profiles of an apartment over 24 hours.

2) Aggregated voltage sensitivity: The advantage of the load sensitivity in [16] is that it allows for aggregation of voltage sensitivity using the provided dataset. The voltage sensitivity of a load aggregation consisting of n loads can be calculated using the equation below:

$$n_{pv,\mathrm{agg}} = \frac{\sum_{i=1}^{i=n}\left(n_{pv,i} \cdot P_{0,i}\right)}{\sum_{i=1}^{i=n} P_{0,i}} \tag{7}$$

$n_{pv,\mathrm{agg}}$ denotes the aggregated voltage sensitivity. $n_{pv,i}$ and $P_{0,i}$ is the voltage sensitivity and the corresponding rated power of the i-th load.

Assume that all the apartments have the same load sensitivity profile but have different time shifts of ±2 hours. Voltage sensitivity profiles of 100 and 10,000 apartments are aggregated with (7) and presented in Fig. 2. It can be seen that the becomes smoother as the number of apartments increases. the voltage sensitivity value remains around 0.6 for low demand and rises to 0.9 and around 1.5 for demand peaks. Therefore, when considering a large number of residential loads and assuming a ±10% voltage magnitude variation range, 6% to 15% of the total power consumption can be controlled by applying the VSDC.

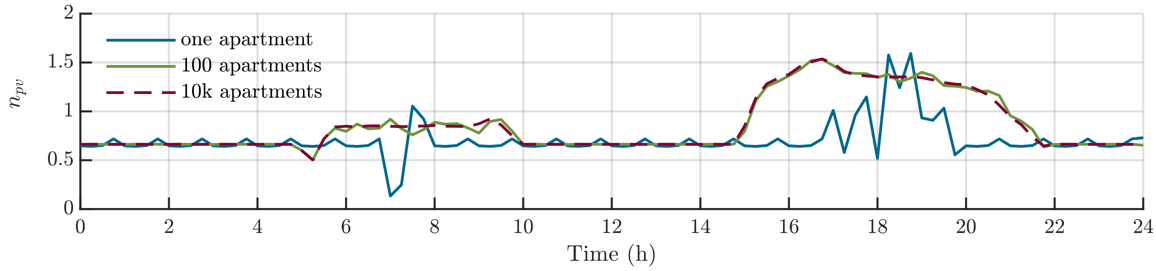

Fig. 2 Aggregated active power-to-voltage sensitivity profiles over 24 hours of one apartment, 100 and 10000 apartments in 15-minute time resolution.

3) Load forecast error compensation: Fig. 3 presents the day-ahead load forecast (top subplot in green) and the actual power consumption (top subplot in blue) of Germany 0n 2024.May.07 provided by entsoe [19]. The actual power consumption is controlled by the VSDC to follow the forecast power as much as possible. Assume that the residential load consists of 25% of the total power consumption in Germany [20] and VSDC is applied to all the residential loads, the compensation results are presented by the yellow dashed lines. The voltage sensitivity profile of 10,000 apartments is used here. As shown in the bottom subplot, the relative estimation error is reduced to 0 for more than half of the day and the maximum error is reduced from 5% to 2.5%. The voltage variation is limited to ±10%. The red dotted lines present the compensation results of applying VSDC to 50% of loads. The forecast error is maintained below 1% and achieved 0 for 80% of the day.

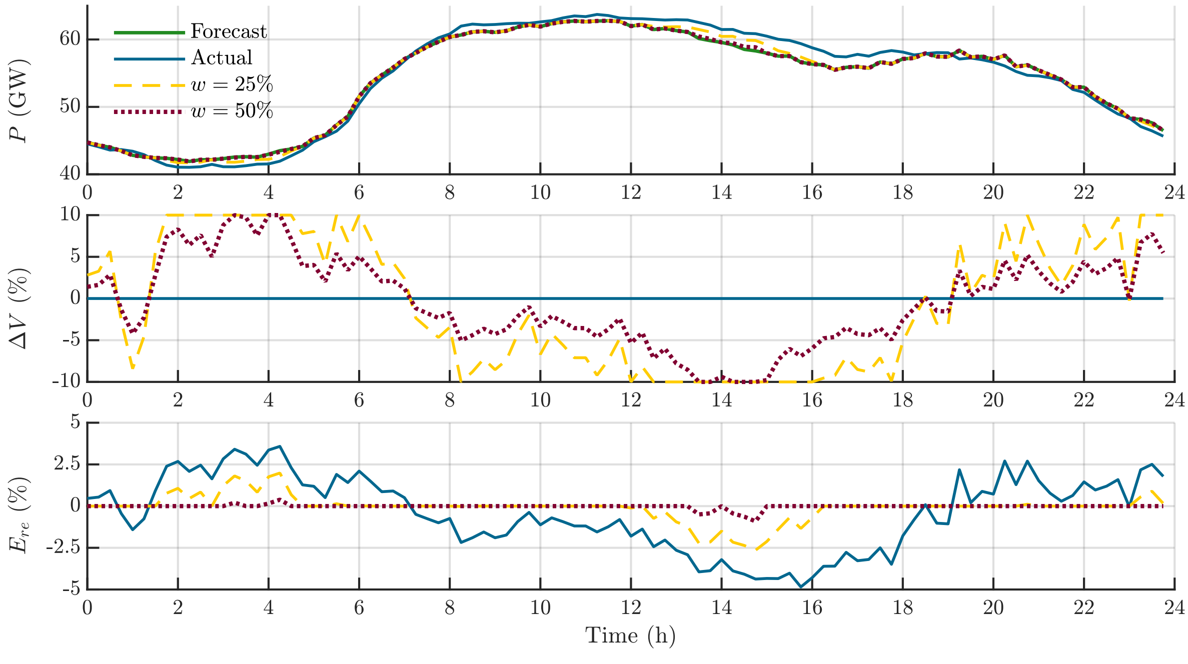

Fig. 3 Day-ahead load forecast of Germany on 2024.May.07 and the compensation results by applying VSDC to 25% or 50% of the loads.

4) Overview of German day-ahead estimation error in 2023: The compensation results based on the data on 2024.May.07 shows that the VSDC can effectively reduce the forecast error. To see if a similar effect can be achieved on other days, an overview of the forecast error during 2023 is provided in *Fig. 4 Overview of German day-ahead relative estimation error in 2023.*Fig. 4. The error is below 5% most of the time, and therefore similar effect can be achieved in most of the days.

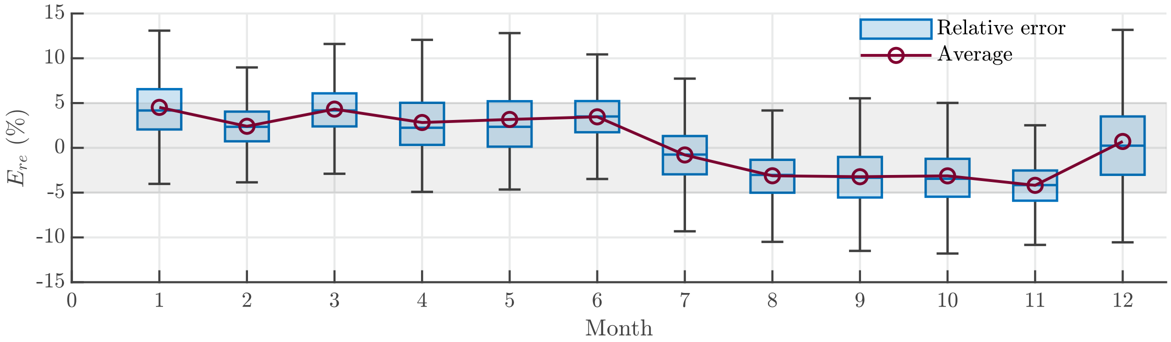

Fig. 4 Overview of German day-ahead relative estimation error in 2023.

IV. Conclusion

This paper estimates the effect of the VSDC control to reduce the day-ahead load forecast error. The voltage sensitivity profile of an aggregation of residential loads (10,000 apartments) is generated based on measurement data of one apartment. The aggregated voltage sensitivity varies between 0.6 and 1.5 during the day. Based on the voltage sensitivity profile, VSDC is applied to have the actual power follow the forecast as much as possible. The maximum allowed voltage magnitude variation is 10%. Real load forecast data of Germany is used to assess the effect. By applying VSDC to 25% of the load, the estimation error on 2024.May.07 is maintained to 0 in half of the day and the peak error is reduced from 5% to 2.5%. By applying VSDC to 50% of the load, the estimation error is maintained to 0 over 80% of the time and the maximum error is reduced to 1%. The same effect can be achieved also on most days in 2023. Therefore, VSDC can reduce the day-ahead load forecast effectively.

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