Uncertainty Quantification in LV State Estimation Under High Shares of Flexible Resources

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Abstract—The ongoing electrification introduces new challenges to distribution system operators (DSOs). Controllable resources may simultaneously react to price signals, potentially leading to network violations. DSOs require reliable and accurate low-voltage state estimation (LVSE) to improve awareness and mitigate such events. However, the influence of flexibility activations on LVSE has not been addressed yet. It remains unclear if flexibility-induced uncertainty can be reliably quantified to enable robust DSO decision-making. In this work, uncertainty quantification in LVSE is systematically investigated for multiple scenarios of input availability and flexibility utilization, using real data. For that purpose, a Bayesian neural network (BNN) is compared to quantile regression. Results show that frequent flexibility activations can significantly deteriorate LVSE performance, unless secondary substation measurements are available. Moreover, it is demonstrated that the BNN captures flexibility-induced voltage drops by dynamically extending the prediction interval during activation periods, and that it improves interpretability regarding the cause of uncertainty.

Index Terms—Bayesian neural network, low-voltage network, quantile regression, state estimation, uncertainty quantification.

I. INTRODUCTION

In light of the European effort to reach carbon neutrality by 2050, distribution networks (DNs) must undergo radical changes. Traditionally designed for the supply of consumers based on centralized generation, DNs turn into carriers of volatile and often bidirectional power flows [1]. Key drivers are the increasing deployment of variable distributed generation, as well as the proliferation of electric vehicles (EVs), heat pumps and residential storage. To balance consumption and generation in renewable-based power systems, it is widely acknowledged that more local consumption flexibility is required [2]. However, controllable distributed energy resources (DERs) may react to price signals with a sudden change of power consumption, resulting in higher coincidence factors in DNs dominated by such resources [3]. As a consequence, transformer or line protections could systematically be triggered, or unacceptably high voltage deviations occur. Since large parts of the DN are unobserved, distribution system operators (DSOs) require techniques for reliable and accurate low-voltage state estimation (LVSE) in order to (i) improve awareness about the potential negative side effects of flexibility utilization and distributed generation, and (ii) be able to mitigate any potential operational problems.

For conventional state estimation (SE), network topology and line parameters must be known. Moreover, since LVSE constitutes a mathematically underdetermined problem, pseudo measurements are typically required to account for low meter coverage [4]. A widely considered approach to overcome these shortcomings is machine learning [4]–[6], whose feasibility and high estimation accuracy have been extensively demonstrated [7]–[9].

A relatively small number of works have investigated the topic of probabilistic LVSE so far. Importantly, the influence of frequent flexibility activations on reliability and accuracy has not been sufficiently addressed. Moreover, it remains unclear whether estimation uncertainty introduced by flexibility can be reliably quantified to support DSO decision making, especially under varying levels of real-time data availability.

A. Related work

A number of works propose the use of neural networks (NNs) for real-time LVSE. For example, [7] proposes and validates the use of a NN, utilizing only real-time secondary substation information. The application is seen as a real-time bus voltage estimator, with smart meter (SM) data being available with a latency of one day. The authors of [10] also propose the use of a NN for estimating voltage magnitudes based on the same input, but do not use real data. Further, the authors stressed that model performance is sufficient, largely because of the relatively simple topology that lacks long side branches, and the lack of significant amounts of photovoltaic (PV) in-feed.

However, given the high variability of low-voltage (LV) network states and the increasing penetration of DERs, a probabilistic approach seems more suitable compared to a deterministic output. The authors of [11] use quantile NNs to provide probabilistic forecasts of the states of an LV network. However, a high degree of observability is assumed (known voltage and bus injections), and focus is given to the model’s forecasting abilities. Further, it is shown that EV charging creates large uncertainty, which the authors mitigate by assuming full knowledge of the EV charging start time and duration by the DSO.

Ref. [12] proposes a data-driven probabilistic LVSE based on an analog search technique and kernel density estimation. This approach relies on finding similar past patterns, and it
assumes real-time information from the secondary substation and voltage values from a number of LV buses, while validation is performed by assessing the impact of varying levels of PV penetration. The authors of [13] apply a variation of weighted least squares (WLS) for probabilistic SE. However, a series of real-time measurements is assumed to be available, and hourly data is used without considerations for flexibility activation.

In [14], a deep learning approach to Bayesian SE is proposed. The authors propose to first learn the distribution of bus injections from SM data. Based on samples drawn from the learned distributions, a traditional feed-forward NN is trained for the minimum mean-squared-error estimation of the system state. Due to the application of a deterministic regression model, the proposed approach is not inherently probabilistic. The work does not consider uncertainty quantification, and it compares results only on deterministic error metrics. Moreover, no flexible resources are considered. The authors in [15] propose a deep belief network for pseudo measurements modeling. Based on an extended WLS estimator, the probability density function of system states is inferred. However, the work assumes partial real-time knowledge of voltage states, and only medium voltage (MV) states are estimated.

B. Contribution and paper structure

The literature review shows that most works on LVSE do not consider probabilistic approaches. Moreover, effects of varying levels of input information and flexibility usage on the estimation and uncertainty quantification performance are rarely studied. In this work, a Bayesian neural network (BNN) is applied for probabilistic estimation of multiple LV bus voltages. The BNN is selected as it constitutes an inherently probabilistic approach, combining benefits of Bayesian uncertainty quantification and the predictive power of NNs. The main contributions of this work are as follows:

- Systematic evaluation of the influence of different flexibility usage and input information scenarios on accuracy and uncertainty of LVSE
- First application of a BNN on LVSE and comparison to a quantile regression (QR) benchmark
- First work considering and discussing epistemic and aleatoric uncertainty for probabilistic LVSE.

The remainder of the paper is structured as follows. In Section II, the use of a BNN for LVSE is motivated and a theoretical description of the applied model and its implementation is provided. Section III presents the experimental setup, including the dataset, flexibility scenarios and feature sets (FSs), as well as the applied performance metrics. In Section IV, results are presented and discussed, followed by a conclusion and a view on future work in Section V.

II. Method

This section first motivates the selection of a BNN. Next, the theoretical background and implementation are described.

A. Model selection

Accurate SE is the basis for the decision-making process of DSOs. However, even an accurate estimator may result in large inaccuracies under specific or new circumstances, such as a certain time of the day or rare social events. Under these conditions, a deterministic estimator fails silently, affecting the DSO decision-making process and potentially impacting critical decisions. In contrast, a probabilistic estimator can capture prediction uncertainty. By expressing what, when and why it does not know, such an estimator increases interpretability of predictions. Thus, incorporating uncertainty quantification in LVSE allows for risk-aware DSOs network operation.

Uncertainty can be classified into aleatoric (data) and epistemic (model). Aleatoric uncertainty is introduced by randomness in the process. In case of LVSE, this randomness is given by factors such as measurement errors and random consumer behavior. Adding to this type of uncertainty, a given substation measurement can correspond to a variety of load realizations and thus LV states, making the mapping of measurements to unobserved states non-unique. Epistemic uncertainty comprises of model structure and parameter uncertainty due to lack of knowledge. In the LVSE problem, this is given for example by data non-stationarity. If a model is only trained on winter months, it will encounter high epistemic uncertainty when predicting summer months, since input features are out-of-distribution. A fundamental difference between epistemic and aleatoric uncertainty is the fact that only the former can be reduced through additional information. To account for total uncertainty in LVSE, a model capable of capturing both components is required.

While quantifying estimation uncertainty is seen as an important requirement, accurate predictions are indispensable. As presented in Section I-A, multiple works have demonstrated the predictive power of NNs for LVSE. However, most of the available models are not able to represent uncertainty.

BNNs constitute a new direction in machine learning [16]. By connecting Bayesian statistics and deep learning, BNNs combine the benefits of Bayesian uncertainty quantification with the predictive power of NNs. In contrast to traditional NNs, model parameters of BNNs are not fixed. Instead, every weight and bias is represented by a conditional probability distribution, representing the uncertainty of the respective parameter. Predictions are generated through posterior inference. By directly sampling from the probabilistic parameters, BNNs are inherently probabilistic, instead of deterministic, models.

B. BNN description

Let $X_{\text{train}} = \{x_1, \ldots, x_{N_{\text{train}}}\}$ and $Y_{\text{train}} = \{y_1, \ldots, y_{N_{\text{train}}}\}$ be the training input and output data, respectively, with $N_{\text{train}}$ being the number of training samples. The BNN can be formulated as

$$\hat{y}, \sigma^2 = f_{\text{BNN}}(x),$$

where $W = \{W_1, \ldots, W_{N_L}\}$ are model parameters and $N_L$ the number of network layers. To consider aleatoric uncertainty, the output of the model is an estimate of both the predictive mean $\hat{y}$ and variance $\sigma^2$. To account for epistemic uncertainty,
a prior distribution is placed over $W$. In this work, a Gaussian prior $\mathcal{N}(0, I)$ is applied since Gaussian priors for BNNs are known to provide the benefit of regularization \[17\]. The posterior distribution $p(W | X_{\text{train}}, Y_{\text{train}})$ over the model parameters, given the training data $\{X_{\text{train}}, Y_{\text{train}}\}$ is calculated by Bayes rule. The predictive distribution for a new observation $x$ is obtained by marginalizing over the posterior distribution $p(W | X_{\text{train}}, Y_{\text{train}})$ according to

$$p(y | x, X_{\text{train}}, Y_{\text{train}}) = \int p(y | x, W)p(W | X_{\text{train}}, Y_{\text{train}})dW.$$  \hspace{1cm} (2)

Due to the non-linearity and non-conjugacy of NNs, the true posterior is typically intractable. By minimizing the Kullback-Leibler (KL) divergence between $p(W | X_{\text{train}}, Y_{\text{train}})$ and a surrogate distribution, the posterior is approximated. In this work, variational inference was used as inference algorithm for approximating the posterior. The surrogate distribution in this case is $\mathcal{N}(\hat{\theta}, \hat{\sigma}^2)$. To allow for simultaneous output of $\hat{y}$ and $\hat{\sigma}^2$, and thus also include aleatoric uncertainty, the loss function in Eq. (2) of the BNN is formulated as

$$L_{\text{BNN}}(\theta) = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} ||y_i - \hat{y}_i||^2 + \frac{1}{2} \log \hat{\sigma}_t^2.$$  \hspace{1cm} (3)

To take epistemic uncertainty into account, multiple predictions of $\hat{y}$ and $\hat{\sigma}^2$ for input $x$ are required. Note that every prediction is based on a new set of sampled model parameters $\hat{W}_t$. The predictive mean is estimated with

$$\mathbb{E}(y) \approx \frac{1}{N_{\text{sample}}} \sum_{t=1}^{N_{\text{sample}}} f_{\text{BNN}}(x),$$  \hspace{1cm} (4)

where $N_{\text{sample}}$ denotes the number of stochastic forward passes through the BNN. The total predictive uncertainty, composed of an epistemic and aleatoric term, is approximated with

$$\tilde{\text{Var}}(y) \approx \left[ \frac{1}{N_{\text{sample}}} \sum_{t=1}^{N_{\text{sample}}} \hat{y}_t^2 - \left( \frac{1}{N_{\text{sample}}} \sum_{t=1}^{N_{\text{sample}}} \hat{y}_t \right)^2 \right]^{\text{epistemic}} + \frac{1}{N_{\text{sample}}} \sum_{t=1}^{N_{\text{sample}}} \hat{\sigma}_t^2.$$  \hspace{1cm} (5)

In this work, all investigated datasets are split into a training, validation and test set. A detailed explanation of the datasets, including input features and output variables, follows in Section III. Unless explicitly defined differently, the partition is 80/10/10. The selection of model structure and hyperparameters is realized based on the validation loss. For all datasets, the smallest validation loss is achieved by using Adam optimizer, tanh activation function, two hidden layers and a batch size of 64. The number of required epochs and units in the hidden layers varies in the range 2000-10000 and 5-12, respectively. The selected models are retrained on the respective training and validation data. Depending on the dataset and input features, the number of trainable parameters varies between 3780 and 26766.

III. EXPERIMENTAL SETUP

This section first describes the considered real network and load dataset, and explains the creation of the various flexibility usage and input information scenarios. Thereafter, metrics used for evaluating the LVSE performance are introduced.

A. Network and used dataset

The network used in this study is a real suburban MV-LV network located in Bornholm, Denmark, and is depicted in Fig. 1. It consists of six 10/0.4 kV secondary substations, all connected to a single primary 60/10 kV substation, whose high voltage side is taken as the reference voltage and is set to 1 pu. The network serves a total of 564 residential customers. A detailed model of the LV network of secondary substation SubS is shown in Fig. 1 while the remainder are modelled as PQ buses that represent the aggregated active and reactive power of all customers connected to the respective substation.

In this work, real 5 minute average active and reactive power measurements from a large number of residential customers on Bornholm are used. Data was collected during the EcoGrid 2.0 project \[21\] and also includes flexibility activation of heating loads, as a result of experimental demonstration of a local flexibility market \[21, 22\]. Project participants are randomly assigned to the leaf nodes below SubS, and to the aggregated PQ profiles of the other secondary substations. This approach was followed because during the project only a small portion of project participants were connected to the depicted network. Time span of the study is the full year 2018.

B. Creating datasets for network states

SM data is assumed to become available to the DSO with a daily delay. Depending on infrastructure and DSO practice, voltage values may also be extracted by SMs. If this is the case, a historical dataset can be created that contains all relevant voltage values. If this information is unavailable, an accurate network model is needed to construct this dataset by using SM consumption data and running power flows.

However, in most cases DSOs have no real-time observability below the secondary substation level. The objective is to provide a probabilistic estimation of such LV states, and more specifically in this study, for voltages at nodes 1 to 6, marked on Fig. 1 given different flexibility utilization scenarios and varying levels of information availability to the DSO. The network model and its accuracy have been validated with real network measurements. Since no voltage measurements are available from the SMs, AC power flow was used to obtain the network states, which serve as ground truth.

C. Flexibility scenarios

1) S1: original data: This scenario considers the original residential profiles dataset, and customers are assigned randomly to the leaf nodes of the LV grid and the other five secondary substations. S1 presents a case with mild flexibility utilization.
2) S2: original data and EVs below adjacent substations: In this scenario the customer placement of S1 is kept, but EVs are added on the five adjacent secondary substations of SubS. EV profiles are taken from [3] and it is assumed that users perform smart charging with the objective of minimizing their costs based on retail prices, which follow the day-ahead spot prices of Danish zone DK2. S2 presents a case with significant use of flexibility, which potentially adds randomness and reduces the correlation between the considered LV nodes and the primary substation.

3) S3: original data and EVs below all substations: In the third scenario, an EV performing smart charging also is added to each customer under SubS. S3 presents a case with high flexibility-induced load variability in the examined network below SubS, potentially complicating voltage estimation.

D. DSO information availability

Observability in LV networks is still rather limited. This work assesses how different levels of DSO information availability affect the performance of probabilistic SE, for each of the aforementioned three flexibility scenarios. Below three FSs with increasing data availability are described.

1) FS1: low availability: The DSO has access to past customer SM data (with a delay of 24 hours), weather data and calendric features (like weekday vs weekend indicators and time of the day). Additionally, the retailer prices are used, which is beneficial for scenarios S2 and S3 (smart charging). FS1 assumes zero DSO real-time observability and the used information can be readily available to every DSO without the installation of additional devices.

2) FS2: medium availability: In FS2 it is assumed that real-time measurements from SubP are available, which is not an unusual operational practice. Therefore, primary substation PQ values are considered as additional features on top of FS1 to construct FS2. Note that adding voltage values from SubP was found to add a negligible benefit to the performance of the models and was thus omitted.

3) FS3: high availability: The high availability case FS3 assumes that the DSO also monitors in real time the secondary substation and thus PQ and voltage values from SubS are added as features on top of the ones from FS2.

E. Evaluation

In this work, the BNN is benchmarked with QR, which is a straightforward method to conduct probabilistic state estimation that showed good performance in many applications [24]. The performance of the models is evaluated for each flexibility scenario (S1, S2 and S3) and each FS (FS1, FS2 and FS3) on the test dataset. For evaluation of the point estimation performance root mean square error (RMSE) is used. The popular Pinball and Winkler scores are considered for assessing the reliability, sharpness, and resolution of the probabilistic estimation. These metrics are calculated for each considered network state $j \in \mathcal{J}$ individually. In Section IV their average, minimum and maximum value are reported. $y_{j,t}$ is the actual value of network state $j$ at the evaluated time step $t$ (out of $n$ steps). $\hat{y}_{j,t}^q$ is the expectation of the predicted value. Note that this expectation corresponds to the median for QR and the mean for the BNN. Finally, $\hat{y}_{j,t}^q$ is the predicted $q$-th quantile. RMSE is defined as

$$RMSE_j = \sqrt{\frac{\sum_{t=1}^n (y_{j,t} - \hat{y}_{j,t}^m)^2}{n}}, \quad \forall j \in \mathcal{J}. \quad (6)$$

The Pinball loss function is given by

$$Pinball_j = \begin{cases} 0, & y_{j,t} \geq \hat{y}_{j,t}^q \\ (y_{j,t} - \hat{y}_{j,t}^q), & y_{j,t} < \hat{y}_{j,t}^q \end{cases}, \quad (7)$$

The average Pinball score for all $n$ steps is calculated for $q = 0.01, \ldots, 0.99$, with a lower value indicating better performance. Finally, Winkler score for a prediction interval (PI) $1 - \alpha$ is given by

$$Winkler_j = \begin{cases} \delta, & y_{j,t} \in \left[\hat{y}_{j,t}^-, \hat{y}_{j,t}^+\right] \\ 2(y_{j,t} - \hat{y}_{j,t}^q) / \alpha + \delta, & y_{j,t} < \hat{y}_{j,t}^q \\ 2(y_{j,t} - \hat{y}_{j,t}^q) / \alpha + \delta, & y_{j,t} > \hat{y}_{j,t}^q, \end{cases} \quad \forall j \in \mathcal{J}, \quad (8)$$

where $\hat{y}_{j,t}^-$ and $\hat{y}_{j,t}^+$ represent the lower and upper PI bounds, respectively. $\delta = \hat{y}_{j,t}^+ - \hat{y}_{j,t}^-$ and $\alpha = 0.1$ because a 90% PI is considered. A lower Winkler score implies a better PI.

IV. RESULTS

In this section the voltage estimation performance of the BNN under varying input feature and flexibility scenarios is evaluated and compared to a QR benchmark. In Subsection IV-A a qualitative evaluation is presented, followed by a quantitative assessment in Subsection IV-B. In Subsection IV-C the behavior of aleatoric and epistemic uncertainty is evaluated over a period of 10 months.

A. Qualitative evaluation of the voltage estimation

Fig. 2 shows the output of the BNN for a 14 hours period of bus voltage 4 under three levels of available information (FS1-FS3). Case S3 is considered, where substantial flexibility activations occur in the examined network below SubS. This is evident during periods 23:00-00:00 and 01:00-02:00, where large load increases occur due to EV charging, leading to low voltage values. For all FSs, aleatoric uncertainty is dominating, which can be explained by the comprehensive training dataset.
However, an increase of the epistemic uncertainty can be noticed during flexibility activations. This can be explained by a lack of knowledge, as they constitute only a small subset of the training data. For all FSs the BNN understands that uncertainty during flexibility activations is higher, resulting in an extended PI. However, for FS1 the model entirely misses the first voltage drop. Under FS1, no real-time network states are considered. It can be concluded that FS1 is not sufficient to estimate flexibility-driven voltage drops. By incorporating primary (FS2) or secondary (FS3) substation measurements the model provides PIs which successfully capture the first voltage drop, as the increased consumption which causes them is reflected on the substation’s power and voltage. An additional advantage of including secondary substation measurements can be seen from the tighter PI.

Next, only FS2 is considered, which is the typical scenario for most DSOs. In Fig. 5 results are depicted for the same period under the three flexibility usage scenarios (S1-S3). In all scenarios epistemic uncertainty is almost entirely reduced by the BNN learning process. This leads to the conclusion that 11 months of training data is sufficient to exploit available information. Remaining uncertainty is mainly introduced by randomness. In S1 load variability and flexibility use are limited. Thus, the BNN is able to provide good voltage estimation with a very tight PI. Similar results are obtained under S2. Visual inspection let assume that frequent flexibility activations below adjacent substations have small impact on the estimation. A quantitative evaluation follows in Subsection IV-B. For S3 substantial flexibility is active in the examined LV network. The wider PI indicates that estimations are less accurate. Moreover, an increase of the PI is noticed during flexibility activations. The high PI resolution allows the BNN to successfully capture the voltage drops.

B. Quantitative evaluation and benchmark comparison

1) Point estimation performance: The results in terms of RMSE accuracy for the different flexibility scenarios and FSs are shown in Fig. 4. The scaled RMSE values are plotted, with unity corresponding to an error of 0.0106 pu.

As assumed, point estimates improve with the level of observability (FS1 to FS3) in all flexibility scenarios. For S3 the decrease of RMSE between FS1 and FS2 is comparatively large, as without real-time network measurements both the BNN and QR cannot accurately capture the frequent flexibility activations in the LV network under consideration (see Fig. 2 (a)). Thus, the inclusion of primary substation information reduces RMSE significantly by 42%. As assumed from the qualitative evaluation, S1 and S2 show similar point estimation performance. However, a large relative RMSE increase can be noticed for S3. The large presence of flexibility activations in the estimated LV network increases load variability and
uncertainty, complicating voltage estimation. Another finding is the superior performance of the BNN compared to the QR for all flexibility scenarios and FSs. On average, the BNN improves RMSE by 10.3%.

2) Probabilistic estimation performance: By considering Pinball and Winkler score, the probabilistic estimation performance is evaluated for reliability, sharpness and resolution. In accordance with the point estimation performance evaluation, the scores are shown in Fig. 5 for S1-S3 and FS1-FS3. Values are scaled to a Pinball score of 0.00328 pu and a Winkler (90\%) score of 0.0478 pu, respectively.

A comparison between S1 and S2 shows that both the BNN and QR for all FSs provide credible PIs also in a scenario with frequent flexibility activation below adjacent secondary substations. Although for FS2 both models, compared to S1, show a performance decrease in the range of 5%, it can be concluded that frequent flexibility activations below adjacent substations only slightly increase randomness, and thus barely deteriorate the correlation between primary substation measurements and bus voltages in the examined LV network. By including secondary substation measurements (FS3) this effect can be fully mitigated. In contrast, for frequent flexibility activations in the investigated LV network (S3) both scores indicate a strong performance decrease for all FSs. However, for S3 the performance gain of the BNN by including secondary substation measurements (FS3) is comparatively large. While for S1 and S2 Pinball decreases by approximately 10 percentage points, a decrease by 22 percentage points is achieved in S3. A similar behavior can be derived from Winkler (90\%). As a result, for FS3 the BNN is able to keep both scores in a comparable performance range as for S1 and S2 with FS1 and FS2. It can be concluded that, especially under frequent flexibility activations in the same LV network, incorporating secondary substation measurements adds great value to probabilistic LVSE. Moreover, although Fig. 5 shows a strong relative performance decrease for S3, from Fig. 2 it can be seen that already for FS2 the BNN provides credible PIs that successfully capture sudden voltage drops.

Another finding is that the considered deterministic and probabilistic performance metrics (see Fig. 4 and 5) show...
a similar behavior. Therefore, the BNN outperforms the QR benchmark across all scenarios, also in terms of probabilistic SE. The average performance improvement for Pinball is 17.2 % and for Winkler 13.4 %. In this context, it should be considered that the large size of the training dataset allowed to reduce epistemic uncertainty to a negligible part (see Fig. 2). In cases of less training data or more frequently changing conditions, such as grid topology changes or newly added EV fleets, it can be assumed that the BNN by capturing both aleatoric and epistemic uncertainty has an even stronger advantage.

C. Evaluation of uncertainty behavior

To shed light on the behavior of aleatoric and epistemic uncertainty under varying conditions, the BNN was trained on January and February data, and used to estimate bus voltage for the remaining 10 months of the year. Note that this is a showcase which intentionally does not consider model retraining. In Fig. 6 both uncertainty types are shown for S1 and FS2. In accordance with the previous findings (see Fig. 2), epistemic uncertainty is low for a recently trained model. However, large peaks can be noticed, which correlate with solar radiation and result from lack of PV generation in the training data. Between April and October, additionally, an increasing trend of epistemic uncertainty is visible. This results from shifting away from the training data, and is induced by higher ambient temperatures. In practice, frequent retraining would keep epistemic uncertainty small during the entire year. From November on, epistemic uncertainty approaches zero again, as data moves towards the distribution of the training set. Due to little PV generation, no peaks occur in December.

Aleatoric uncertainty decreases between April and October. In fact, it exhibits a strong correlation with substation loadings, which are lower during this period because of lower heating demand. The fact that aleatoric uncertainty is higher for a recently trained model shows that, in contrast to epistemic uncertainty, frequent retraining cannot reduce it as it stems from randomness rather than a lack of knowledge.

The following conclusions can be drawn. For a recently trained model, aleatoric uncertainty is highly dominant, justifying the application of models for LVSE capable of capturing it. However, without the epistemic counterpart, uncertainty induced by sudden or ongoing changes is not quantified, which can be seen from the PV-induced peaks and increasing trend, respectively, in Fig. 6. As such changes are present in LV networks, a model which additionally considers epistemic uncertainty is beneficial for LVSE, both for improved estimation accuracy, but also for better interpretability. While sudden peaks are an indicator for unknown events, an increasing trend of epistemic uncertainty indicates retraining need. Thus, by providing accurate quantification of both uncertainties, the BNN is seen as a valuable approach for LVSE.

V. CONCLUSION

In this work, uncertainty quantification in LVSE is investigated for various flexibility usage scenarios. For that purpose, a BNN capable of capturing both epistemic and aleatoric uncertainty is implemented and compared to a QR benchmark. Estimation and uncertainty quantification performance are systematically evaluated from a qualitative and quantitative perspective, and for multiple scenarios of input information availability and flexibility utilization, using real data. Results show that flexibility activations below adjacent secondary substations only have minor impact on LVSE, while activations in the same network decrease performance significantly. However, it is also shown that including secondary substation measurements allows retaining an acceptable degree of performance. By dynamically extending the PI during flexibility activation periods, the BNN is able to capture flexibility-induced voltage drops, enabling a more reliable LVSE. Moreover, it shows superior performance compared to the QR benchmark for all considered cases. By considering and differentiating between epistemic and aleatoric uncertainty, it improves interpretability, as it provides insights in occurrence of unknown events or retraining need. Future work will be directed towards applying the BNN for uncertainty quantification in LV state forecasting.

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