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Echo State Network Based Smart Meter Data-driven Short-term Voltage Forecasting for Future Power Grids

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***Abstract*—Future power grids are expected to host high penetrations of low-carbon technologies such as rooftop photovoltaics (PVs), electric vehicles (EVs), and energy storage systems. The increasing integration of these technologies can introduce significant voltage deviations in low-voltage (LV) distribution networks. This paper proposes a data-driven, real-time voltage forecasting method based on Echo State Networks (ESNs), chosen for their computationally efficient recurrent neural network architecture, enabling fast training. Unlike many deep learning approaches that require metaheuristic optimization or signal preprocessing to improve forecasting, the proposed ESN model uses only smart meter data, specifically, active and reactive power measurements, together with prior voltage estimates, to forecast node voltages one step ahead. The model is evaluated using one-minute resolution smart meter data from a real residential household equipped with both PV and EV systems within an LV feeder. Results show that the ESN achieves high forecasting accuracy, with most errors within ±2 V, and significantly improves computational efficiency, averaging just 0.03 seconds per training run. These advantages make the ESN a promising tool for enabling dynamic grid management strategies in future distribution networks.**

***Index Terms*—Echo State Networks, low-carbon technologies, power distribution networks, smart meters, voltage forecasting.**

I. Introduction

The global transition to low-carbon power systems is driving a rapid increase in the penetration of distributed energy resources (DER), including rooftop solar photovoltaics (PVs), plug-in electric vehicles (EVs), and residential energy storage systems. While these technologies contribute to decarbonization, they also pose significant operational challenges for low-voltage (LV) distribution networks, particularly in maintaining voltage levels within statutory limits [1]. To manage these challenges, distribution network operators (DNOs) typically impose static export limits on prosumers based on worst-case assumptions, which constrain the output of DERs such as rooftop PVs and residential batteries [2]. Similarly, low-carbon loads like EVs and heat pumps may be subject to power import limitations or controlled charging during periods of grid congestion or voltage instability. Although this approach ensures network safety, it often leads to underutilization of network capacity, curtailment of prosumer generation, and restricted operation of flexible demand-side technologies. A more flexible alternative is the Dynamic Operating Envelopes (DOEs), which sets time- and location-specific limits that reflect actual network conditions [3]. In practice, these limits can be updated in near real-time and communicated to prosumers' devices, enabling more efficient and flexible use of DERs. As real time approaches, providing more frequent and fine-grained forecasts enables DOEs to more accurately reflect network capability and support higher DER hosting levels [2]. However, their effective implementation relies on accurate, near-real-time forecasting of node-level voltages across the network.

Data-driven voltage estimation has emerged as a scalable and low-cost alternative to traditional model-based methods, which rely on detailed network models and computationally intensive power flow calculations [4]. Instead of explicitly modeling the grid, this approach uses historical measurements, typically from smart meters, to learn the statistical relationships between power measurements and node voltages through machine learning techniques [5]. This enables voltage estimation without the need for conventional power flow analysis. As advanced metering infrastructure (AMI) becomes more widespread, these data-driven methods are increasingly

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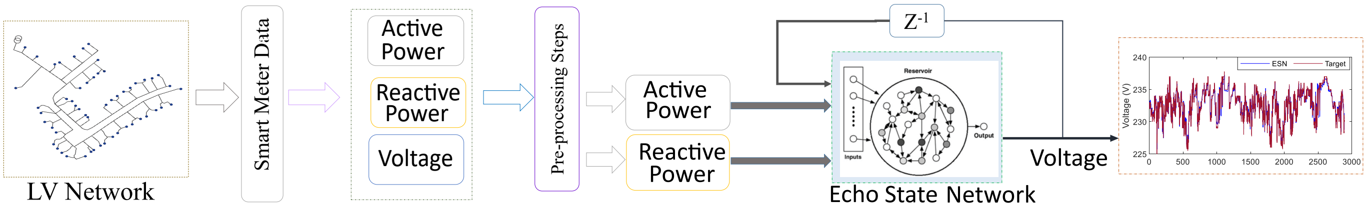

Fig. 1. The proposed ESN-based voltage forecasting framework.

viable. For instance, Bassi et al. in [5] employed an artificial neural network (ANN) trained on AMI data to estimate LV node voltages from active and reactive power measurements. The findings demonstrated that a conventional single-hidden-layer neural network (NN) is most suitable for short-term operational tasks, such as real-time PV curtailment, while a multi-input multi-output NN architecture is better suited for long-term planning applications, including PV and EV hosting capacity analysis. It was also shown that once trained, these data-driven models provide significantly faster voltage estimations compared to traditional power flow calculations. Similarly, Balduin et al. in [6] demonstrated that data-driven models can significantly reduce simulation time compared to conventional power flow calculations. ANN-based models achieved the highest speed-up in larger grids and the lowest forecasting error of below 0.1%, while linear regression and k-NN models were effective for smaller networks. In contrast, the long short-term memory (LSTM) network showed the least performing accuracy among the models evaluated. In [1] and [7], the Single Candidate Optimizer (SCO) was integrated into the Extreme Learning Machine (ELM) to mitigate overfitting and improve computational efficiency. It was shown that this integration significantly reduced the computation time of the smart meter data–driven model without compromising accuracy, enabling near-real-time voltage forecasting.

Ferdowsi et al. in [4] employed standard feedforward NNs for LV voltage estimation, training them with synthetically degraded data to handle measurement noise. Multiple ANNs were developed for different grid configurations, and a configuration identification unit was introduced to detect the active topology in real time and switch to the corresponding model. In [8], an active learning strategy is proposed to reduce training simulations by iteratively selecting the most informative operating points based on model uncertainty. The performances of ANNs, support vector machines (SVMs), and random forests (RFs) are compared for PMU-based voltage stability prediction in transmission systems. The results show that RF and SVM models benefit most from data reduction while maintaining high accuracy, whereas ANNs require larger datasets to perform well. Afifi et al. in [9] integrated linear and deep learning models into a hybrid ARIMA–LSTM framework to improve EV charging load forecasts. This combination outperformed both ARIMA and LSTM when used individually. Xiao et al. in [10] proposed an LSTM-based dynamic state estimation method for PV-rich distribution networks, which incorporates PV forecasts from real-time measurements and meteorological data to estimate node voltages and phase angles. While effective, the approach relies on detailed network models and complex training. Zhang et al. in [11] proposed a hybrid deep learning approach for voltage spatial-temporal perception in EV-enriched distribution networks, combining deep neural networks (DNN)s with fuzzy power flow models and applying mixed-precision quantization for edge deployment. The method requires training both on operational data and power flow approximations, which may limit its scalability for short-term voltage forecasting. Su et al. in [12] use a Box-Cox transformed Extreme Learning Machine (ELM) to generate prediction intervals for voltage stability margins, providing probabilistic estimates with quantified confidence. Their results demonstrate the value of fast, adaptive forecasting in handling uncertainty and changing grid conditions. Although their focus is on transmission-level stability, the study highlights the importance of low computational complexity, real-time capable models for future power systems with high DER integration. While these studies demonstrate promising accuracy in LV voltage forecasting, many, such as LSTM, hybrid models, and power flow-informed DNNs, rely on complex model architectures or computationally intensive training, limiting their suitability for fast, real-time applications in distribution networks.

Building on our earlier work [1], which reduced voltage forecasting computation time using a metaheuristic-optimized ELM, this study further enhances real-time capability. We propose a data-driven short-term voltage forecasting method based on the Echo State Network (ESN), a recurrent neural network (RNN) architecture well-suited for time-series prediction due to its fast training and low computational cost [13]. ESNs train only the output weights, while the recurrent reservoir is fixed and randomly initialized, eliminating the need for time-consuming backpropagation used in LSTM or Gated Recurrent Unit (GRU) networks. This simplification significantly reduces training complexity and enables efficient deployment at the edge of the grid (e.g., in a smart meter or local controller). As outlined in Fig. 1, the proposed framework relies solely on historical smart meter data to forecast node voltages. It uses active and reactive power measurements at one-minute resolution from a real LV network with high DER penetration. These inputs, together with the forecasted node voltages from the previous time step (*t-1*), are used to estimate the voltage at the current time step (*t*). We develop and train the ESN model and evaluate its forecasting accuracy and computational efficiency against a benchmark

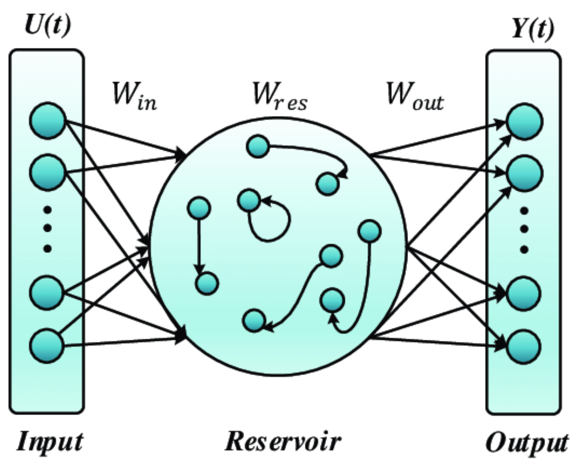

Fig. 2. Architecture of the Echo State Network model [16].

ELM model. The results demonstrate the ESN's suitability for near-real-time voltage forecasting without the need for external optimization.

II. Echo State Network Model

Traditional RNNs have limited practical use due to difficulties in training (e.g. vanishing gradients, long training time, and instability). ESN was developed to overcome these difficulties and greatly simplified the learning process [14]. The ESN architecture consists of three main layers, as shown in Figure 2:

- Input Layer where time series data enters the model.
- Reservoir: A hidden neural network that processes the dynamic information obtained from the input data, is connected (usually 1%-10% density of connections), large in size, randomly generated, and has fixed weights.
- Output Layer: It outputs a linear or non-linear combination of states from the reservoir. Simple but effective algorithms like Ridge Regression are usually used to train the weights of this layer.

To model the complex behavior of dynamical systems, the ESN model uses a large and constant reservoir. This reservoir exhibits a structure that is sensitive to past inputs but does not depend on the initial state [15]. The working sequence of the model can be summarized as follows:

1) Input data is fed into the reservoir.
2) The reservoir generates a state vector reflecting the temporal dynamics of the input data.
3) The output layer generates the prediction from this state vector by a linear transformation.
4) Only the weights in the output layer are updated during training.

The ESN operates by processing input signals through a dynamic reservoir and producing outputs via a trainable linear output layer [17]. In the following, we present the mathematical formulation of the ESN.

First, the state of the reservoir evolves according to the following equation:

$$\begin{gathered}\mathbf{x}(t) = f\left(\mathbf{W}_{in}\cdot\mathbf{u}(t) + \mathbf{W}_{res}\cdot\mathbf{x}(t-1)\right), \\ \text{where } \mathbf{u}(t)\in\mathbb{R}^{N_u}, \mathbf{x}(t)\in\mathbb{R}^{N_x} \\ \mathbf{W}_{in}\in\mathbb{R}^{N_x\times N_u}, \mathbf{W}_{res}\in\mathbb{R}^{N_x\times N_x}\end{gathered} \tag{1}$$

Here, $\mathbf{u}(t)$ represents the input vector at time t, $\mathbf{x}(t)$ denotes the reservoir state vector at time t, $\mathbf{W}_{in}$ is the input weight matrix, $\mathbf{W}_{res}$ is the reservoir weight matrix (fixed and randomly initialized), $f(\cdot)$ represents the activation function (commonly *tan*h), and N_u, N_x denote the dimensions of the input and reservoir layers, respectively. Second, the output is computed as a linear combination of the reservoir states and inputs by

$$\begin{gathered}\mathbf{y}(t) = g\left(\mathbf{W}_{out}\cdot\mathbf{x}(t)\right), \\ \text{where } \mathbf{y}(t)\in\mathbb{R}^{N_y},\ \mathbf{W}_{out}\in\mathbb{R}^{N_y\times N_x}\end{gathered} \tag{2}$$

Here, $\mathbf{y}(t)$ is the output vector at time t, $\mathbf{W}_{out}$ is the output weight matrix (trainable), $g(\cdot)$ represents the activation function in the output layer, and N_y denotes the dimensions of the output layer. During training, the state of the reservoir is updated at each step according to the following equation:

$$\begin{aligned}\mathbf{x}(t) = {} & (1-\alpha)\cdot\mathbf{x}(t-1) \\ & + \alpha\cdot f\left(\mathbf{W}_{in}\cdot\mathbf{u}(t) + \rho\cdot\mathbf{W}_{res}\cdot\mathbf{x}(t-1)\right),\end{aligned} \tag{3}$$

where α represents the leak rate and ρ denotes the spectral radius. These parameters are very important for the ESN model. The leak rate (α) controls the rate at which the reservoir updates its state. A value of $\alpha = 1$ corresponds to full replacement of the previous state, while smaller values ($\alpha < 1$) allow the reservoir to retain memory of its previous state. This is particularly useful for modeling slow-changing signals. The spectral radius (ρ) is the largest absolute eigenvalue of the reservoir weight matrix $\mathbf{W}_{res}$. It determines the reservoir's stability and dynamic capacity. To ensure the echo state property where the reservoir's response depends only on recent inputs and not on initial conditions, ρ is usually set to below 1. In this study, α and ρ are set to 0.3 and 0.5, respectively, to control state update dynamics and stability during training.

In training process, only the output weights $\mathbf{W}_{out}$ are updated. This is typically achieved using Ridge Regression:

$$\mathbf{W}_{out} = \mathbf{Y}_t\cdot\mathbf{X}^T\cdot(\mathbf{X}\cdot\mathbf{X}^T + \lambda\mathbf{I})^{-1}, \tag{4}$$

where $\mathbf{Y}_t$ denotes the target output matrix, $\mathbf{X}$ represents the collected reservoir states over time, and λ is the regularization parameter (set to $1\cdot 10^{-8}$).

III. Voltage Forecasting Results and Analysis

The ESN model is applied to perform short-term voltage forecasting using smart meter data collected from a residential household equipped with rooftop PV and an EV. The household is located within a real LV distribution network characterized by a high penetration of low-carbon technologies.

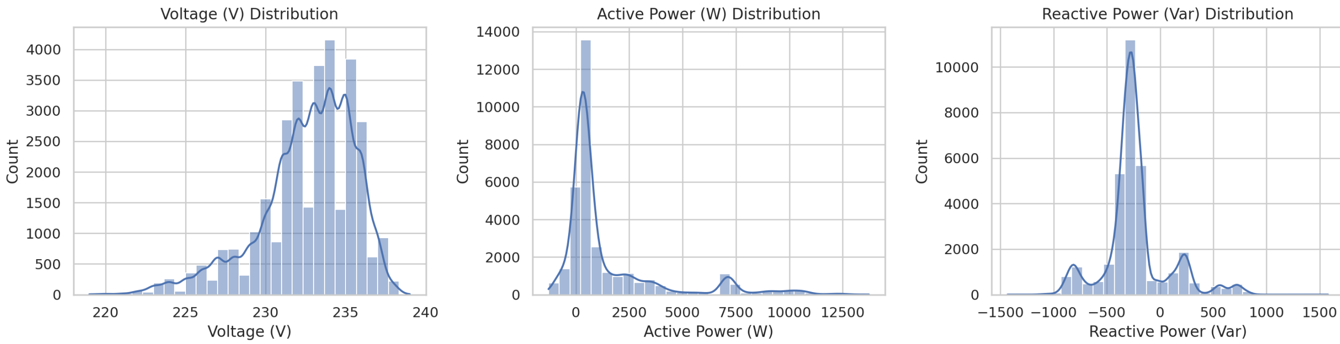

Fig. 3. Voltage, active power, and reactive power distributions at a household with PV and EV systems.

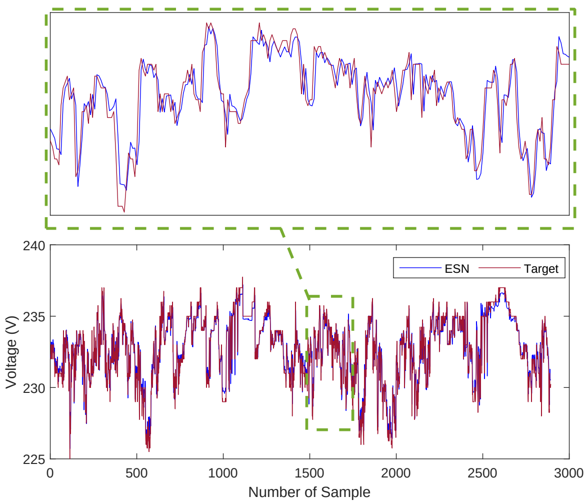

Fig. 4. The forecasting results of the test phase.

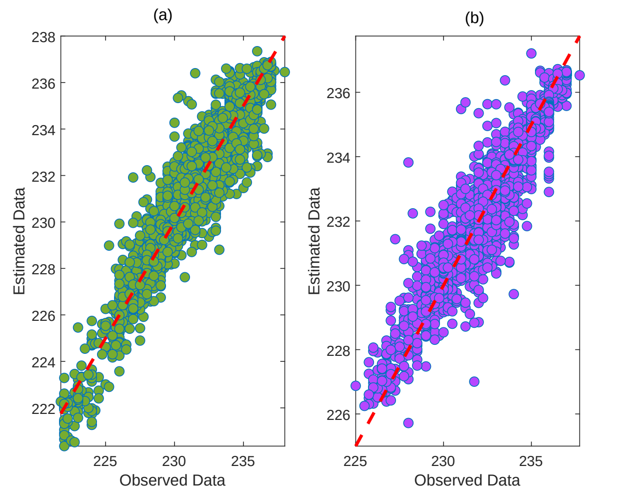

Fig. 5. Scatter plots between of original and forecasted values for the implemented models of LV network dataset for (a) training phase (b) test phase.

Figure 3 displays the distributions of voltage, active power, and reactive power measurements recorded at one-minute intervals for a residential node. The voltage distribution (left chart) is slightly skewed to the right, with most values between 230 V and 236 V. This suggests that the house is proximity to the distribution transformer or that the local grid is lightly loaded. It is also observed that voltage values dropped to 220V on some nights due to the EV charging demand. The active power distribution (middle chart) has two clear peaks: one at low consumption levels and another with a long tail going above 12kW. This indicates occasional high energy usage, most likely associated with EV charging. The negative values reflect PV export during periods of surplus generation. The reactive power distribution (right chart) is centered slightly below zero with a symmetric shape and small peaks on both sides. This indicates frequent switching between capacitive and inductive operation—likely due to PV inverters, household appliances, and EV chargers with power factor correction.

Figure 4 presents the voltage forecasting results of the ESN model on the test dataset. The close alignment between the forecasted and actual voltage values demonstrates the model's capacity to effectively learn the temporal dependencies in the voltage signal. The narrow spread between curves indicates strong generalization ability under diverse operating conditions. The scatter plots comparing the actual and forecasting voltage values for both the training and test phases are presented in Fig. 5 (a) and (b), respectively. The data displays cluster closely around the diagonal line that indicates high forecasting accuracy and minimal bias in both phases. The distribution of points suggests in Fig. 5 (b) that the ESN model does not overfit the training data, maintaining consistent performance when deployed on new data. This robustness is particularly valuable for real-time voltage forecasting tasks. While our earlier approach in Ref [1] demonstrated similarly high correlation ($R^2 > 0.90$), the ESN achieves comparable performance with a more lightweight architecture and faster convergence without need for a metaheuristic optimizer.

Figure 6 presents a comprehensive view of the forecasting errors during training. The upper subplot shows error values fluctuating around zero, with no significant drift or trend,

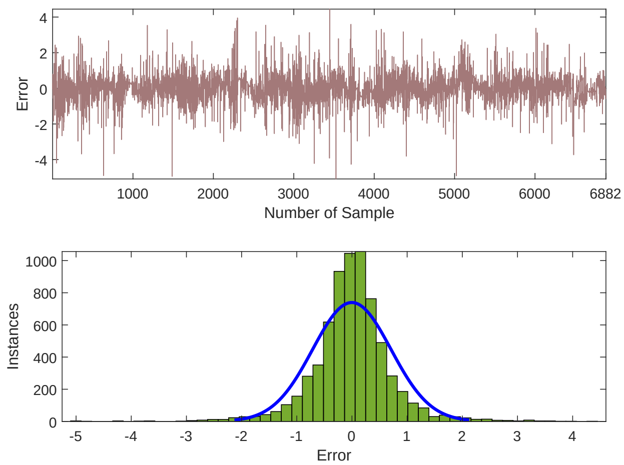

Fig. 6. Variations of error per training sample data

indicating model stability. The lower histogram displays a symmetric, zero-centered error distribution that highlightes the model's unbiased estimation across different time steps. The majority of errors lie within the ±2 V range, confirming the ESN model's high forecasting accuracy. Compared to the normalized probabilistic error margins reported in [7], the ESN exhibits a narrower error spread, even when evaluated in absolute voltage terms. Although the previous work used normalized values, the underlying error distribution was broader, further reinforcing the superior precision of the ESN model.

Table I summarizes the ESN model's training performance using statistical metrics, i.e., Mean Squared error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of determination (R^2). The model achieves a mean MSE of 0.534 and a mean R^2 of 0.929, which is a strong fit to the training data. The low standard deviations across all metrics demonstrate consistent model behavior. Moreover, the average training time per run is only 0.03 seconds, which demonstrates the ESN's computational efficiency. In contrast, our previous meta-heuristic based model in [7] required significantly longer training durations due to its multi-layer optimization structure. The ESN therefore achieves comparable accuracy with substantially lower computational cost.

Table II presents the test-phase performance metrics, where the ESN achieves a mean RMSE of 0.822 V and an R^2 of 0.876. While there is slightly higher than the training phase, the forecast accuracy remains within operationally acceptable limits. These results confirm that the ESN model effectively captures the temporal voltage dynamics, despite not relying on LV network electrical parameters.

The demonstrated forecasting accuracy and computational efficiency of the proposed ESN model have direct implications for DOEs. As outlined in [2], DOE limits can be updated in near real-time to reflect prevailing local network conditions and communicated to prosumers' devices. In practice,

TABLE I
ESN MODEL PERFORMANCE METRICS (TRAINING PHASE)

Metric	Best	Worst	Median	Mean	Std
MSE	0.50285	0.56058	0.53761	0.53412	0.01778
RMSE	0.70912	0.74872	0.73322	0.73074	0.01223
MAE	0.48285	0.49798	0.49222	0.49155	0.00458
R^2	0.93354	0.92591	0.92894	0.92941	0.00235
Run Time (s)	0.02783	0.03219	0.03022	0.03010	0.00146

TABLE II
ESN MODEL PERFORMANCE METRICS (TEST PHASE)

Metric	Best	Worst	Median	Mean	Std
MSE	0.58182	0.92073	0.66624	0.67868	0.09590
RMSE	0.76277	0.95955	0.81622	0.82213	0.05556
MAE	0.53005	0.60129	0.56623	0.56303	0.02243
R^2	0.89401	0.83227	0.87863	0.87636	0.01747

future power grid operators may provide forecasts of likely constraints well ahead of real time, such as day-ahead or rolling one-hour-ahead intervals, before issuing the final DOE signal immediately before operation. The ESN can deliver node-level voltage forecasts in milliseconds, making it suitable for both advance forecasts and final near-real-time updates. Its low computational cost supports frequent re-forecasting as real-time approaches, reducing uncertainty and enabling finer-grain DOE intervals (e.g., 5 minutes). Such accurate and frequent forecasts enable DOEs to more precisely reflect true network capability, facilitating the safe and efficient integration of higher DER levels. Future work will validate the model's performance under diverse LCT operating scenarios to further assess robustness and adaptability in future LV network environments. Overall, the ESN provides a fast, accurate, and computationally efficient solution for near-real-time voltage forecasting, making it well-suited to support DOEs and enable higher DER integration in future power grids.

IV. CONCLUSIONS

This study presented a data-driven short-term voltage forecasting framework based on the ESN for LV distribution networks with high penetration of low-carbon technologies. Unlike traditional approaches that require detailed network models or complex optimization strategies, the proposed method uses only historical smart meter active and reactive power measurements, along with voltage estimates from the previous time step, to forecast node voltages in near real-time.

The ESN model was evaluated using real-world one-minute resolution smart meter data from a residential node equipped with rooftop PV and an EV within the LV feeder. The results demonstrate that the ESN achieves high forecasting accuracy, with most test-phase errors falling within ±2 V. Compared to a previously published metaheuristic-optimized ELM model, the ESN provides comparable accuracy while significantly reducing training time and computational cost. These findings provide an evidence of the ESN's suitability as a real-time voltage forecasting tool for future distribution networks, supporting advanced grid management strategies such as DOEs. Future work will investigate the scalability of the ESN model across multiple nodes and under diverse LCT operating scenarios, as well as its integration into adaptive control schemes for grid-edge applications. Additionally, the proposed model will be benchmarked against state-of-the-art deep learning architectures to compare forecasting accuracy while maintaining its demonstrated computational efficiency.

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