



DBSCAN klasterlash va MLP neyron tarmoqlari asosida elektr energiyasi isroflarini gibridd prognozlash modelini ishlab chiqish

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Dolzarbli: taqsimlovchi elektr tarmoqlarining real ekspluatatsion ma'lumotlarida shovqin, chet qiymatlar va turli ish rejimlariga mansub lokal strukturalar mavjudligi neyron tarmoqlarni o'qitish barqarorligini pasaytirishi mumkin. Shu sababli elektr energiyasi isroflarini prognozlashda ma'lumotlarni intellektual filtrlash, zichlik bo'yicha strukturaviy ajratish va lokal nolinear modellarni yagona gibridd arxitekturada birlashtirish dolzarb masala hisoblanadi.

Maqsad: DBSCAN zichlikka asoslangan klasterlash algoritmi va lokal ko'p qatlamli perseptronlarni birlashtiruvchi gibridd prognozlash arxitekturasini ishlab chiqish, uning strukturaviy mexanizmini asoslash va prognoz aniqligiga ta'sirini baholash.

Usullari: real ekspluatatsion ma'lumotlar DBSCAN zichlikka asoslangan klasterlash algoritmi yordamida dastlabki strukturaviy filtrlashdan o'tkazildi. Kirish fazosi faol quvvat, tashqi havo harorati va nisbiy namlikdan shakllantirildi. PCA proyeksiyasi asosida DBSCAN parametrlari $\epsilon=0,4$ va $\text{minPts}=5$ etib tanlandi. Har bir ajratilgan klaster uchun alohida MLP modeli o'qitilib, yakuniy prognoz kompozitsion Y_{hybrid} strukturasida orqali shakllantirildi. Aniqlik MAPE mezoni bo'yicha baholandi.

Natijalar: bazaviy MLP modelining MAPE qiymati 2,58 % ni tashkil etdi. DBSCAN yordamida shovqinli kuzatuvlarni ajratish va klasterlar bo'yicha lokal MLP modellarni o'qitish natijasida gibridd modelda MAPE 2,10 % gacha kamaydi, ya'ni bazaviy MLP ga nisbatan prognoz xatoligi 18,6 % ga pasaydi. Train, validation va test bosqichlaridagi haqiqiy va prognoz qiymatlar yaqin moslikni ko'rsatdi.

Kalit so'zlar: elektr energiyasi isroflari, taqsimlovchi elektr tarmog'i, DBSCAN, MLP, PCA, klasterlash, anomal kuzatuvlarni filtrlash, gibridd prognozlash.

Разработка гибридной модели прогнозирования потерь электроэнергии на основе кластеризации DBSCAN и нейронных сетей MLP

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Актуальность: реальные эксплуатационные данные распределительных сетей содержат шум, выбросы и локально неоднородные режимы, способные исказить обучение нейронных сетей и снижать устойчивость прогноза. Поэтому актуальной является интеграция интеллектуальной фильтрации, плотностного структурирования данных и локального нелинейного прогнозирования в единую гибридную архитектуру.

Цель: разработать и оценить гибридную архитектуру прогнозирования потерь электроэнергии, объединяющую плотностную кластеризацию DBSCAN и локальные модели MLP, а также количественно оценить вклад предварительного структурирования данных в повышение точности прогноза.

Методы: реальные эксплуатационные данные предварительно структурировались методом плотностной кластеризации DBSCAN. Пространство входных признаков формировалось активной мощностью, температурой наружного воздуха и относительной влажностью. Параметры $\epsilon=0,4$ и $\text{minPts}=5$ были выбраны на основе PCA-проекции. Для каждого выявленного кластера обучалась локальная MLP-модель, а итоговый прогноз формировался композицией Y_{hybrid} . Точность оценивалась по MAPE.

Результаты: гибридная модель обеспечила MAPE 2,10 % против 2,58 % у базовой MLP, что соответствует снижению относительной ошибки на 18,6 %. Графическое сопоставление фактических и прогнозных данных на обучающей, валидационной и тестовой выборках подтверждает устойчивость и отсутствие выраженного переобучения.

Ключевые слова: потери электроэнергии, распределительная сеть, DBSCAN, MLP, PCA, кластеризация, фильтрация аномалий, гибридное прогнозирование.



Development of a hybrid electricity-loss forecasting model based on DBSCAN clustering and MLP neural networks

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Relevance: operational data from distribution networks contain noise, outliers and locally heterogeneous operating regimes that may distort neural-network training and reduce forecast robustness. This creates a need for an integrated architecture in which density-based structural filtering and local nonlinear forecasting are treated as complementary stages of one predictive process.

Aim: to develop and validate a hybrid electricity-loss forecasting architecture that combines density-based DBSCAN clustering with local multilayer perceptron models, and to quantify the accuracy gain attributable to the preliminary structural decomposition of the data.

Methods: real operational data were subjected to density-based structural filtering using DBSCAN. The input feature space comprised active power, ambient temperature and relative humidity. PCA-assisted analysis was used to select $\epsilon=0.4$ and $\text{minPts}=5$. A separate MLP was trained for each detected dense cluster, and the final forecast was generated through a composite Y_{hybrid} structure. Forecast accuracy was evaluated using MAPE.

Results: the baseline MLP achieved a MAPE of 2.58 %, whereas the DBSCAN–MLP architecture reduced MAPE to 2.10 %, corresponding to an 18.6 % relative error reduction. Actual-versus-predicted trajectories remained closely aligned for training, validation and test subsets, supporting the robustness of the hybrid architecture.

Keywords: electricity losses, distribution network, DBSCAN, MLP, PCA, clustering, anomaly filtering, hybrid forecasting.

1. Introduction

Loss forecasting in distribution networks is becoming increasingly data-driven because advanced metering infrastructure provides dense streams of historical measurements. This creates opportunities for direct prediction of network losses without requiring a fully parameterized electrical model. At the same time, real operational datasets contain missing observations, measurement errors, outliers and regime changes that can substantially degrade the quality of a forecasting model.

Machine-learning approaches have already demonstrated their ability to estimate or forecast losses from smart-meter and operational data. Matijašević et al. developed a machine-learning framework for loss forecasting in a real distribution network using smart-meter measurements, emphasizing both the value of data-driven modelling and its sensitivity to data errors [8]. Liu et al. showed that data-cleaning procedures based on outlier detection can materially improve distribution-network loss prediction [9]. Recent work on neural-network-based energy-loss management has also incorporated DBSCAN in preprocessing to detect anomalous observations before training [10].

For nonlinear loss dynamics, multilayer perceptrons are attractive because they can approximate complex relationships between active power, weather variables and target losses. Previous studies by the author demonstrated that neural-network models outperform several classical approaches when the input structure is sufficiently complex [2,3,7]. Nevertheless, the baseline MLP remains sensitive to the statistical quality and local structure of the training sample. Outlying observations may disproportionately affect the gradient-based learning process, while heterogeneous operating regimes may force a single global network to approximate relationships that are locally different.

Density-based spatial clustering of applications with noise (DBSCAN) offers a useful preprocessing mechanism because it does not require the number of clusters to be specified a priori, can identify clusters of arbitrary shape, and explicitly labels low-density observations as noise [11]. These properties are particularly relevant for distribution-network data, where abnormal switching conditions, meter errors, temporary load distortions and atypical weather-load combinations may appear as sparse observations in feature space.

The scientific problem addressed in this paper is not merely to apply an additional neural network, but to determine whether density-based structural decomposition can improve the stability and accuracy of nonlinear forecasting under heterogeneous operating conditions. The proposed solution integrates PCA-assisted DBSCAN filtering, cluster-specific MLP models and an explicit composite routing rule. Its novelty lies in converting clustering from a standalone preprocessing operation into an integral component of the predictive architecture.

The aim of the study is to develop and validate a hybrid DBSCAN–MLP architecture for electricity-loss forecasting under noisy and structurally heterogeneous operating data, and to quantify the accuracy gain produced by density-based decomposition before neural modelling.

2. Methods and materials

Input variables and experimental design. The study used real operational measurements from a distribution network. The input space was formed by three physically interpretable variables—active power, ambient temperature and relative humidity—that had passed statistical screening in the source dataset. In the present study, these variables are treated as the three-dimensional feature space for density analysis and local nonlinear modelling; the methodological focus is structural decomposition rather than repeated factor selection.

To ensure a fair comparison, the same prepared input space was used for both the baseline MLP and the hybrid DBSCAN-MLP architecture. Model development was performed with mutually exclusive training, validation and test subsets so that improvements produced by the clustering stage could be evaluated independently of the neural-network fitting process.

The evaluation protocol preserved independent validation and test subsets throughout the experiments. This design makes it possible to distinguish genuine generalization gains from changes that merely improve the fit to the training data.

Baseline MLP model. The baseline neural model was a feed-forward multilayer perceptron with three input neurons corresponding to P, T and RH, two hidden layers and one output neuron representing the forecast electricity loss. A cross-validation experiment was conducted by varying the number of neurons in each hidden layer from 1 to 10. The best configuration contained 9 neurons in the first hidden layer and 3 neurons in the second hidden layer.

The selected architecture was therefore 3/9/3/1. ReLU was used as the activation function, and the number of training epochs was selected experimentally from a range of 1–500. The minimum forecast error was obtained at 21 epochs. The baseline MLP produced a MAPE of 2.58 %, which served as the reference level for evaluating the contribution of DBSCAN-based preprocessing.

Table 1. Baseline MLP architecture and training settings

Parameter	Baseline MLP setting
Input variables	P, T, RH
Architecture	3/9/3/1
Hidden layers	2
Activation function	ReLU
Epochs	21
Evaluation protocol	Independent training, validation and test subsets
MAPE	2.58 %

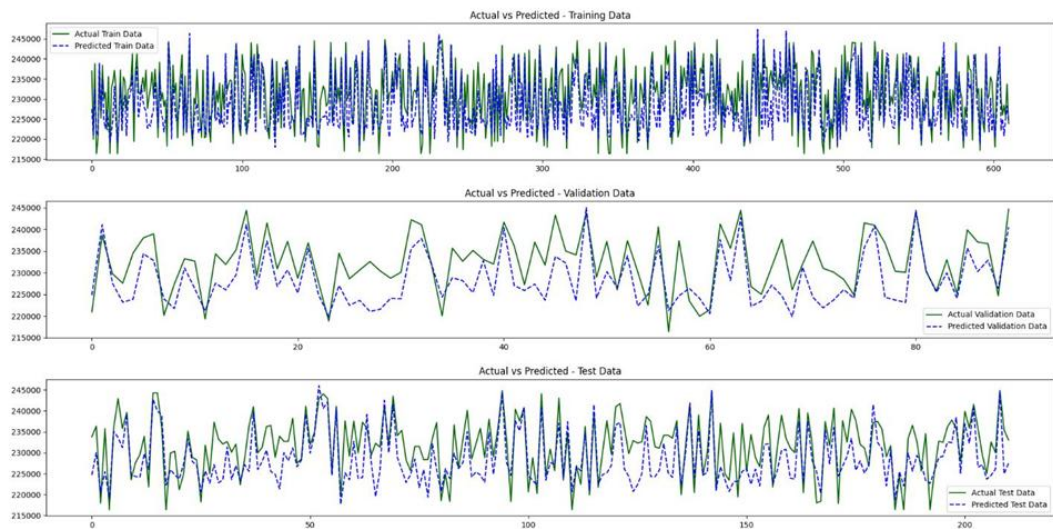


Fig. 1. Actual and predicted electricity losses for the baseline MLP on training, validation and test subsets

DBSCAN filtering and PCA-assisted parameter selection. The key modification introduced in the hybrid method is the replacement of direct training on the entire sample by density-based structural filtering. DBSCAN forms clusters according to local point density. For a point p in dataset D , the ε -neighborhood is defined as:

$$N_{\varepsilon}(p) = \{q \in D \mid \rho(p, q) \leq \varepsilon\} \quad (1)$$

A point p is treated as a core point when the number of observations in its ε -neighbourhood is not smaller than minPts :

$$|N\varepsilon(p)| \geq \text{minPts} \quad (2)$$

Observations that are not density-connected to any cluster are classified as noise and excluded from local neural-network training:

$$\text{Noise} = \{p \in D \mid p \notin iUC_i\} \quad (3)$$

To support parameter selection and visualize the internal structure of the three-dimensional predictor space (P,T,RH), principal component analysis was used to project observations onto PC1 and PC2. Empirical inspection of the resulting density structure led to $\varepsilon=0.4$ and $\text{minPts}=5$. Decreasing ε caused excessive fragmentation of the dense regions, whereas increasing ε absorbed irrelevant sparse observations. Values of minPts above 5 reduced sensitivities to smaller dense structures. The selected minPts also satisfies the common heuristic $\text{minPts} \geq D+1$ for $D=3$.

The selected parameter pair separated three dense clusters and a set of sparse noise observations. In this role, DBSCAN acts as an intelligent filter: it preserves internally consistent operating regimes while preventing statistically isolated observations from influencing the subsequent MLP training process.

Table 2. DBSCAN configuration used in the hybrid architecture

DBSCAN parameter	Selected value	Rationale
ε	0.4	Balance between fragmentation and absorption of irrelevant sparse points
minPts	5	Preserves small dense structures; consistent with $\text{minPts} \geq D+1$ for $D=3$
Visualization space	PC1–PC2	PCA projection of the original P–T–RH feature space

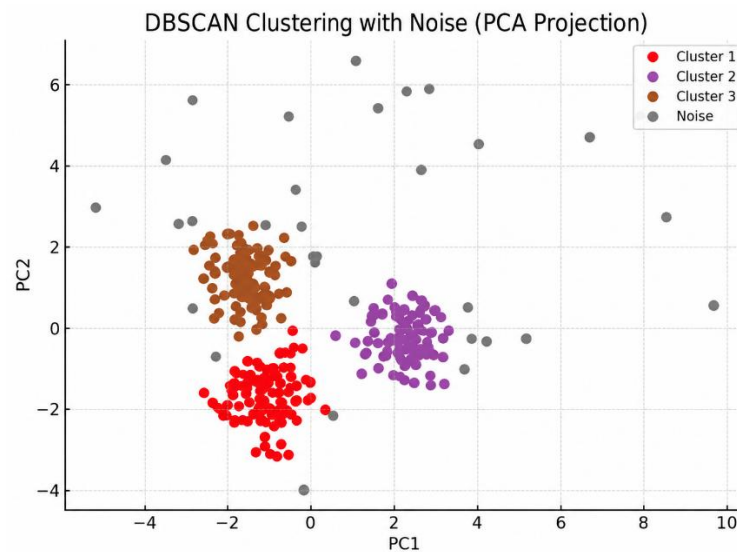


Fig. 2. DBSCAN clustering with noise in the PCA projection of the input feature space

Hybrid DBSCAN–MLP architecture. After clustering, the final predictive structure is constructed as a mixture of local neural models. Let $CL = \{CL_1, \dots, CL_N\}$ be the set of dense clusters identified by DBSCAN. For each cluster CL_i , an individual MLP_i is trained only on the observations belonging to that local region. This allows each network to approximate the nonlinear relationship between P, T, RH and electricity losses within a more homogeneous operating regime.

For a new observation x , the hybrid model first determines the cluster to which x is density-compatible and then activates the corresponding local MLP. The final predictor can be represented as:

$$\hat{y}(x) = MLP_k(x), \text{ if } x \in CL_k \quad (4)$$

The resulting composite model is denoted $Y_{\text{hybrid}} = \text{DBSCAN}\{MLP(CL_1), MLP(CL_2), \dots,$

MLP(CLN)}. In the obtained experimental structure, three principal clusters were identified and serviced by separate local MLP models.

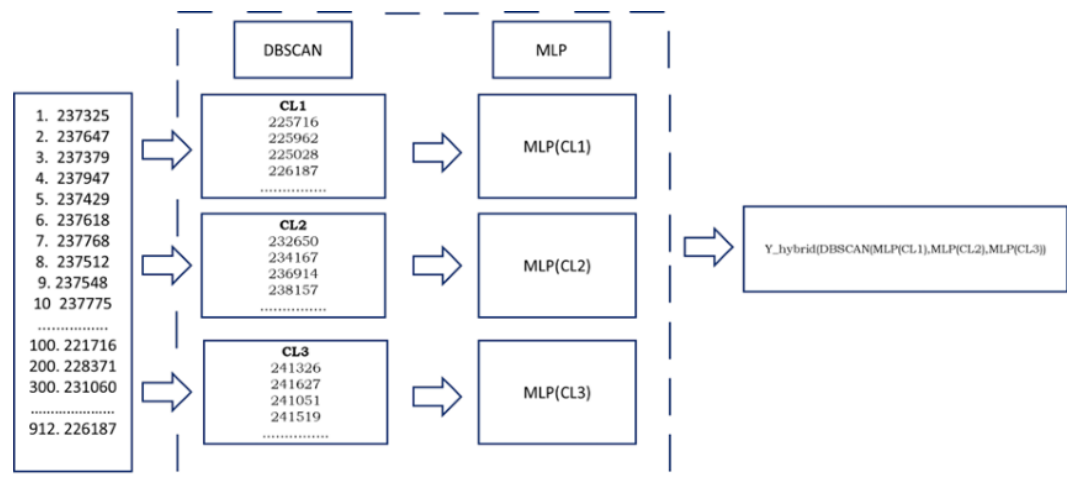


Fig. 3. Schematic representation of the proposed hybrid DBSCAN–MLP architecture

After the composite predictor is formed, forecast quality is evaluated on the held-out data. If the resulting MAPE exceeds the admissible threshold of 3 %, the input features are renormalized and the local training models are reconfigured. Once the error satisfies the threshold, the composite structure is stored as the functional predictive module.

$$MAPE = \left(\frac{100}{n} \right) \sum \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (5)$$

3. Results and discussion

Effect of density-based filtering on prediction accuracy. The baseline MLP reached a MAPE of 2.58 %. After DBSCAN filtering and cluster-specific local training, the hybrid model achieved a MAPE of 2.10 %. The absolute decrease was 0.48 percentage points. Relative to the baseline MLP, the forecasting error decreased by approximately 18.6 %:

$$\Delta MAPE_{rel} = (2.58 - 2.10) / 2.58 \times 100 \% = 18.6 \% \quad (6)$$

This reduction is practically important because the baseline MLP was already the most accurate standalone model among the investigated non-hybrid approaches. The observed improvement therefore reflects not a transition from a weak model to a strong model, but an additional gain obtained by restructuring and filtering the same operational information before neural modelling.

Table 2. Accuracy gain produced by the DBSCAN–MLP architecture

Model	Preprocessing structure	MAPE, %	Relative change vs. MLP
MLP	Global training on prepared data	2.58	Reference
DBSCAN–MLP	PCA-assisted DBSCAN + cluster-specific MLPs	2.10	-18.6 %

Training, validation and test behaviour of the hybrid model. The actual-versus-predicted trajectories of the hybrid model are shown in Fig. 4. On the training subset, the predicted series reproduces the high-frequency variation of the measured losses without forming a visibly over-smoothed profile. On the validation subset, the forecast preserves the main amplitude and direction of local changes. The test subset shows the most important result: despite independent observations and several local extrema, the predicted trajectory remains close to the measured series throughout the evaluation interval.

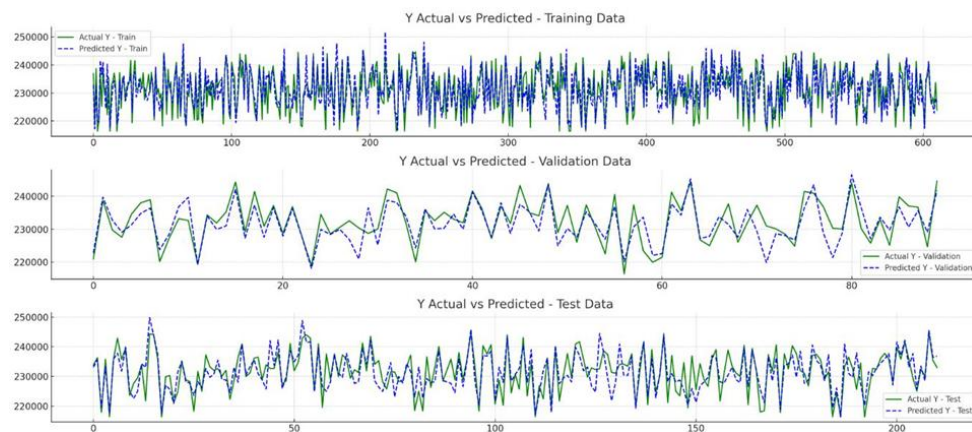


Fig. 4. Actual and predicted electricity losses for the hybrid DBSCAN–MLP model on training, validation and test subsets

The close agreement among the three subsets indicates that the gain in accuracy is not confined to the training sample. The absence of a pronounced divergence between training and test behaviour supports the conclusion that density-based filtering did not simply increase model flexibility; rather, it improved the structural consistency of the information used by the local predictors.

Interpretation of the improvement mechanism. The improvement can be explained by three complementary mechanisms. First, sparse observations labelled as noise are prevented from shifting the neural-network weights during training. Second, cluster-specific learning reduces the need for a single global MLP to approximate several operating regimes simultaneously. Third, the routing mechanism of the composite predictor uses the local model associated with the relevant regime, thereby reducing approximation bias in structurally heterogeneous regions.

This interpretation is consistent with recent distribution-network studies in which data cleaning and anomaly treatment improved predictive performance. Liu et al. reported that cluster-based outlier handling enhanced network-loss forecasting accuracy [9]. Blinov et al. used DBSCAN as part of a two-stage preprocessing procedure for anomaly handling in operational distribution-network data before deep-neural forecasting [10]. These studies support the broader conclusion that robust preprocessing is an integral component of data-driven grid forecasting rather than an auxiliary step.

4. Conclusion

The results demonstrate that the main contribution of the hybrid architecture lies in how it organizes the learning problem. A conventional MLP receives all admissible observations in a single optimization process. This is efficient when the relationship between predictors and target is globally homogeneous, but it becomes less suitable when several local operating regimes coexist. The DBSCAN–MLP architecture decomposes this global mapping into a set of local nonlinear mappings, while simultaneously rejecting low-density observations.

The use of DBSCAN is particularly appropriate for the present application because the number and geometry of operating regimes are not known in advance. Unlike centroid-based clustering, density-based clustering does not force all observations into clusters and therefore provides a natural mechanism for identifying potential anomalies. The original DBSCAN formulation by Ester et al. established this ability to discover arbitrarily shaped dense regions and mark sparse observations as noise [11], while later clustering literature has confirmed the method's relevance for irregular data structures [12].

The selected parameter combination $\epsilon=0.4$ and $\text{minPts}=5$ was obtained empirically from the PCA projection and should therefore be interpreted as calibrated for the investigated dataset rather than as a universal setting. This is an important methodological limitation. A different network, sampling interval, climate regime or consumer composition may require another ϵ or minPts . Nevertheless, the selection logic itself is transferable: project or otherwise inspect the feature structure, test density stability, and choose parameters that preserve dense operational regimes while excluding sparse anomalies.

A second limitation concerns the routing of new observations. In practical deployment, an observation may appear near cluster boundaries or in a previously unseen low-density region. A production-grade implementation should therefore include a fallback rule, such as assignment to the nearest density-compatible cluster, use of the global MLP, or a confidence-based rejection mechanism. This is a natural direction for further development of the information system.

From an operational perspective, the hybrid approach is attractive because it does not require replacement of the MLP model itself. Instead, it adds an intelligent structural layer in front of the neural



predictor. This is compatible with existing AMI-based analytical systems and can be implemented as a preprocessing and model-routing module. The result is a modular architecture in which data quality control, operating-regime identification and nonlinear forecasting are explicitly separated.

The methodological contribution is the explicit separation of data-quality control, operating-regime identification and nonlinear forecasting into interconnected stages. DBSCAN is not used only to discard outliers, and MLP is not used only as a single global approximator. Instead, the density structure determines how observations are routed to local predictors, turning clustering into a functional part of the forecasting mechanism itself.

1. A hybrid DBSCAN–MLP architecture was developed for forecasting electricity losses from real operational distribution-network data under noisy and structurally heterogeneous conditions.

2. The input feature space comprised active power, ambient temperature and relative humidity. The baseline neural predictor used a 3/9/3/1 architecture with ReLU activation and 21 training epochs, providing a consistent reference for evaluating the contribution of density-based preprocessing.

3. PCA-assisted density analysis led to DBSCAN parameters $\epsilon=0.4$ and $\text{minPts}=5$. The clustering stage identified dense operating regimes and excluded sparse noise observations before neural-network training.

4. Local MLP models were trained for the DBSCAN clusters and integrated into a composite Y_{hybrid} predictor. The hybrid architecture reduced MAPE from 2.58 % for the baseline MLP to 2.10 %, corresponding to an 18.6 % relative reduction in forecasting error.

5. Actual-versus-predicted trajectories on training, validation and test subsets showed close agreement and no pronounced evidence of overfitting. The proposed architecture can therefore serve as a robust predictive module in intelligent analytical systems for distribution networks.

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