# Spatio-temporal deep learning for joint forecasting of distributed renewable generation and electricity demand under uncertainty*

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## Abstract

Global decarbonization and mass integration of distributed renewable energy create a level of topological, meteorological and stochastic complexity that traditional statistical tools and basic machine learning (ML) algorithms are fundamentally unable to cope with with proper operational reliability. The work investigates the performance of modern neural network architectures for the task of forecasting electricity generation and consumption. An important aspect of the research is the comparison of uncertainty assessment methodologies. Successful implementation of the proposed comprehensive spatiotemporal methodology can not only radically minimize the financial costs of operators for operational errors and maintaining excess reserves, but also opens the only possible path to reliable, sustainable and economically justified operation of energy systems of the future.

## Keywords

Deep learning, uncertainty quantification, forecasting, renewable generation, electricity demand [1]

## 1. Introduction

The global energy paradigm is undergoing an unprecedented transformation driven by the imperative of decarbonization and the transition to sustainable energy sources. Modern energy systems are evolving from a traditional centralized model based on fossil fuels with predictable generation levels to decentralized Smart Grids [1]. These new grids are characterized by a high level of penetration of distributed renewable energy sources, such as solar photovoltaic plants and wind turbines, integrated directly at the consumer or distribution network level. This transition, despite its environmental feasibility, introduces a colossal level of stochasticity, volatility and nonlinear dynamics into the processes of balancing and managing the electricity grid. Unlike traditional generation, energy production from renewable sources is deeply weather-dependent, intermittent and extremely difficult to directly control. This fundamentally disrupts the classical dispatch paradigm, where generation flexibly adapted to a relatively predictable demand schedule.

In such conditions of high uncertainty, accurate short- and medium-term forecasting of both electricity demand and generation becomes a critical tool for ensuring the reliability, system stability [2] and economic efficiency [3] of power systems. Even a small increase in forecast accuracy has a large economic and operational impact. For example, according to research, increasing the accuracy of load forecasting by just one percent can save up to £10 million annually

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across the UK national grid by optimizing the allocation of reserve capacity, reducing costs in the balancing market and avoiding imbalance penalties [4, 5]. Traditionally, demand (load) forecasting and generation forecasting have been considered as two separate, independent dispatching tasks. However, with the massive spread of prosumers – active consumers who are also energy producers (e.g. households with rooftop solar panels and storage systems) – there has been an urgent need to jointly forecast the so-called "net load". Net load, which is the difference between total macroeconomic demand and local renewable generation, exhibits extremely complex behaviour, as forecast errors in both components can overlap and reinforce each other.

## 2. State-of-the-art

The data continuously generated in modern smart grids by supervisory control and data acquisition (SCADA) systems, smart meters, and high-frequency power measurement units (PMUs) are of a complex spatiotemporal nature [6]. Consumption and generation at any grid node depend not only on its own historical performance or local weather conditions (time dependence), but also on the state of neighbouring nodes, power flows, line capacity, and the global topology of the grid itself (spatial dependence) [7]. As a result, isolated one-dimensional time series forecasting models are giving way to integrated spatiotemporal paradigms based on artificial intelligence and deep learning. These advanced architectures can automatically model complex, hidden correlations between different physical and meteorological components [8] of the grid under conditions of high uncertainty [9], enabling the transition to proactive power system management [10].

With the exponential growth of data volumes and computing power, the industry has shifted its focus to classical machine learning algorithms [11]. Such algorithms have significantly improved the ability of forecasting systems to capture complex nonlinear relationships between a large number of meteorological factors and energy load or generation indicators. For example, in comparative studies [12-14] XGBoost and Random Forest consistently demonstrate high accuracy in wind energy forecasting, outperforming simple linear regressions by ensemble decision trees. However, classical machine learning faces a number of fundamental limitations when working with large-scale spatiotemporal data [15].

The performance of such algorithms critically depends on the quality of data preprocessing and the manual feature construction process [16]. Domain experts must manually create lag variables, calculate moving averages, trend indicators, and statistical moments to feed them into the model. This not only makes the development process slow and dependent on human factors, but also limits the model's ability to detect non-obvious, deep patterns in raw data that humans simply cannot conceptualize [17]. Traditional ML algorithms have extremely limited spatial awareness [18, 19]. They mostly treat prediction as an isolated task for each point (node) or require "flattening" multidimensional spatiotemporal matrices [20] into flat one-dimensional feature vectors. In addition, classical models, especially those based on decision trees (RF, GBM), have fundamental difficulties with extrapolation, i.e. the ability to generate adequate predictions for values that go beyond the historical range of the training sample [21]. In the context of global climate change, when extreme weather events, including heat waves, abnormal frosts, and consumption peaks, are becoming increasingly unprecedented, this weakness of classical ML can lead to critical errors in network management [22-24].

It should be noted that many engineering systems [25], particularly in the energy sector [26], use quantitative uncertainty assessment [27-29], which is due to a number of requirements for software development for such systems [30, 31].

Thus, to create a predictive framework, a comprehensive statistical and intellectual analysis of data should be conducted, as well as taking into account the specifics of forecasting climatic indicators [32, 33].

# 3. Methodology

## 3.1. The dual nature of uncertainty

Despite the proven high accuracy of point forecasts based on deep spatiotemporal learning, they provide the system dispatcher or control algorithm with only a single expected average value of generation or demand. This approach is fundamentally dangerous because it completely ignores the statistical probability of deviations. In the new paradigm of smart grids with a high proportion of stochastic and unstable renewable sources, making decisions based only on point forecasts makes the power system strategically vulnerable to extreme events.

Energy management requires an inevitable transition to probabilistic forecasting. Instead of a single number, the model should provide a complete continuous probability distribution of future system states, or at least Prediction Intervals (PIs) with an operator-specified confidence level (e.g., 90%, 95%, or 99%).

To provide reliable Uncertainty Quantification (UQ), modern deep learning models must correctly model and separate two fundamentally different types of uncertainty:

1. Aleatoric Uncertainty is also known as data uncertainty. This is the objective, inherent "noise" in the observational data itself. It is caused by measurement errors, inaccuracies in the input numerical weather predictions (NWP), or the natural stochasticity and randomness of wind flows at the micro level. An important feature of aleatoric uncertainty is that it cannot be reduced, even if an infinite amount of training data is collected.
2. Epistemic Uncertainty is also known as model uncertainty. This is the subjective uncertainty that arises from the lack of knowledge of the neural network itself. It can be a consequence of insufficient or unbalanced representativeness of the training sample (for example, the model has never seen data on the behavior of solar panels during a powerful dust storm or a category 1 hurricane) or due to an incorrect choice of the network architecture itself (insufficient depth or capacity). Unlike aleatory uncertainty, epistemic uncertainty systematically decreases as more quality training data is accumulated.

## 3.2. Dataset

The study used a Renewable Power Generation and weather Conditions dataset [34] from Kaggle that contains information on renewable energy generation and weather conditions. Thus, it is possible to comprehensively analyze not only the time series of generation and consumption, but also other factors such as time of day, season, and weather conditions. Dataset includes 196776 records. There are 17 features:

- Time;
- Energy delta;
- GHI;
- Temperature;
- Pressure;
- Humidity;
- Wind speed;
- Rain possibility in next 1 h;
- Snow possibility in next 1 h;
- Clouds coverage;
- Is Sun;
- Sunlight time;
- Day Length;

- Sunlight time / Day Length;
- Weather type;
- Hour;
- Month.

### 3.3. Forecasting framework

To predict the values of the time series, a number of models were selected, both classical machine learning models [35], such as ridge regression, random forest (RF), gradient boosting machine (GBM), and deep learning methods, in particular multilayer perceptron (MLP), long short-term memory (LSTM), transformer, and spatio-temporal graph neural network (ST-GNN). To evaluate the performance of the model, the following metrics were selected:

- Mean Absolute Error (MAE);
- Root Mean Squared Error (RMSE);
- Prediction Interval Coverage Probability (PICP);
- Mean Prediction Interval Width (MPIW);
- Train time.

In renewable energy forecasting, deep learning models face extreme data volatility due to changing weather conditions. Evaluating these models requires two levels of evaluation: accuracy, which measures how close the forecast is to the actual value, and a quantitative assessment of uncertainty, which measures how reliable and precise the forecast boundaries are. The metrics MAE, RMSE, PICP, and MPIW form a standard evaluation framework for this two-level evaluation. A generalized research methodology is presented in Figure 1.

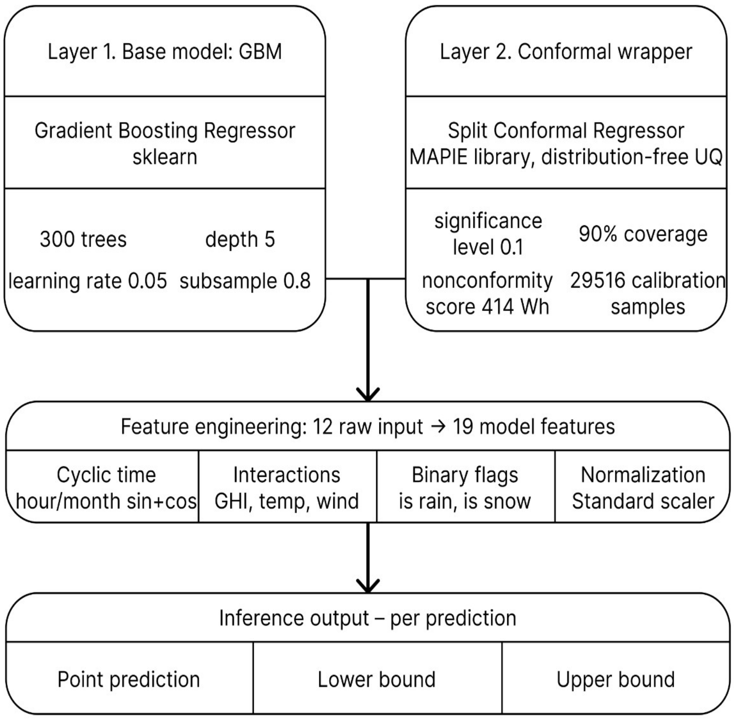


**Figure 1:** Generalized research methodology.

# 4. Results

## 4.1. Analysis of Uncertainty Quantification methods in deep learning

When implementing Uncertainty Quantification in a spatiotemporal deep learning model, several mathematical methodologies are used, each of which offers its own trade-off between the quality of uncertainty estimation and the cost of computational resources. A generalized analysis of the methodologies is presented in Table 1.

The comparative analysis revealed that deep ensemble methods and MC Dropout typically demonstrate the best calibration of results and the most accurate assessment of epistemic uncertainty among all methods. At the same time, despite the mathematical elegance of Bayesian neural networks, their deployment in real-world energy management environments is often limited by the problem of variance shrinkage or mode collapse in complex spatiotemporal data, where traditional quantile regression, despite ignoring the epistemic part, gives practically more useful results.

The integration of probabilistic methods, in particular the BNN architecture or simple MC Dropout with advanced spatiotemporal ST-GNN modules allows the system not only to detect that the energy network is approaching a state of instability, but also to quantify the model's confidence in this forecast. The use of such confidence intervals in subsequent dispatching algorithms, for example, in stochastic optimization or deep reinforcement learning, significantly reduces the overall operating costs of the network and minimizes the enormous amounts of financial resources that would otherwise have to be spent on imbalance penalties or emergency purchases of expensive balancing energy.

The results of experiment presented in Table 2.

Model’s metrics comparison is presented in the Figure 2. Figure 3 shows models’ performance radar. The analysis of the metrics suggests that conformal prediction is the most reliable for deployment, as it is the only method that provides a 90% coverage guarantee (PICP = 0.907) and has the lowest MAE. Its coverage is theoretically guaranteed by design, not just empirically expected. The MC Dropout method provides the best point accuracy ($R^2$ = 0.896) with a reasonable interval width, making it the best compromise between efficiency and accuracy. Furthermore, its deployment is faster than the full ensemble.

The Bayesian neural network achieved the sharpest intervals (MPIW = 43.4 Wh), but it is significantly under-covered (PICP = 0.508), which means that its uncertainty estimates are overconfident, i.e. it narrows the intervals too aggressively.

The GBM-based quantile regression has significant overlap (PICP = 0.979) over very wide intervals, but has poor point accuracy on this dataset. This means that it does not capture the nonlinear dynamics of solar radiation well enough.

Figure 4 shows predicted and observed data of renewable generation. Figure 5 presents residual distributions. The uncertainty peaks in the winter months and at night, which is consistent with the physical reality, as solar generation is zero at night, so the models are essentially making assumptions within the zero-energy regime. Figure 6 displays 500-sample window for 90% prediction intervals. A comparison of Uncertainty width vs Absolute Error is presented in Figure 7. Figure 8 shows Empirical vs Nominal Coverage Calibration.

## 4.2. Forecasting

Table 3 presents a comparative evaluation of seven predictive models, ranging from traditional baseline (ridge regression) and ensemble methods (random forest, gradient boosting machine) to advanced deep learning architectures (multilayer perceptron, long short-term memory, transformer, and spatiotemporal graph neural network), evaluated on various metrics for both point prediction accuracy (Figure 9, 10) and prediction interval reliability (Figure 11), as well as computational cost using the corresponding metrics. Figure 12 presents multi-metric radar.

**Table 1**
Generalized analysis of Uncertainty Quantification methodologies

| Uncertainty Quantification Methodology | Mechanism of work and implementation | Key Benefits for Smart Grids | Disadvantages and system limitations |
|---|---|---|---|
| Quantile Regression, QR | Replaces the standard loss function with an asymmetric Pinball Loss. The network is designed to output a set of specific quantiles (e.g., 10th, 50th, 90th percentiles) simultaneously. | Model-agnostic, does not require assumptions about the shape or symmetry of the error distribution (distribution-free), which is ideal for wind energy. | Ignores epistemic uncertainty; quantiles can sometimes cross, violating the logic of the forecast (crossing quantiles problem). |
| Deep Ensembles | Parallel or sequential training of N structurally identical models with different random weight initializations and data subsampling (bootstrapping). The variance of their outputs determines the interval. | Relatively simple implementation, consistently guarantees excellent calibration and estimation of both types of uncertainty. | Requires N times more computational resources and memory for training and deployment, which limits use at the edge. |
| Bayesian Neural Networks, BNN | Radical change in architecture: deterministic point weights are replaced with probability distributions (e.g. Gaussian). Learning is done through variational inference. | Provides the most mathematically rigorous and comprehensive assessment of epistemic uncertainty, extremely resistant to the problem of overfitting. | High computational complexity; extremely sensitive to the choice of priors; prone to mode collapse. |
| MC Dropout | Enabling Dropout mechanisms not only during training, but also during working inference. Multiple runs form the empirical distribution. | BNN approximation, does not require intervention in the classical optimization process; low setup complexity. | Slightly weaker calibration compared to deep ensembles; requires multiple runs of the network, which generates latency. |
| Conformal Prediction | A statistical meta-method for post-hoc calibration. Analyzes non-conformity scores on a deferred sample. | Provides strict finite-sampling interval coverage guarantees without any distribution assumptions; applies to any off-the-shelf DL model. | Critically dependent on the ideal representativeness of the calibration sample; may give too wide intervals in case of data shift. |

**Table 2**
Metrics of Uncertainty Quantification Models

| Model | MAE | RMSE | $R^2$ | PICP(90%) | MPIW |
|---|---|---|---|---|---|
| Quantile Regression | 572.6 | 1194 | −0.299 | 0.979 | 883.9 |
| Deep Ensembles | 133.9 | 336.1 | 0.897 | 0.674 | 114.7 |
| Bayesian Neural Net | 141.5 | 343.3 | 0.893 | 0.508 | 43.4 |
| MC Dropout | 140.4 | 336.3 | 0.897 | 0.835 | 324.2 |
| Conformal Prediction | 133.6 | 340.8 | 0.894 | 0.907 | 575 |

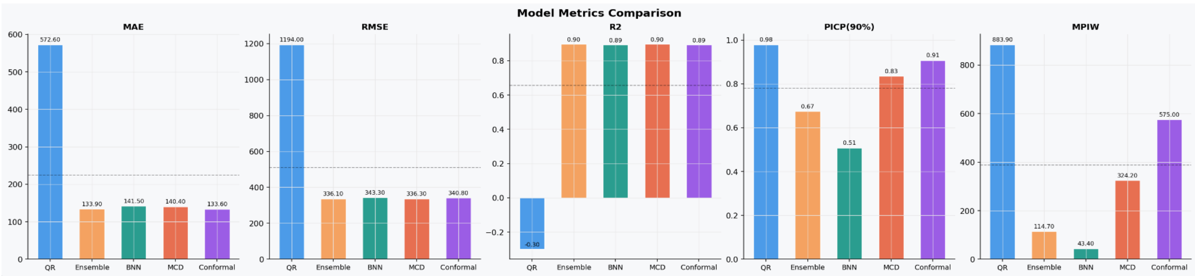


**Figure 2:** Model's metrics comparison.

Deterministic performance measures show a clear stratification between the linear baseline and nonlinear machine learning models. Ridge regression serves as a poor predictor for this dataset, yielding the highest error rates and the lowest coefficient of determination. This indicates that the dynamics of the underlying data have significant nonlinearities that linear regularized frameworks cannot capture. Conversely, the remaining six models demonstrate highly competitive and densely clustered point prediction capabilities. Random Forest achieves the lowest overall error profile. It should be noted that increasing the architectural complexity using sequence-based networks (LSTM, Transformer) and spatial networks (ST-GNN) does not yield a negligible improvement in prediction accuracy.

This suggests that for average deterministic tracking, ensemble decision trees remain very robust or that global features are very informative with respect to only sequential/spatial dependencies. Estimating the probability intervals provides a critical insight into how well these models quantify the prediction variance at the intended target confidence level. All evaluated models demonstrate strong empirical calibration, as their probability of covering the prediction interval closely approaches or exceeds the nominal threshold. The transformer model provides the most conservative and robust coverage at , while ridge regression represents the lower bound of acceptable calibration. Although the coverage probabilities are almost the same for all nonlinear models, the average prediction interval width reveals significant differences in model performance. Ridge regression yields an extremely wide and uninformative band, indicating excessive uncertainty and lack of predictive resolution.

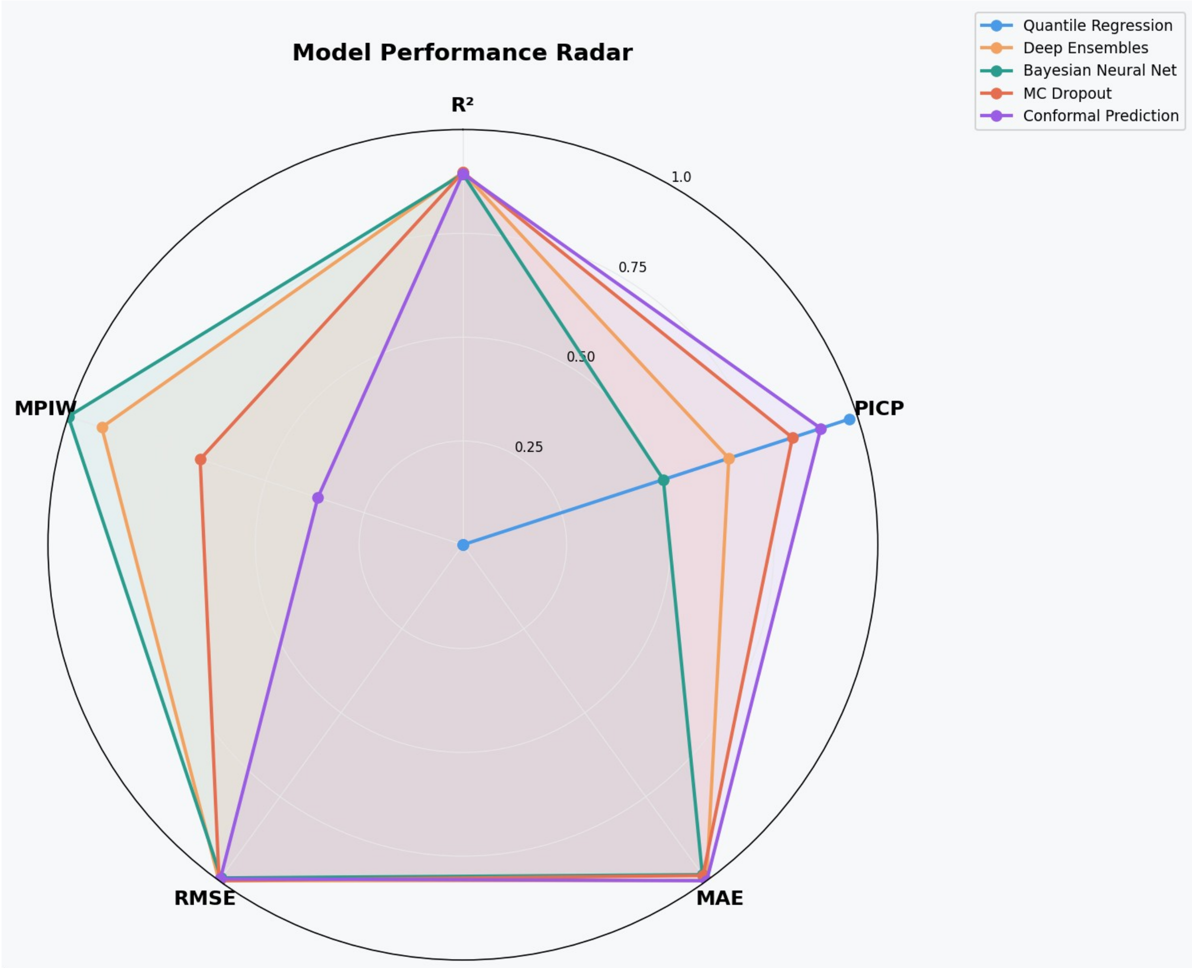


**Figure 3:** Model's performance.

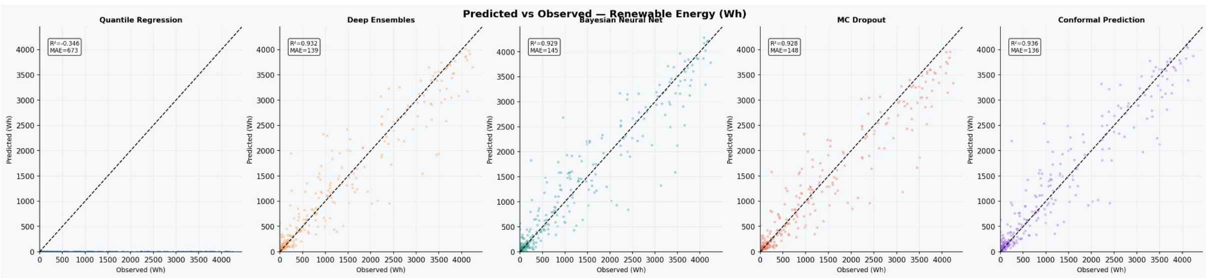


**Figure 4:** Predicted vs Observed data for Renewable Energy.

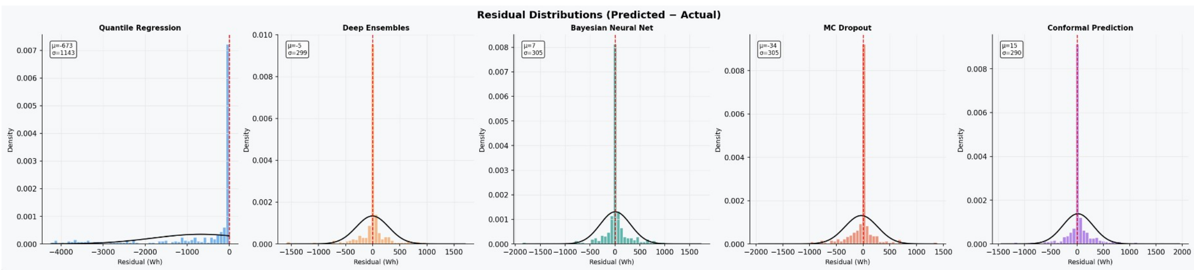


**Figure 5:** Residual Distributions.

Figure 13 demonstrates coverage and interval efficiency for conformal wrapper. Figure 14 shows conformal prediction intervals on 120 sample window for each architecture.

Among the high-performance models, MLP and ST-GNN achieve the narrowest prediction intervals. ST-GNN exhibits excellent UQ optimization: it achieves identical coverage probabilities to Random Forest and GBM, but does so with a significantly narrower interval width. This indicates that the spatiotemporal structure creates sharper, more reasonable uncertainty bounds without compromising empirical coverage. However, the need for significant computational resources and long training time make it inefficient. Thus, MLP becomes the best solution among the considered models.

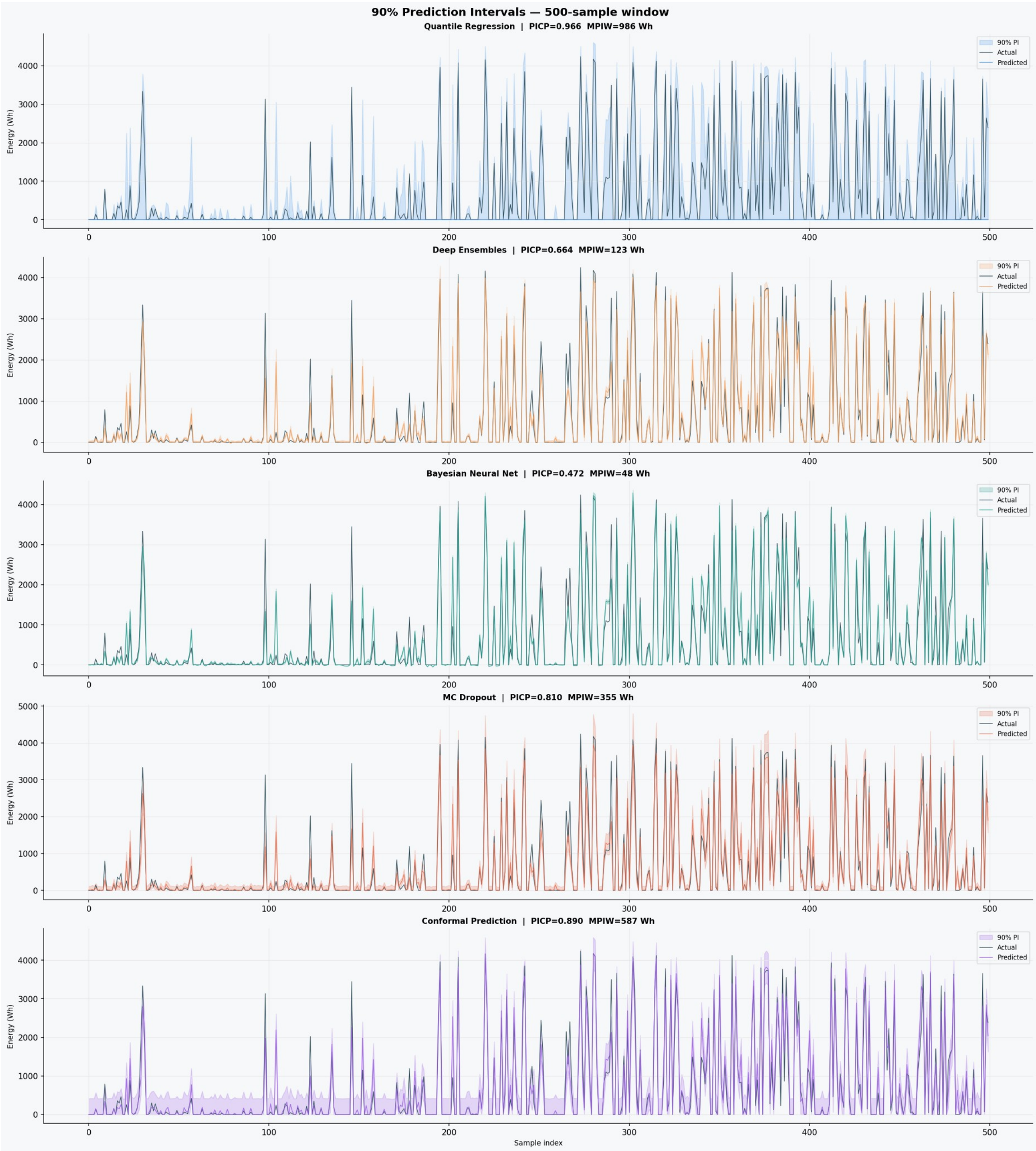


**Figure 6:** 500-sample window for 90% prediction intervals.

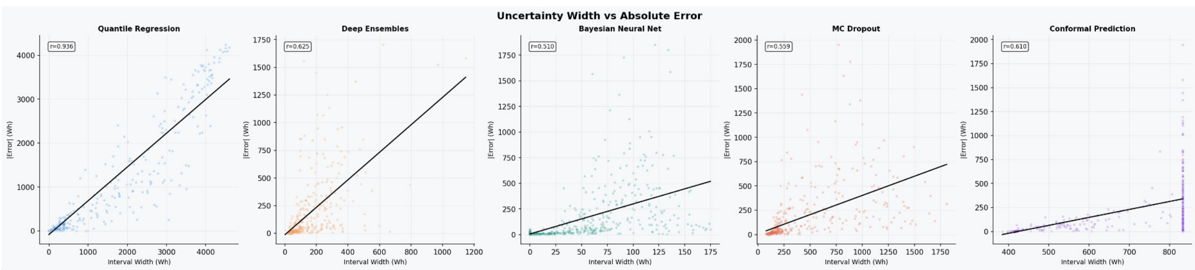


**Figure 7:** Uncertainty width vs Absolute Error comparison.

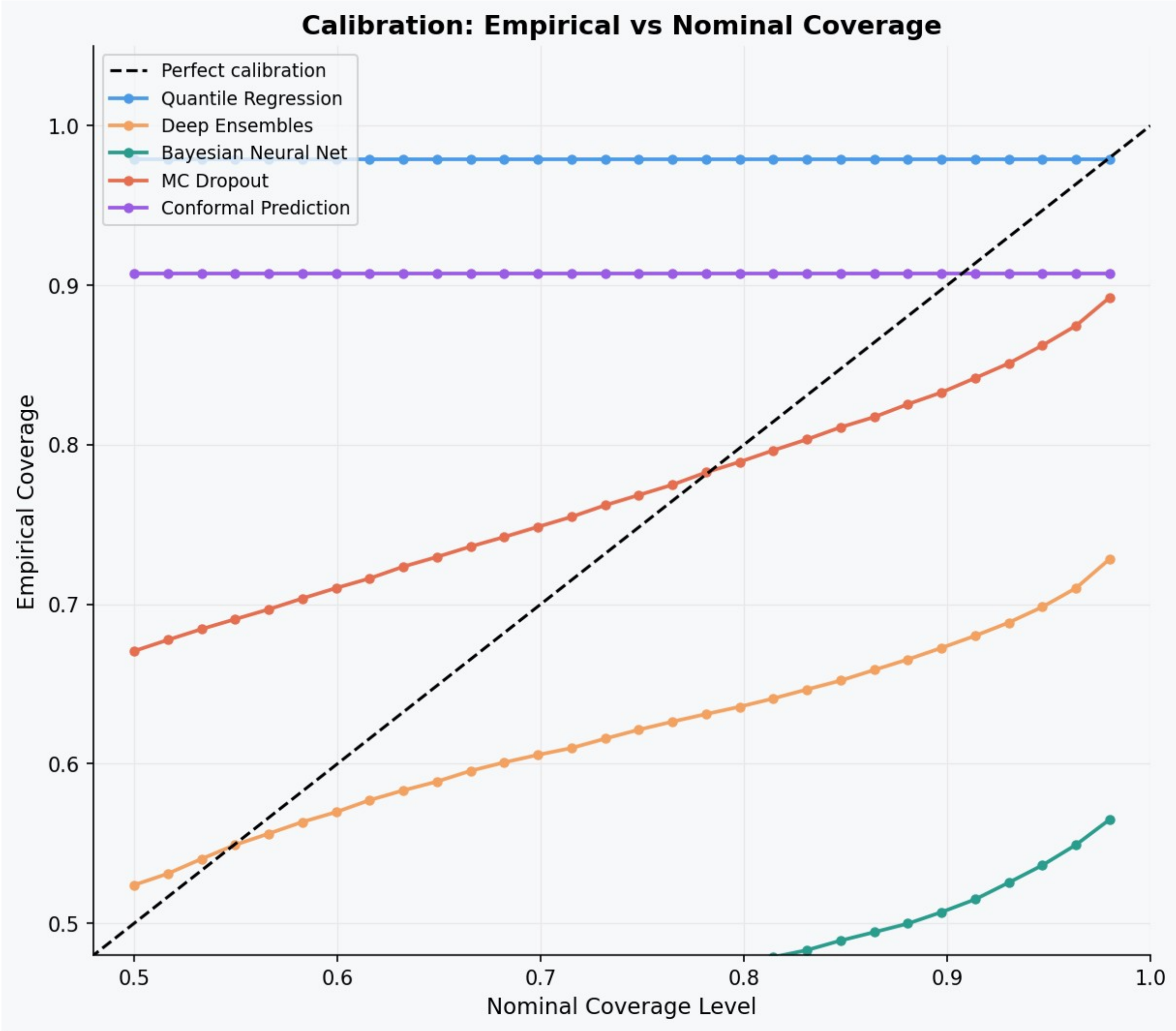


**Figure 8:** Empirical vs Nominal Coverage Calibration.

**Table 3**
Metrics of Uncertainty Quantification Models

| Model | MAE | RMSE | $R^2$ | PICP | MPIW | Train time, s |
|---|---|---|---|---|---|---|
| Ridge | 213.3 | 420.4 | 0.839 | 0.895 | 841.3 | 0 |
| Random Forest | 129.1 | 339.8 | 0.895 | 0.908 | 567.2 | 8.9 |
| GBM | 132.9 | 340.2 | 0.895 | 0.908 | 570.9 | 86.6 |
| MLP | 130.1 | 347.1 | 0.89 | 0.905 | 539.7 | 131 |
| LSTM | 131.6 | 355.3 | 0.885 | 0.909 | 563.3 | 523.3 |
| Transformer | 130.8 | 358.7 | 0.883 | 0.912 | 563 | 2845.4 |
| ST-GNN | 131.4 | 358.6 | 0.883 | 0.908 | 550.7 | 35441.9 |

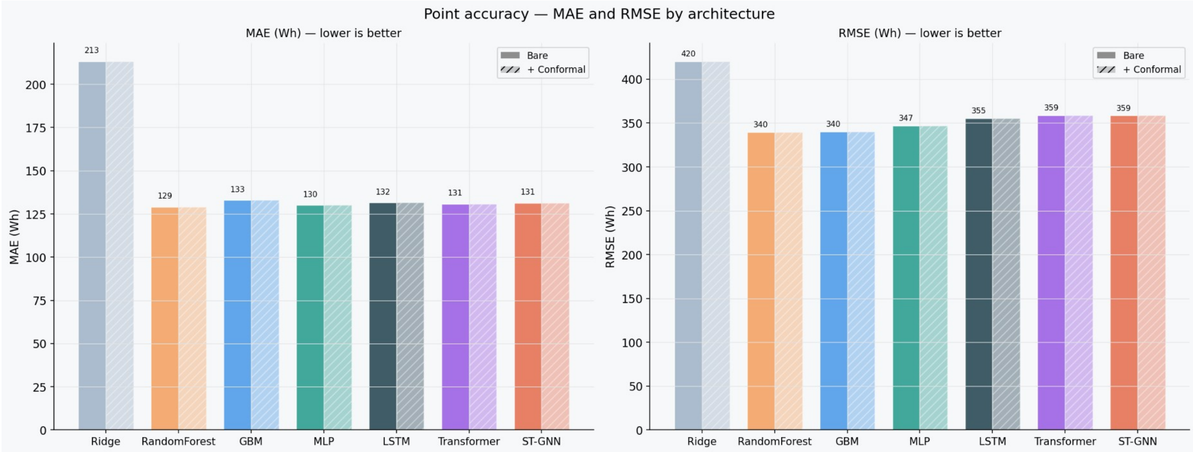


**Figure 9:** Prediction accuracy metrics.

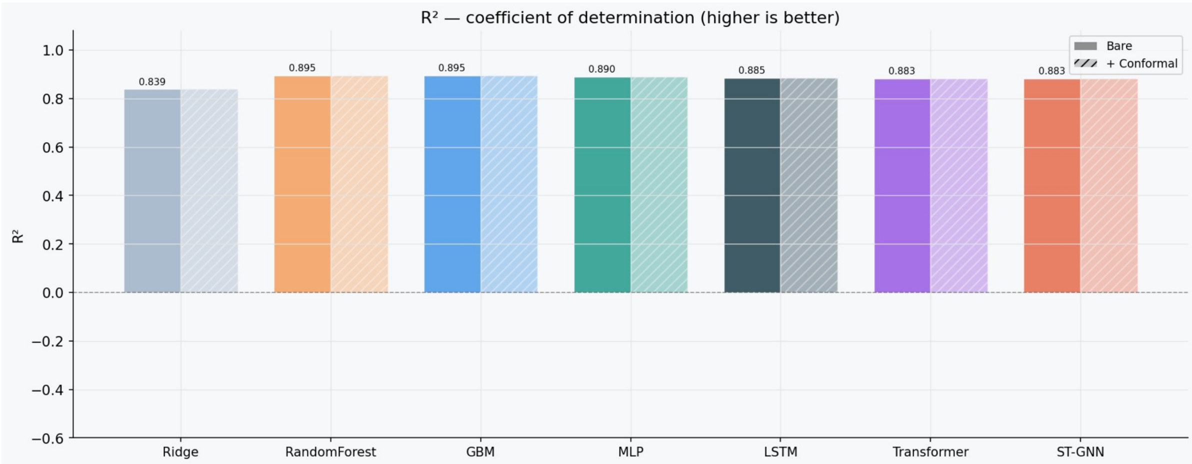


**Figure 10:** Coefficient of determination metrics.

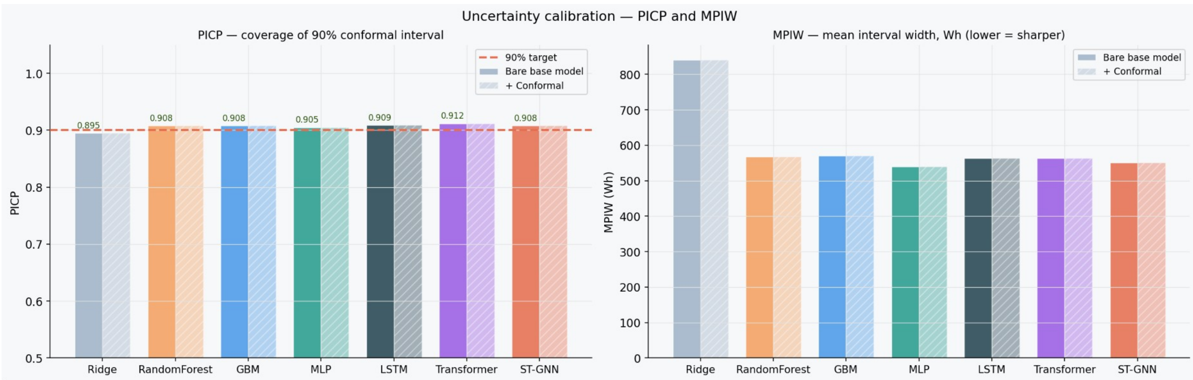


**Figure 11:** Prediction interval reliability metrics.

## 5. Discussion

The quantile regression metrics demonstrate the model's failure. $R^2 = -0.299$ indicates that the model performs worse than the constant mean predictor. The GBM-based quantile regression independently fits the individual quantile functions, resulting in overlapping intervals and unstable medians on this dataset. The extreme PICP value ($0.979 > 0.90$) confirms the overly wide intervals (MPIW = 884 Wh ≈ 6.6× MAE), which is a classic sign of underfitted quantile models where the intervals do not adapt to the structure of local variance.

The Bayesian neural network exhibits significant undercoverage. PICP = 0.508 versus the nominal 90% represents a −38% coverage gap, which is a critical failure for any security-related deployment. The posterior variance of the BNN is severely underestimated (MPIW = 43.4 Wh is implausibly narrow compared to MAE = 141.5). This pathology is consistent with a posterior collapse in the variational mean-field inference, where the approximate posterior moves towards the prior faster than the probability can expand it. The BNN is overconfident by a factor of about 3.

The MC dropout shows partial calibration recovery: PICP = 0.835 represents a −6.5% gap from the 90% target. The MC dropout recovers a significantly larger posterior uncertainty than the BNN (MPIW = 324.2 Wh), but remains miscalibrated. The dropout coefficient (p = 0.20) acts as a fixed epistemic prior; it does not adapt to heteroscedastic aleatory noise in the data. An example is near-zero energy at night versus highly dispersed solar generation at noon.

The deep ensembles show the best accuracy. The metric $R^2 = 0.897$ and the lowest RMSE = 336.1 Wh. However, the PICP = 0.674 (−22.6% gap), which is surprisingly low for a 5-member ensemble. The variance of the member differences (intermodel variance) is insufficient to capture the full forecast uncertainty on this dataset.

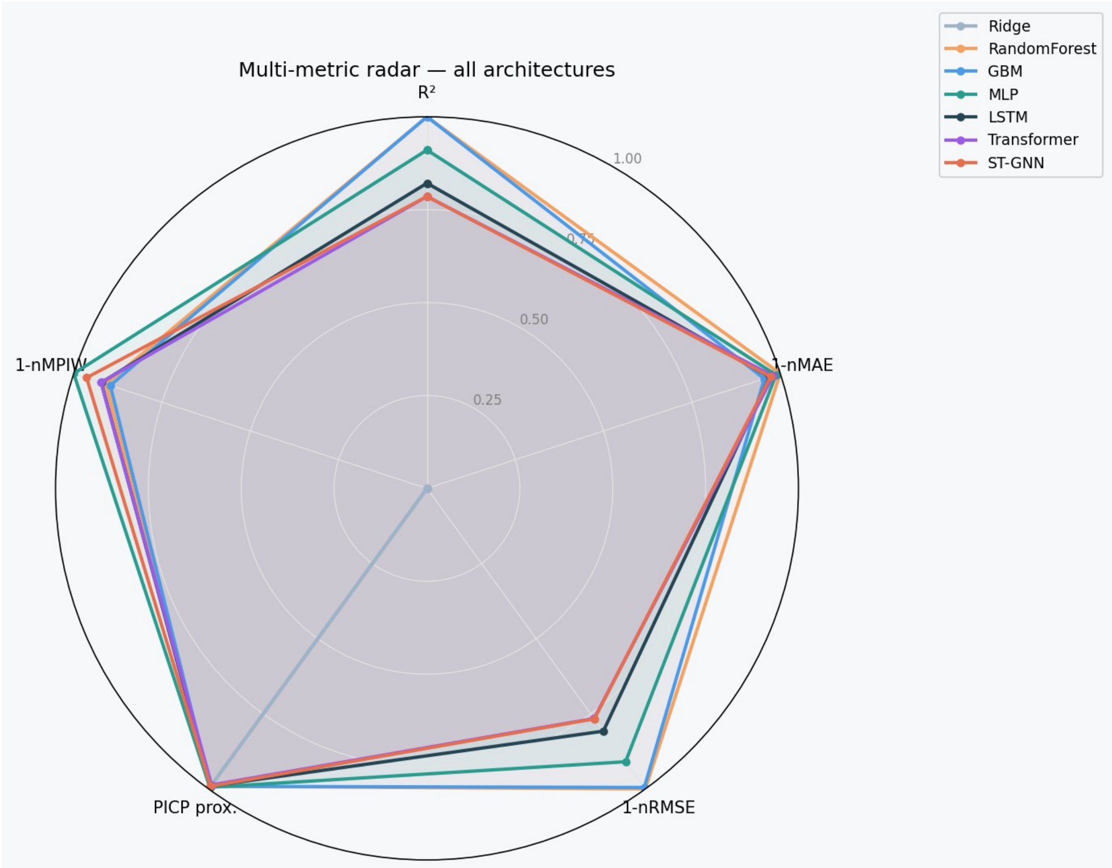


**Figure 12:** Multi-metric radar.

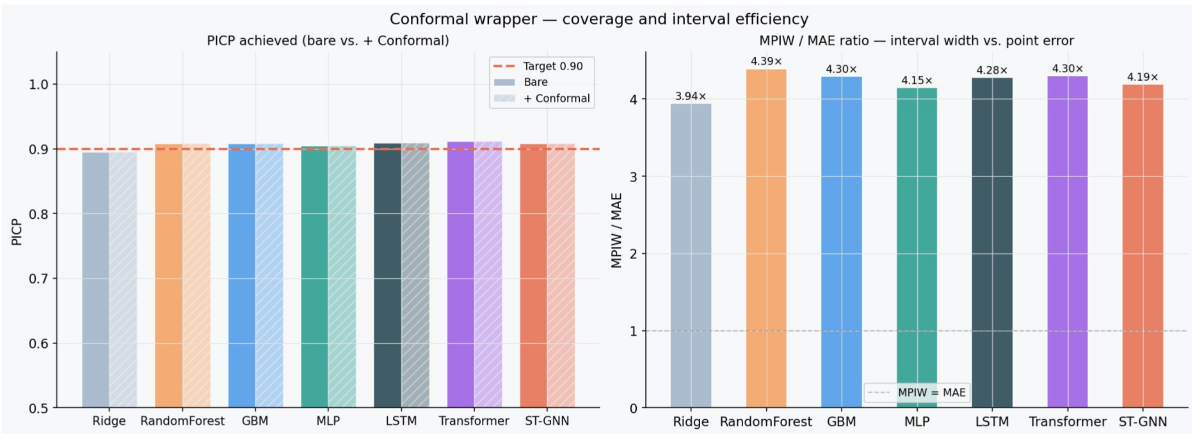


**Figure 13:** Coverage and interval efficiency for conformal wrapper.

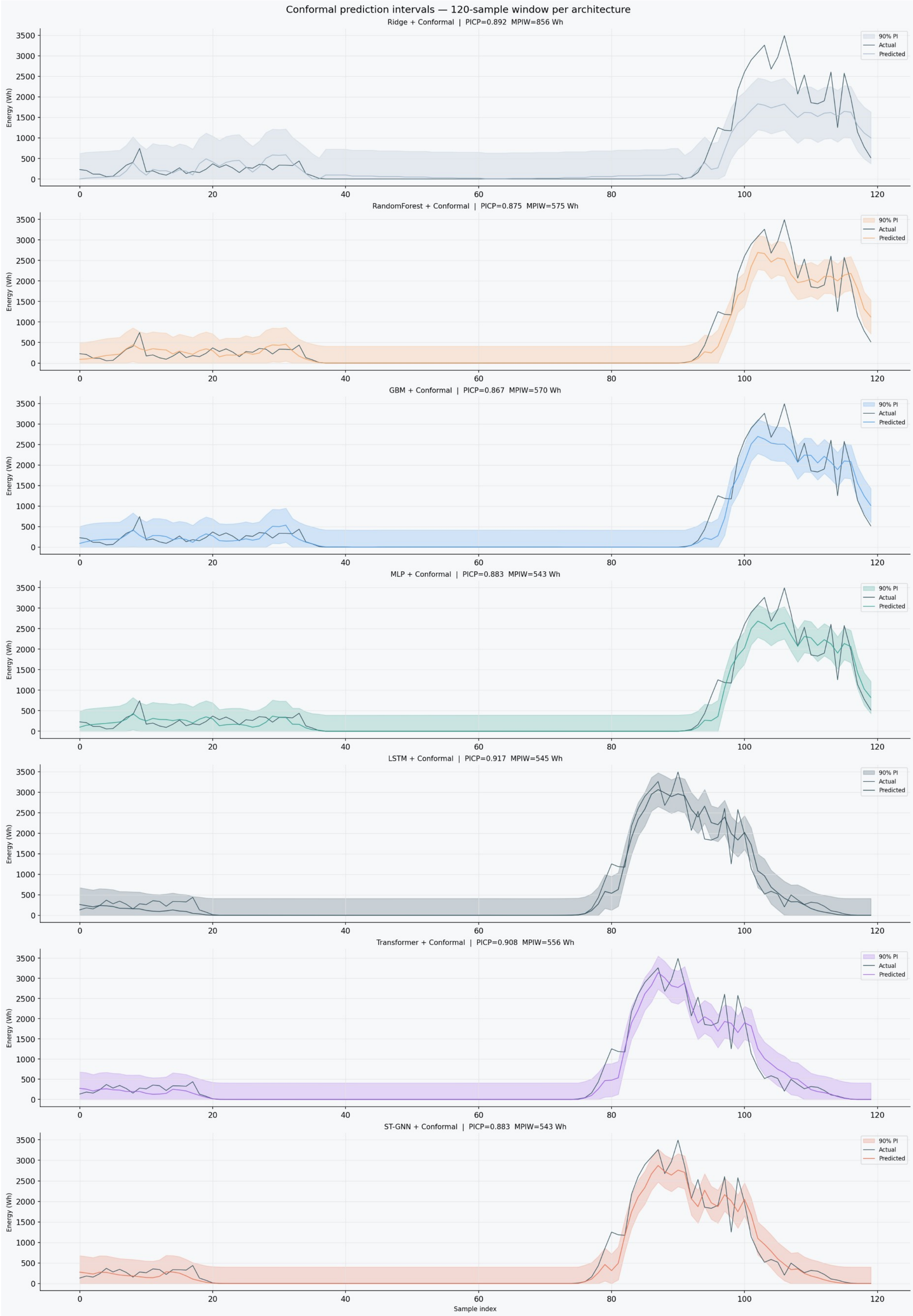


**Figure 14:** Conformal prediction intervals on 120 sample window for each architecture.

Conformal forecasting is the only method that achieves a nominal coverage of PICP = 0.907 (+0.7% above target) with a theoretically guaranteed coverage factor under the assumption of interchangeability. This is a defining property of conformal forecasting. That is, it is the only method with a finite sample validity guarantee, rather than an asymptotic one. The price is the interval width MPIW = 575.0 Wh, which is wider than in ensembles and MCD because the split conformal procedure uses a single global quantile of the discrepancy estimate rather than the input conditional widths.

## 6. Conclusions

The analysis demonstrates that the combination of deep learning methods, in particular the multilayer perceptron architecture, and modern methods of quantitative uncertainty assessment, such as conformal analysis, forms the most mathematically advanced and engineering-based technical basis for the operational management of future smart grids.

The transition from classical deterministic, isolated forecasting to multidimensional probabilistic prediction changes the very philosophy of power grid management, because instead of constantly reactively responding to sudden frequency or voltage imbalances, system operators receive a powerful tool for predictive optimization of reserves based on clearly quantified risk intervals.

At the same time, the practical widespread deployment of these intelligent systems is hindered by severe real-world engineering barriers, including the unstable quality of sensor telemetry, growing cybersecurity threats such as data integrity attacks, and the extremely high computational cost of deep mathematical models. Effectively solving these problems requires a comprehensive approach and synergy of various branches of computer science, in particular, the use of neural networks themselves for continuous self-healing and data cleaning in real time, as well as the active transfer of lightweight, quantized forecasting algorithms directly to the edge computing level (Edge Computing).

The successful implementation of the proposed complex spatio-temporal methodology can not only radically minimize the financial costs of operators for operational errors and the maintenance of excess reserves, but also opens the only possible path to reliable, sustainable and economically justified operation of energy systems of the future with almost one hundred percent penetration of renewable energy sources. Artificial intelligence in this context ceases to be just an analytical tool, but turns into a central element of the new generation energy infrastructure.

## Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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