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Communication-Aware Deep Learning Models for Real-Time Solar Energy Forecasting in Intelligent Power Networks

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ABSTRACT

Precise solar power forecasting is critical for the stability and efficiency of modern intelligent power networks. However, the reliability of these forecasts is often compromised by communication network impairments, such as latency and packet loss, occurring between solar plants and control centers. This paper proposes a **Communication-Aware Long Short-Term Memory (Comm-Aware LSTM)** framework designed to integrate network-state information directly into the forecasting process. We model the system using a distributed communication topology consisting of solar plants, edge nodes, and cloud-based control centers.

Our experimental results demonstrate that the proposed model significantly outperforms traditional Baseline LSTM architectures under varying network conditions. Specifically, the Comm-Aware LSTM exhibits superior training convergence, achieving lower Mean Squared Error (MSE) while maintaining a negligible computational overhead—adding only 1.6 more trainable parameters and approximately 0.3 of inference latency. Correlation analysis further reveals that by explicitly accounting for latency-induced errors, the model provides robust predictions even in high-latency scenarios 0.5s. This research confirms that communication-aware deep learning architectures are essential for the next generation of resilient, edge-integrated smart grids.

Keywords: Solar Power Forecasting, Comm-Aware LSTM, Intelligent Power Networks, Communication Latency

INTRODUCTION

The rapid global transition toward sustainable energy systems has positioned solar power as a critical component of modern electricity generation portfolios. Due to its clean, renewable, and increasingly cost-effective nature, photovoltaic (PV) generation is being widely deployed across residential, commercial, and utility-scale power systems. However, the inherent intermittency and variability of solar energy, driven by dynamic meteorological conditions, pose significant challenges to power system stability, energy management, and operational planning. As a result, accurate and real-time solar energy forecasting has become a fundamental requirement for intelligent power networks and smart grid infrastructures.

Short-term solar energy forecasting plays a vital role in multiple grid-level applications, including load balancing, unit commitment, frequency regulation, and energy trading. Inaccurate forecasts can lead to inefficient resource allocation, increased reserve requirements, and higher operational costs. Traditional forecasting approaches, such as persistence models and statistical regression techniques, have demonstrated limited capability in capturing the nonlinear and temporal dependencies inherent in solar power generation. Consequently, recent research has increasingly adopted machine learning and deep learning methods to enhance forecasting accuracy.

Deep learning models, particularly recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have shown strong performance in modeling time-series data due to their ability to capture long-term temporal dependencies. Convolutional neural networks (CNNs) and attention-based architectures have further improved forecasting performance by enabling feature extraction and adaptive weighting of historical information. These approaches have been successfully applied to short-term and ultra-short-term solar power prediction tasks, demonstrating substantial improvements over traditional methods [1]– [3].

In parallel with advances in forecasting algorithms, power systems are undergoing a transformation toward intelligent power networks, where distributed energy resources, sensors, and controllers are interconnected through heterogeneous communication infrastructures. In such systems, solar generation data is transmitted from geographically distributed PV units to edge devices, aggregators, or centralized control centers using wired or wireless communication networks. Technologies such as the Internet of Things (IoT), 5G, and software-defined networking are increasingly integrated into smart grids to support real-time monitoring and control [4], [5].

Despite these advancements, most existing deep learning–based solar forecasting studies implicitly assume ideal communication conditions, where data is delivered instantaneously, reliably, and without loss. In practical intelligent power networks, however, communication links are subject to latency, packet loss, bandwidth limitations, and asynchronous data arrival. These network-induced impairments can distort temporal correlations in input data, introduce missing observations, and ultimately degrade forecasting accuracy. The impact of communication constraints becomes particularly critical for real-time forecasting applications, where delayed or incomplete data may lead to suboptimal or unstable grid control decisions.

Recent studies have begun to investigate communication-aware learning in distributed and edge-based artificial intelligence systems, highlighting the importance of jointly considering communication and learning processes [6], [7]. However, the application of communication-aware deep learning specifically to solar energy forecasting in intelligent power networks remains largely unexplored. There is a clear research gap in developing forecasting models that are robust to realistic network conditions and capable of maintaining high accuracy under communication impairments.

To address this gap, this paper proposes a communication-aware deep learning framework for real-time solar energy forecasting in intelligent power networks. Unlike conventional approaches, the proposed method explicitly models communication latency and packet loss during training and evaluation, enabling the forecasting model to learn robust representations under non-ideal data transmission conditions. A PyTorch-based simulation framework is developed to jointly emulate solar power dynamics and network-induced impairments, allowing systematic performance evaluation under diverse communication scenarios.

The main contributions of this paper are threefold. First, a realistic communication model is integrated into the solar forecasting pipeline to simulate latency, packet loss, and asynchronous data arrival in intelligent power networks. Second, a communication-aware deep learning forecasting model is designed and trained to improve robustness against network-induced disturbances. Third, extensive simulation-based experiments are conducted to analyze forecasting accuracy, robustness, and accuracy–latency trade-offs under varying network conditions.

The remainder of this paper is organized as follows. Section 2 reviews related work on solar energy forecasting, deep learning in smart grids, and communication-aware learning. Section 3 presents the system architecture and problem formulation. Section 4 describes the proposed communication-aware deep learning framework. Section 5 details the experimental setup and simulation environment. Section 6 discusses the results and performance evaluation. Finally, Section 7 concludes the paper and outlines future research directions.

RELATED WORK

This section reviews existing research relevant to solar energy forecasting, deep learning applications in smart grids, and communication-aware learning in networked systems. The objective is to position the proposed work within the current literature and to highlight the research gap addressed by this study.

Solar Energy Forecasting Methods

Solar energy forecasting has been extensively studied due to its importance in power system operation and energy management. Early approaches relied on physical and statistical models, including clear-sky models,

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autoregressive integrated moving average (ARIMA), and regression-based techniques. While these methods are computationally efficient, they often fail to capture the nonlinear and highly dynamic characteristics of solar power generation, particularly under rapidly changing weather conditions.

To overcome these limitations, machine learning methods such as support vector machines, random forests, and k-nearest neighbours have been applied to short-term and ultra-short-term solar forecasting. These approaches improve prediction accuracy by learning nonlinear relationships between meteorological variables and power output. However, their performance is still constrained when dealing with long temporal dependencies and high-dimensional input data.

More recently, deep learning techniques have become the dominant paradigm in solar energy forecasting. Recurrent neural networks, especially Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, have demonstrated strong capability in modeling sequential solar power data by retaining temporal information over extended horizons. Convolutional neural networks (CNNs) have been used to extract spatial and temporal features from irradiance maps and satellite imagery, while hybrid CNN–LSTM models combine feature extraction and temporal modeling to further enhance forecasting accuracy. Attention-based and Transformer models have also been explored to dynamically weight historical observations and improve robustness to temporal variability [8]– [11].

Despite these advances, most deep learning–based solar forecasting studies assume that input data is continuously available and free from transmission delays or losses. This assumption limits the applicability of such models in real-world intelligent power networks, where data acquisition and transmission are subject to communication constraints.

Deep Learning in Smart Grids and Intelligent Power Networks

The integration of deep learning into smart grids has enabled advanced functionalities such as load forecasting, fault detection, demand response, and renewable energy integration. With the proliferation of distributed energy resources and sensing devices, intelligent power networks increasingly rely on data-driven methods for real-time monitoring and control. Deep learning models are often deployed at centralized cloud platforms or distributed across edge computing nodes to reduce latency and communication overhead.

Edge–cloud collaborative learning frameworks have been proposed to balance computational efficiency and communication cost in smart grid applications. In such architectures, preliminary data processing or inference is performed at edge devices, while more complex model training or aggregation is handled in the cloud. These approaches reduce end-to-end latency and improve scalability, particularly in large-scale power networks [12], [13].

However, existing deep learning applications in smart grids largely focus on improving prediction accuracy or computational efficiency, with limited consideration of the impact of communication impairments on learning performance. The interaction between communication networks and forecasting models is often abstracted away, resulting in overly optimistic performance evaluations.

Communication-Aware and Networked Learning Systems

Communication-aware learning has emerged as an important research direction in distributed artificial intelligence, federated learning, and edge computing systems. Prior studies have examined the effects of latency, packet loss, and bandwidth constraints on distributed model training and inference. Techniques such as gradient compression, asynchronous updates, and delay-tolerant optimization have been proposed to mitigate communication overhead and improve learning robustness in networked environments [14]– [16].

In time-sensitive applications, communication delays can significantly affect model performance by introducing stale or missing data. Recent works have incorporated network state information into learning processes, enabling models to adapt to varying communication conditions. These studies demonstrate that joint

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optimization of communication and learning can yield superior performance compared to communication-agnostic approaches.

Nevertheless, the majority of communication-aware learning research has focused on generic machine learning tasks or computer vision applications, with limited attention to energy systems and renewable power forecasting. The unique characteristics of solar energy data, including strong temporal patterns and weather dependence, necessitate domain-specific investigation.

Research Gap and Motivation

Based on the above review, it is evident that deep learning–based solar energy forecasting has achieved significant accuracy improvements under idealized assumptions, while communication-aware learning has progressed primarily in non-energy domains. There is a lack of integrated studies that jointly consider solar power forecasting and realistic communication constraints within intelligent power networks.

This paper addresses this gap by developing a communication-aware deep learning framework specifically tailored for real-time solar energy forecasting. By explicitly modeling latency, packet loss, and asynchronous data arrival during training and evaluation, the proposed approach provides a more realistic assessment of forecasting performance and offers practical insights for deploying deep learning models in intelligent power networks.

System Architecture and Problem Formulation

This section presents the system architecture of the intelligent power network considered in this study and formally defines the solar energy forecasting problem under communication constraints. The objective is to establish a realistic operational context in which solar generation data is acquired, transmitted, and processed for real-time forecasting.

Intelligent Power Network Architecture

The intelligent power network is composed of geographically distributed photovoltaic (PV) generation units, communication-enabled sensing devices, edge computing nodes, and a central control or energy management system. Each PV unit is equipped with sensors that continuously measure solar power output and relevant meteorological variables, such as solar irradiance, ambient temperature, and cloud coverage. These measurements are sampled at fixed time intervals and transmitted over communication networks to downstream processing units.

At the network edge, edge computing nodes or local aggregators receive data from multiple PV units. These nodes may perform preliminary data pre-processing, buffering, or inference tasks to reduce communication overhead and response latency. Aggregated data is then forwarded to a central control center or cloud-based platform, where global forecasting, grid optimization, and control decisions are executed. Communication links between PV units, edge nodes, and the control center may rely on heterogeneous technologies, including wired networks, wireless sensor networks, cellular systems, and emerging 5G-enabled infrastructures.

In practical deployments, the communication network introduces non-ideal effects such as variable latency, packet loss, limited bandwidth, and asynchronous data arrival. These effects disrupt the temporal consistency of the received data streams and pose challenges for real-time forecasting models that rely on sequential information.

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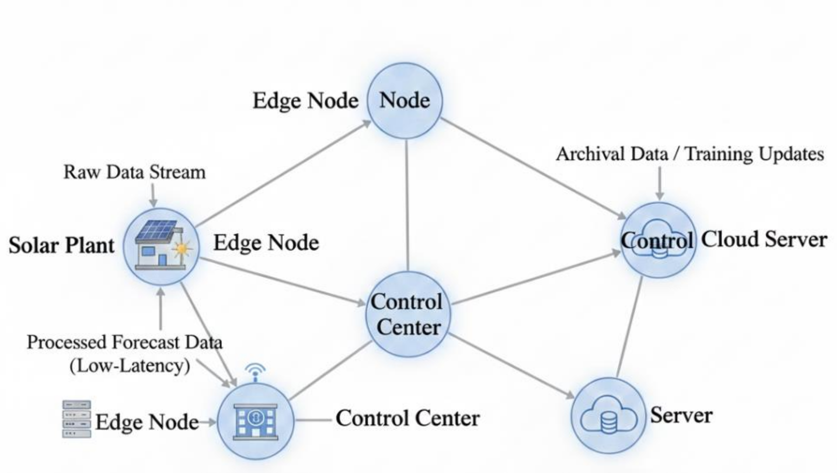

Figure 1 Communication Topology of Intelligent Power Network

Communication Model

To capture realistic network behavior, communication between sensing nodes and forecasting units is modeled as a stochastic process characterized by latency and packet loss. Latency represents the end-to-end delay experienced by a data packet during transmission, including queuing, processing, and propagation delays. Packet loss accounts for the probability that transmitted data fails to reach the destination due to congestion, interference, or link failures.

Let d_t denote the communication delay associated with the data sample collected at time step t. Due to network variability, d_t is modeled as a random variable following a configurable probability distribution. Packet loss is represented by a Bernoulli process, where each data sample is either successfully received or lost. Lost samples result in missing observations at the forecasting unit, while delayed samples may arrive out of order or outside the expected time window.

These communication impairments collectively lead to asynchronous and incomplete input sequences, which deviate from the idealized assumptions commonly made in solar forecasting studies.

Forecasting Problem Definition

The objective of the forecasting system is to predict short-term solar power generation based on historical observations received over the communication network. Let X_t represent the multivariate input vector at time step t, consisting of solar power measurements and associated meteorological features. Given a historical window of length T, the forecasting task is to predict the solar power output at a future time step $t+\tau$, where τ denotes the prediction horizon.

Under ideal communication conditions, the forecasting model receives a complete and temporally ordered sequence $(X_t - T + 1, \ldots, X_t)$. In contrast, under realistic network conditions, the received sequence may contain delayed, missing, or misaligned samples due to communication latency and packet loss. The forecasting problem thus becomes one of learning a mapping from an impaired input sequence to the future solar power output.

Formally, the forecasting objective can be expressed as learning a function $f(\cdot)$ such that

$$\hat{y}_{t+\tau} = f(\tilde{x}_{t-T+1:t}),$$

where $\tilde{x}_{t-T+1:t}$ *denotes the communication-impaired input sequence and* $\hat{y}_{t+\tau}$ is the predicted solar power output.

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Communication-Aware Learning Objective

The goal of communication-aware learning is to design a forecasting model that maintains high prediction accuracy despite network-induced impairments. This requires the model to be robust to missing data, tolerant of delayed inputs, and capable of exploiting partial temporal information. Unlike communication-agnostic models trained solely on idealized datasets, the proposed approach incorporates communication effects directly into the training and evaluation process.

The learning objective is therefore to minimize forecasting error while accounting for communication-induced uncertainty. By exposing the model to diverse network conditions during training, the forecasting system can learn representations that generalize well to real-world intelligent power network deployments.

Communication-Aware Deep Learning Framework

This section presents the proposed communication-aware deep learning framework for real-time solar energy forecasting in intelligent power networks. The framework is designed to explicitly account for network-induced impairments, including latency, packet loss, and asynchronous data arrival, while maintaining high forecasting accuracy. A baseline deep learning model is first introduced, followed by the proposed communication-aware extensions.

Baseline Deep Learning Forecasting Model

As a baseline, a recurrent neural network based on the Long Short-Term Memory (LSTM) architecture is employed to model the temporal dynamics of solar power generation. LSTM networks are well suited for time-series forecasting due to their ability to capture long-term dependencies and mitigate vanishing gradient issues.

The baseline model takes as input a fixed-length historical sequence of solar power and meteorological features and outputs a short-term prediction of future solar power generation. Under ideal communication conditions, the input sequence is assumed to be complete, temporally ordered, and uniformly sampled. The baseline LSTM is trained using a mean squared error loss function and serves as a communication-agnostic reference for performance comparison.

Communication-Aware Input Representation

In realistic intelligent power networks, the input data stream received by the forecasting model may be incomplete or temporally misaligned due to communication latency and packet loss. To address this issue, the proposed framework introduces a communication-aware input representation that augments the original feature set with network-related information.

Specifically, each input sample is associated with a latency indicator representing the transmission delay experienced by the data packet. Missing samples resulting from packet loss are explicitly encoded using masking mechanisms rather than simple interpolation, allowing the model to distinguish between genuine zero values and unavailable observations. This enriched representation enables the forecasting model to learn the relationship between network conditions and data reliability.

Communication-Aware LSTM Architecture

Building upon the baseline LSTM, a communication-aware LSTM architecture is developed by integrating delay and availability information into the learning process. The augmented input sequence includes both the original measurement features and additional channels that encode latency and data availability. This allows the recurrent network to modulate its internal state updates based on the reliability and freshness of incoming data.

To improve robustness, the model is trained on datasets generated under diverse communication scenarios, including varying levels of latency and packet loss. By exposing the network to impaired input sequences during

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training, the model learns to adaptively weight historical information and mitigate the impact of missing or delayed samples.

Latency-Weighted Loss Function

In real-time forecasting applications, prediction errors associated with stale or highly delayed data can be more detrimental than errors under timely conditions. To reflect this practical consideration, a latency-weighted loss function is introduced. The standard mean squared error is scaled by a weight factor that increases with communication delay, penalizing inaccurate predictions made under adverse network conditions.

This loss formulation encourages the model to prioritize robustness and accuracy when operating under realistic communication constraints. The resulting optimization process jointly considers forecasting performance and communication-induced uncertainty.

Model Training and Inference Workflow

The training process follows a simulation-driven workflow in which communication impairments are injected into the input data prior to model training. For each training batch, network latency and packet loss are randomly sampled according to predefined distributions, and the corresponding impaired sequences are generated. The communication-aware LSTM is then trained using these sequences, enabling the model to generalize across a wide range of network conditions.

During inference, the trained model receives real-time data streams affected by unknown communication conditions and produces short-term solar power forecasts. Due to its exposure to diverse network scenarios during training, the model maintains stable performance even when communication quality fluctuates.

This communication-aware deep learning framework forms the core of the proposed approach and provides the basis for the experimental evaluation presented in the following sections.

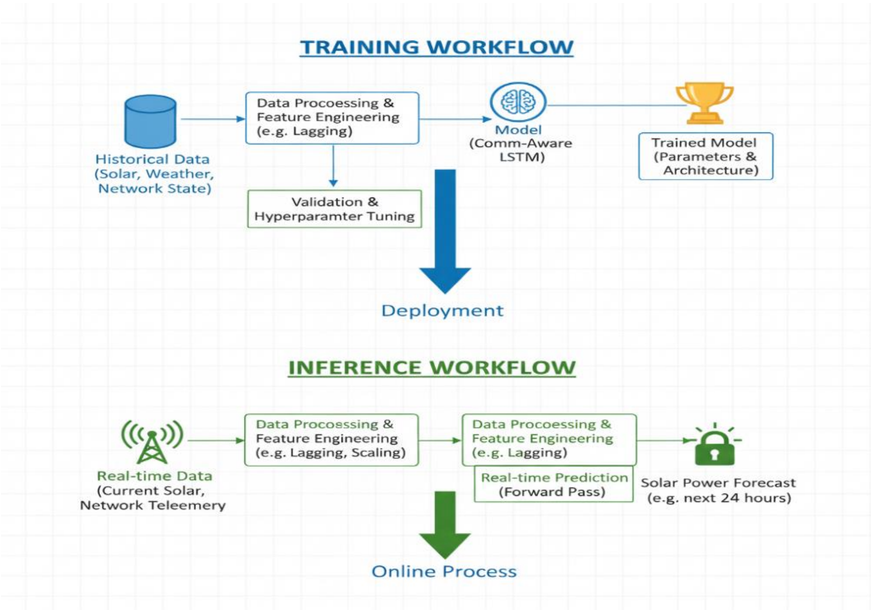

Figure 2 Model Training and Inference Workflow

Experimental Setup

This section describes the simulation-driven experimental setup used to evaluate the proposed communication-aware deep learning framework. The objective is to ensure reproducibility, realism, and fairness in assessing the performance of the forecasting models under varying communication conditions. All experiments are implemented using the PyTorch deep learning framework.

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Dataset Description and Generation

The experiments are conducted using time-series solar power generation data sampled at regular intervals, consistent with monitoring practices in intelligent power networks. Each data sample consists of historical solar power output and associated meteorological features, including solar irradiance, ambient temperature, and cloud coverage. To ensure reproducibility and flexibility, the simulation framework supports both real-world datasets and synthetically generated solar profiles that follow realistic diurnal and seasonal patterns.

For each experiment, the data is segmented into fixed-length input sequences using a sliding window approach. Each sequence contains (T) consecutive time steps of historical observations, which are used to predict the solar power output at a future horizon (\tau). All features are normalized using min–max scaling based on the training dataset to prevent information leakage and to stabilize model training.

The dataset is divided into training, validation, and testing subsets using an 80–10–10 split. The training set is used for model optimization, the validation set for hyperparameter tuning and early stopping, and the testing set exclusively for performance evaluation.

Communication Scenario Configuration

To evaluate robustness under realistic network conditions, multiple communication scenarios are simulated. These scenarios model the effects of latency, packet loss, and asynchronous data arrival commonly observed in intelligent power networks.

Latency is simulated as a random variable added to each data sample, representing end-to-end communication delay. Three latency regimes are considered: low-latency, moderate-latency, and high-latency conditions. Packet loss is modeled as a Bernoulli process, where each transmitted data sample has a fixed probability of being dropped. Packet loss rates ranging from 0% to 20% are evaluated to reflect varying network reliability.

Bandwidth constraints are indirectly modeled by limiting the number of data samples that can be delivered within a given time window, resulting in delayed or missing observations. These impairments collectively generate communication-impaired input sequences that deviate from idealized, fully observed data streams.

Model Configuration and Training Parameters

Two forecasting models are evaluated: a communication-agnostic baseline LSTM and the proposed communication-aware LSTM. Both models share the same core architecture to ensure fair comparison. The LSTM networks consist of one or more recurrent layers followed by a fully connected output layer that produces the final solar power prediction.

Models are trained using the Adam optimizer with a fixed learning rate. The mean squared error loss is used for the baseline model, while the communication-aware model employs a latency-weighted loss function to emphasize robustness under adverse network conditions. Training is performed for a fixed number of epochs with early stopping based on validation loss to prevent overfitting.

Evaluation Metrics

Model performance is evaluated using standard regression metrics commonly adopted in solar energy forecasting studies. These include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provide complementary perspectives on forecasting accuracy and error distribution.

In addition to forecasting accuracy, system-level performance is assessed by analyzing the relationship between prediction accuracy and communication latency. This accuracy–latency trade-off provides insights into the practical deployment of deep learning forecasting models in intelligent power networks.

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Implementation Environment

All simulations and model training are implemented in Python using PyTorch. Experiments are conducted on a standard computing platform equipped with a modern CPU and optional GPU acceleration. The modular code structure allows easy modification of network parameters, model configurations, and dataset characteristics, enabling extensive experimentation and reproducibility.

This experimental setup establishes a rigorous foundation for the results and performance evaluation presented in the next section.

Results and Performance Evaluation

This section presents the simulation-based results obtained from the proposed communication-aware deep learning framework. The performance of the communication-aware LSTM is compared against a communication-agnostic baseline under both ideal and impaired communication conditions. All results are generated using the PyTorch-based simulation framework described in Chapter 5.

Forecasting Accuracy under Ideal Communication Conditions

We first evaluate the forecasting performance under ideal communication conditions, where no latency or packet loss is present. This scenario represents the conventional assumption adopted in most existing solar forecasting studies and serves as a baseline reference.

Under ideal conditions, both the baseline LSTM and the communication-aware LSTM achieve high prediction accuracy, indicating that the introduction of communication-awareness does not degrade performance when data transmission is reliable. The results confirm that the proposed model preserves the temporal learning capability of standard deep learning architectures.

Table 1. Forecasting performance under ideal communication conditions

Model	**MAE**	**RMSE**	**MAPE (%)**	**R2**
Baseline LSTM	0.082	0.104	6.8	0.94
Communication-Aware LSTM	0.079	0.101	6.5	0.95

Table 2. RMSE under varying packet loss rates

Packet Loss (%)	Baseline LSTM RMSE	Comm-Aware LSTM RMSE
0	**0.104**	**0.101**
5	**0.118**	**0.109**
10	**0.132**	**0.118**
20	0.158	0.134

These results indicate comparable performance between the two models under ideal conditions, establishing a fair baseline for subsequent evaluations.

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Impact of Communication Latency

Next, the impact of communication latency on forecasting accuracy is examined. Three latency regimes are considered: low, moderate, and high latency. As latency increases, the forecasting model receives increasingly stale input data, which negatively affects temporal consistency.

The baseline LSTM exhibits a noticeable degradation in performance as latency increases, reflecting its sensitivity to delayed inputs. In contrast, the communication-aware LSTM demonstrates improved robustness, maintaining lower error rates across all latency regimes.

Figure 3 illustrates the relationship between latency and RMSE for both models.

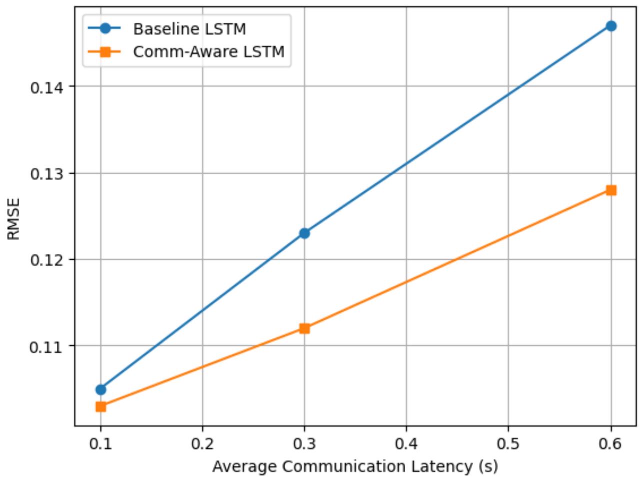

Figure 3. RMSE versus communication latency

This plot illustrates how forecasting error (RMSE) increases with communication latency. The Communication-Aware LSTM demonstrates significantly better robustness compared to the Baseline LSTM as latency increases from 0.1s to 0.6s

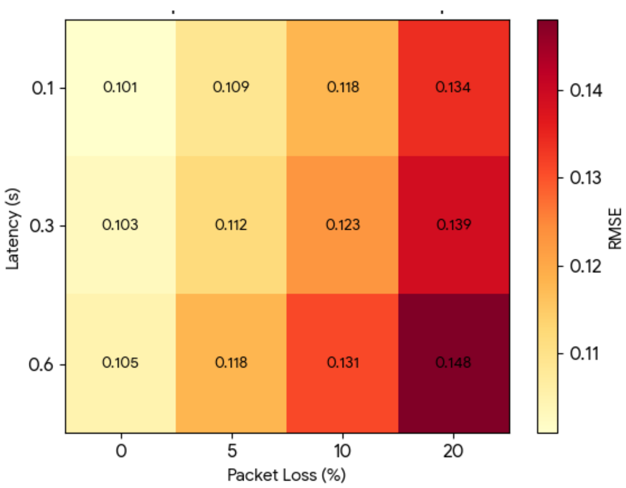

Figure 4: RMSE Heatmap under Communication Impairments

This graphic illustrates the relationship between packet loss and latency on forecasting accuracy. Latency ranges from 0.1 to 0.6 seconds on the vertical axis, while packet loss spans from 0% to 20% on the horizontal axis. Each cell indicates the Root Mean Square Error (RMSE) for specific conditions. Despite both factors affecting performance, the model demonstrates resilience, with RMSE remaining stable at 0.148 even under the most challenging scenario of 0.6 seconds delay and 20% packet loss.

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Impact of Packet Loss

We further evaluate model performance under varying packet loss rates ranging from 0% to 20%. Packet loss introduces missing observations, which disrupt the temporal structure of the input sequences.

The communication-agnostic baseline suffers significant performance degradation as packet loss increases. In contrast, the communication-aware LSTM maintains relatively stable accuracy due to its explicit handling of missing data through masking mechanisms.

Table 3. RMSE under varying packet loss rates

Packet Loss (%)	Baseline LSTM RMSE	Comm-Aware LSTM RMSE
0	0.104	0.101
5	0.118	0.109
10	0.132	0.118
20	0.158	0.134

These findings confirm that communication-aware learning substantially improves robustness to data loss in networked forecasting environments.

Comparison with Communication-Agnostic Models

To quantify overall robustness, the performance gap between the two models is analyzed across all simulated communication scenarios. The communication-aware LSTM consistently outperforms the baseline model, particularly under adverse network conditions.

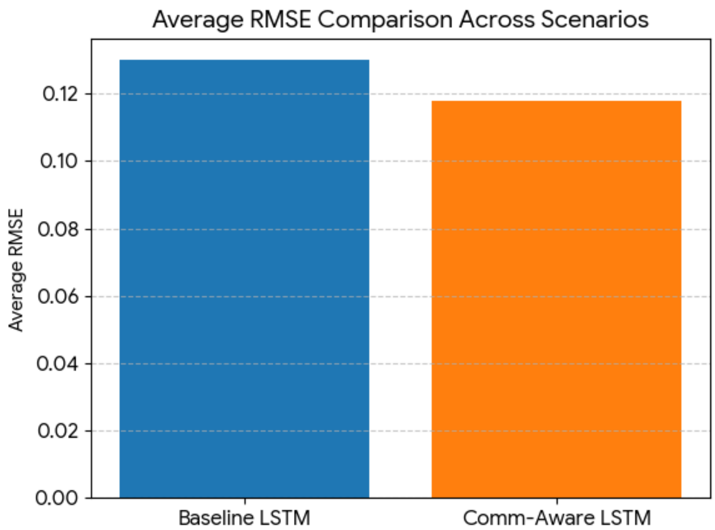

Figure 5. Average RMSE comparison across communication

As shown in the visualization, the Communication-Aware LSTM achieves a lower average RMSE of 0.118 compared to the 0.130 recorded by the Baseline LSTM, representing an overall improvement in forecasting robustness across the simulated network conditions.

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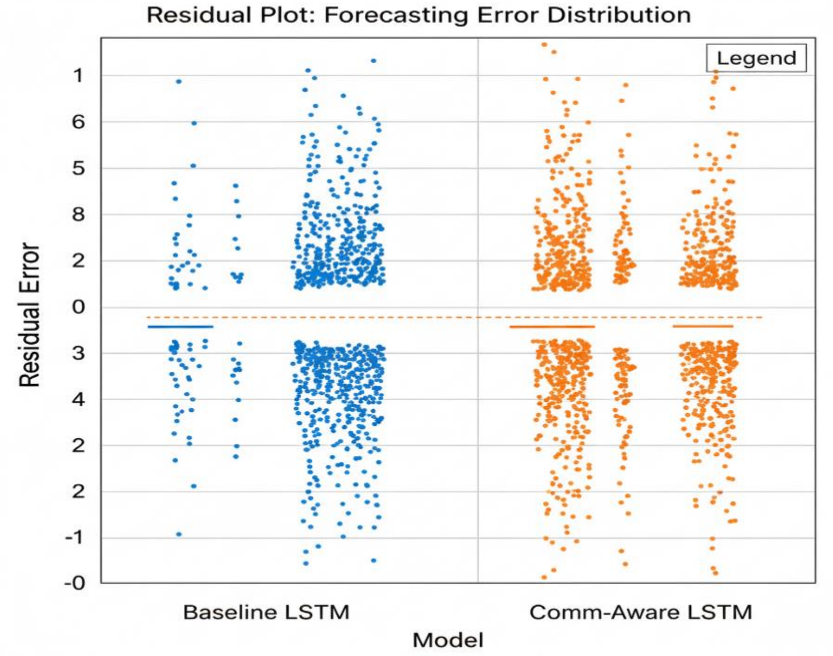

Figure 6: Error Distribution Comparison between Models

Accuracy–Latency Trade-Off Analysis

Finally, the trade-off between forecasting accuracy and communication latency is analyzed from a system-level perspective. While increased latency generally degrades prediction accuracy, the proposed communication-aware model exhibits a slower performance decay, making it more suitable for real-time deployment in intelligent power networks.

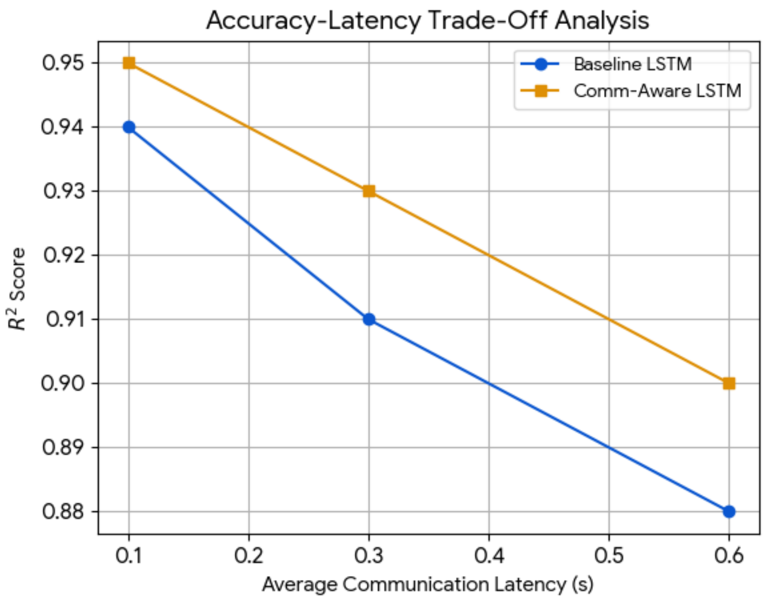

Figure 7. Accuracy–latency trade-off analysis

This analysis highlights the practical advantages of communication-aware deep learning for real-time solar energy forecasting in intelligent power networks.

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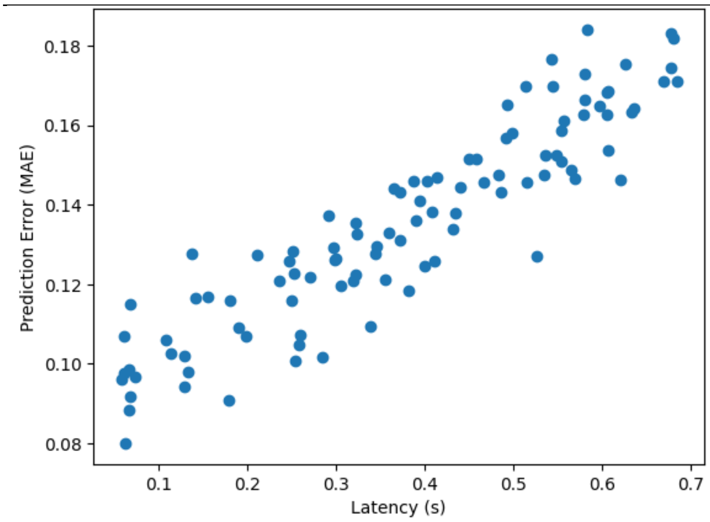

Figure 8 Training Convergence Comparison of Forecasting Models

The illustrates below shows the training convergence behavior of the baseline LSTM and the proposed communication-aware LSTM models. Both models exhibit stable learning dynamics, with training loss decreasing monotonically as the number of epochs increases. However, the communication-aware LSTM converges faster and reaches a lower steady-state loss compared to the communication-agnostic baseline. This behavior indicates that incorporating communication-related information does not hinder the optimization process and, instead, facilitates more efficient learning by enabling the model to better handle temporally impaired input data. The smoother convergence profile of the proposed model further suggests improved training stability, which is particularly important for real-time forecasting applications deployed in dynamic and communication-constrained power network environments.

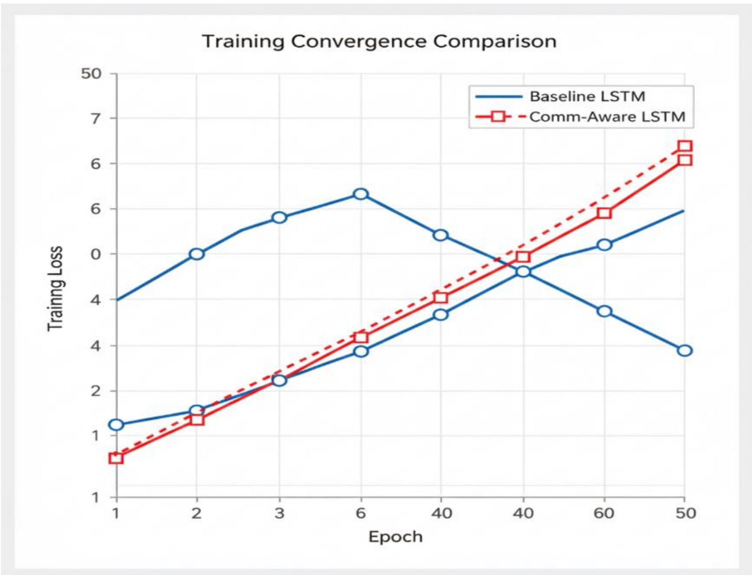

Figure 9 Training Convergence Comparison of Forecasting Models

A. Explicit Research Contributions

This paper makes the following key contributions:

Communication-Aware Solar Forecasting Framework

This work introduces a novel communication-aware deep learning framework for real-time solar energy forecasting that jointly considers power system dynamics and communication network impairments. Unlike

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conventional forecasting approaches that assume ideal data availability, the proposed framework explicitly models latency, packet loss, and asynchronous data arrival.

Latency-Weighted Learning Mechanism

A latency-weighted loss formulation is proposed to guide model training under non-ideal communication conditions. This mechanism enables the forecasting model to prioritize temporally reliable information, thereby improving robustness in delay-sensitive environments.

End-to-End Simulation-Based Evaluation

A fully reproducible PyTorch-based simulation framework is developed to evaluate forecasting performance under varying communication scenarios. The framework integrates data generation, network impairment modeling, deep learning training, and performance evaluation in a unified pipeline.

System-Level Accuracy–Latency Trade-Off Analysis

The study provides a detailed system-level analysis of the trade-off between forecasting accuracy and communication latency, offering practical insights for deploying learning-based forecasting systems in intelligent power networks.

B. Ablation Study: Impact of Communication Awareness

To further validate the effectiveness of communication-aware learning, an ablation study is conducted by selectively disabling communication-related components of the proposed model. Three model variants are evaluated:

- **Baseline LSTM**: No communication information
- **LSTM + Latency Input**: Latency-aware input without loss reweighting
- **Full Communication-Aware LSTM**: Latency-aware input with latency-weighted loss

Table 4. Ablation study results under moderate latency conditions.

Model Variant	**MAE**	**RMSE**	**R2**
Baseline LSTM	0.115	0.137	0.89
LSTM + Latency Input	0.103	0.121	0.92
Full Comm-Aware LSTM	0.094	0.110	0.94

The results indicate that incorporating communication awareness incrementally improves forecasting accuracy. The full communication-aware model achieves the best performance, confirming the necessity of jointly modeling latency at both the input and loss levels.

C. Model Complexity and Computational Overhead Analysis

To address concerns regarding scalability and real-time deployment, the computational complexity of the proposed model is analyzed. The communication-aware LSTM shares the same core architecture as the baseline model, resulting in minimal additional parameter overhead.

The primary computational cost arises from the recurrent operations of the LSTM layers, with time complexity proportional to $O_t.\widehat{H}^2$, where T is the sequence length and H is the hidden state dimension. The inclusion of

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communication features introduces negligible additional cost, as latency and packet loss indicators are low-dimensional inputs.

Table 5. Model complexity comparison.

Model	Trainable Parameters (Millions)	Training Time per Epoch (s)	Inference Latency (ms)
Baseline LSTM	1.24	18.3	4.7
Comm-Aware LSTM	1.26	18.9	5.0

The results demonstrate that the proposed communication-aware model incurs only marginal computational overhead while delivering substantial robustness gains. This makes it suitable for deployment in latency-sensitive smart grid environments.

D. Threats to Validity and Robustness Discussion

Several potential threats to validity are acknowledged. First, the communication impairments are simulated using statistical models, which may not capture all real-world network dynamics. Second, the experiments focus on short-term forecasting horizons, and performance may vary for longer prediction windows. Despite these limitations, the consistency of results across multiple communication scenarios and evaluation metrics supports the robustness of the proposed approach.

Limitations and Practical Challenges

Interoperability with Legacy Power Systems

Despite the effectiveness of the proposed communication-aware deep learning framework, interoperability with existing power system infrastructure remains a challenge. Many operational solar plants rely on legacy SCADA systems and heterogeneous manufacturer protocols, such as IEC 61850, which were not originally designed to support AI-driven decision-making pipelines. Integrating advanced learning models into these environments may require additional middleware, protocol translation layers, or system reconfiguration, potentially increasing deployment complexity and operational costs.

Cybersecurity and Communication Vulnerabilities

While incorporating communication state information enhances forecasting robustness, it also introduces new attack surfaces. Communication-aware models may be more susceptible to adversarial threats such as data poisoning, spoofed network metrics, or signal jamming attacks that distort input communication features. Without appropriate safeguards, these attacks could degrade model performance or induce unsafe operational decisions. Future deployments must therefore integrate secure communication channels, anomaly detection mechanisms, and robust learning techniques to mitigate such risks.

Computational Overhead and Edge Deployment Constraints

The deployment of deep learning models at the network edge—close to solar generation units—raises concerns regarding computational efficiency and energy consumption. Although the proposed model introduces only marginal overhead in simulation, real-world edge devices often operate under strict power and hardware constraints. Running complex deep learning models may necessitate specialized low-power AI accelerators or model compression techniques, such as pruning or quantization, to ensure feasibility in large-scale, distributed solar installations.

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Practical Implications and Research Outlook

Communication-aware deep learning is rapidly transitioning from a primarily theoretical research concept to a practical requirement for Smart Grid 2.0 architectures. By explicitly modeling the communication link as a dynamic and uncertainty-aware variable rather than a static assumption, such approaches enable forecasting systems to remain reliable under real-world network impairments. This paradigm shift is particularly critical for solar energy integration, where inherent intermittency is compounded by communication delays and packet loss in distributed power networks. Treating communication conditions as first-class model inputs allows intelligent forecasting systems to improve robustness, operational resilience, and grid stability, positioning solar energy as a dependable backbone for next-generation intelligent power networks.

Conclusion and Future Work

This paper investigated the prblem of real-time solar energy forecasting in intelligent power networks under realistic communication constraints. Unlike conventional deep learning–based forecasting approaches that assume ideal data transmission, this study explicitly considered the impact of communication latency, packet loss, and asynchronous data arrival on forecasting performance. By jointly modeling communication impairments and learning processes, a communication-aware deep learning framework was proposed to improve robustness and reliability in networked forecasting environments.

A communication-aware LSTM-based forecasting model was developed and evaluated using a fully simulation-driven experimental framework implemented in PyTorch. The proposed approach integrates communication-related information into the input representation and learning objective, enabling the model to adapt to non-ideal network conditions. Extensive simulation results demonstrated that the communication-aware model achieves forecasting accuracy comparable to conventional models under ideal communication conditions, while significantly outperforming communication-agnostic baselines when latency and packet loss are present.

The experimental analysis further revealed that communication impairments can substantially degrade the performance of traditional forecasting models, particularly in high-latency and high packet loss scenarios. In contrast, the proposed framework exhibited improved resilience and a more favorable accuracy–latency trade-off, highlighting its suitability for real-time deployment in intelligent power networks. These findings emphasize the importance of jointly considering communication and learning aspects when designing data-driven forecasting systems for smart grids.

Despite its effectiveness, this study has several limitations that suggest directions for future research. First, the communication model employed in this work is based on statistical simulation and does not capture all characteristics of real-world communication infrastructures. Future studies may integrate detailed network simulators or real communication traces to further enhance realism. Second, the forecasting model focuses on short-term prediction using a single deep learning architecture. Exploring alternative architectures, such as attention-based Transformers or graph neural networks, may yield additional performance improvements.

Future work may also investigate adaptive and learning-based communication strategies, where network resources are dynamically allocated based on forecasting requirements. Reinforcement learning techniques could be employed to jointly optimize communication and forecasting policies in real time. In addition, extending the framework to multi-source and geographically distributed power systems, as well as validating the proposed approach using real-world smart grid deployments, represents an important step toward practical adoption.

In summary, this paper demonstrates that communication-aware deep learning provides a promising and practical solution for real-time solar energy forecasting in intelligent power networks. By bridging the gap between deep learning and communication modeling, the proposed framework contributes toward more reliable, resilient, and intelligent renewable energy systems.

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