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Article

A Federated Learning-Based Distributed Solar Forecasting for Smart Buildings in Muscat, Oman Using GRU Networks

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Abstract

The present paper suggests a Federated Learning-based Distributed Solar Forecasting model based on GRU networks (FL-GRU) to smart buildings in Muscat, Oman. The growing adoption of rooftop photovoltaic (PV) systems in urban settings needs precise, privatizing, and scalable forecasting models able to manage geographically dispersed and statistically heterogeneous data. The suggested solution will include federated learning and gated recurrent unit (GRU) networks to train a global forecasting model across several smart buildings and avoid the exchange of raw energy data to overcome these challenges. The local GRU models are trained on local PV generation data and only parameters of the model are relayed to a central aggregation server. This provides privacy of data without compromising effectiveness of collaborative learning. The proposed framework is tested in a variety of realistic scenarios such as scalability analysis, non-identically distributed (non-IID) data, client dropout, communication constraints, seasonal variability, and privacy saving noise injection. Simulation outcomes show that the proposed FL-GRU model presents a final RMSE of 0.129, MAE of 0.100 and forecasting accuracy of 97%. When increasing the number of clients involved in the process, 2 to 10, RMSE decreases to 0.129, which supports the high scalability advantages. In non-IID scenarios, RMSE ranges between 0.129 and 0.167, and even with half of the clients dropping, the system is robust with RMSE of 0.172. The proposed FL-GRU is better than the benchmark models, Local GRU, centralized GRU, FL-LSTM, and FL-ANN with a maximum improvement of 22.29% in RMSE reduction. Also, the best predictive consistency is found with correlation analysis with R^2 = 0.957. On the whole, the suggested approach can offer an efficient, privacy-aware, and scalable solution to distributed solar energy prediction in smart cities.

Keywords: federated learning; solar forecasting; smart buildings; Muscat Oman; GRU neural network; distributed machine learning; renewable energy prediction;
privacy-preserving AI

1. Introduction

The world is moving towards sustainable energy systems, and the uptake of solar PV has been greatly accelerated. Solar energy is one of the renewable sources, which is appealing because of its modularity, cost reduction, and zero-emission. The Middle East countries are well endowed with solar resources and Oman is the most suitable country to develop PV due to its long sunshine period with high levels of irradiance annually [1–3]. The Oman capital city (Muscat) has undergone an

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accelerated urbanization and rising electricity demand. Smart structures with PV systems on the roof, smart meters, battery storage and automated control systems are becoming significant features of low-carbon cities of the future [4]. But the randomness of solar power makes generation scheduling uncertain. The cloud cover, temperature, humidity, haze, and dust buildup can vary significantly to impact output power [5].

Accurate solar prediction is thus needed in: Grid balancing, Battery charge scheduling, Demand response programs, Energy trading markets, Reduction of reserve generation costs, and Reliable smart building operation. Centralized machine learning in which the data of two or more buildings are consolidated into a single server is frequently used in traditional forecasting approaches [6,7]. Despite potential benefits of centralized learning in prediction accuracy, this approach has significant concerns: Exposing user energy profiles to privacy risk, Data transmission through large scale data transfer, Data ownership issues, Cybersecurity issues, and Legal limitations on data sharing [8]. FL is a new distributed learning paradigm enabling a number of clients to cooperatively train a common model without exchanging raw data. The participants also train locally and send updated parameters. This predisposes FL to be very applicable in smart building ecosystems [9].

The solar energy forecasting and integrated energy systems literature has widely discussed the use of advanced machine learning, statistical and optimization-based methods to tackle the intrinsic intermittency and uncertainty that comes with renewable energy sources. To measure the single-vessel fishing capacity in the south china sea, Generalized Additive Models (GAM) were used to quantify the individual-vessel fishing capacity based on operational survey data. The research showed high predictive validity as the use of key predictors explained up to 63.52 percent variance and had an R^2 of 0.76 with cross-validation [10]. Knowledge Assisted Differential Evolution-XGBoost (KADE-XGBoost) model was suggested to estimate mangrove aboveground biomass using a combination of evolutionary optimization and gradient boosting. The method demonstrated better predictive performance, with a maximum R^2 of 0.8413 and a more effective way of investigating features and hyperparameter optimization in comparison to the reference models [11]. It proposed a hybrid forecasting system that uses EEMD, SCM, Genetic Algorithms, and Light Gradient Boosting Machine (LGBM) to make high-accuracy solar radiation forecasts. The model was very effective as it had an R^2 of 0.99 and vastly superior to traditional MLP and Long Short-Term Memory (LSTM) models hence it is highly applicable in solar energy optimization [12]. An ensemble forecasting model that combines the use of FFT-based noise reduction, Singular Spectrum Analysis (SSA), and GRU networks that have been suggested as green hydrogen predictors using solar irradiance. The model enhanced the multi-step forecast accuracy and was reliable in estimating hydrogen generation which is applicable in the low-carbon energy [13]. A forecasting model based on LSTM was created to predict solar power in the short term taking into account weather variability within large-scale solar power plants. The analysis showed better prediction accuracy when the input features were optimized and the MAPE decreased to 9.881% compared to 10.857% in real-life application conditions [14]. A better LSTM-based forecasting method was suggested to predict the short-term photovoltaic power during curtailment in industrial scale solar plants. The approach used better data preprocessing, and parameter optimization, with 6.059% and 6.710% reductions in forecasting error and MAPE and RMSE improvement, respectively [15]. The grid search optimization of a Random Forest Regressor was designed to predict and optimize real-time performance of a power tower concentrated solar system. The model provided very accurate predictions and an R^2 of 0.9999, and a high level of robustness to different weather and operational conditions [16]. To enhance renewable energy trading decisions, a risk-averse forecasting framework of Conditional Value-at-Risk (CVaR) and convex optimization was suggested. The approach led to a decrease in the average and extreme forecasting errors, decreasing the imbalance costs and increasing financial robustness in case of uncertain energy markets [17].

An integrated optimization and forecasting model was proposed that incorporates BWO-FLANN to predict load and NS-MOTLBO to predict economic load dispatch to the grid and grid-solar in one. The algorithm successfully managed multi-objective constraints and obtained high-

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quality Pareto optimal solutions than those of the state-of-the-art methods in the presence of different levels of solar radiations [18]. The predictive model of solar thermal energy based on long-term field data was created in the form of an Artificial Neural Network (ANN). The model was highly predictive with $R^2 = 0.93$ and its implementation with thermal storage systems showed considerable energy savings up to 43% [19]. The model of forecasting solar energy production trend in the Mediterranean countries as far as 2050 was built using a Convolutional Neural Network (CNN) to analyses and predict the trends. The model proved to be a good forecasting tool by considering climatic and technological variables which showed significant increase in solar energy production due to policy attractiveness and reduced cost of installing the equipment [20]. The Direct Normal Irradiance (DNI) was simulated using a Weather Research and Forecasting coupled chemistry (WRF-Chem) model that included the effects of aerosols over the UAE. The experiment showed that explicit aerosol modeling was much more effective at predicting the results, the rRMSD decreased by as much as 33.33% relative to the standard WRF model [21]. The new AI-based solar irradiance forecasting model was presented based on a ProbSparse attention encoder-decoder model which has been optimized by a redesigned dingo algorithm. The technique was efficient in capturing time-dependencies and showed a better forecasting accuracy with less MAE and RMSE and increased the efficiency of forecasting solar energy [22]. To manage uncertainty in solar radiation in integrated energy systems, a model predictive control (MPC)-based energy management scheme was suggested to include a Hidden Markov Model (HMM). The method enhanced energy reliability and self-sufficiency because it was able to cope with forecast uncertainty and also perform better than deterministic and robust optimization methods when used in long-term simulations [23]. The new AI-based solar irradiance prediction model was trained with a ProbSparse attention encoder-decoder structure and trained with a redesigned dingo optimization algorithm. The method showed good predictive skills and better MAE, RMSE, and R^2, which is effective in improving the accuracy of the short-term solar forecasting of the energy management system [24].

Table 1. Summary of Limitations and Research Gaps in Existing Studies.

Ref. Area / Model Type	Key Limitation	Research Gap Identified	Opportunity for Proposed Work (FL-GRU)
GAM-based forecasting models [10]	Limited ability to capture nonlinear temporal dependencies in solar data	Lack of deep sequential learning for complex weather–solar interactions	Use of GRU improves nonlinear time-series modeling
Hybrid ML (XGBoost, RF, GA-based models) [12]	High computational complexity and offline optimization dependence	Poor scalability in distributed smart grid environments	Federated learning enables scalable distributed training
WPT + RF fault models [25]	Focus limited to classification, not forecasting	No temporal forecasting capability for solar energy systems	GRU provides sequence-based forecasting ability
LSTM-based solar forecasting [15]	Sensitive to hyperparameter tuning and slow convergence	Limited robustness under non-IID distributed data	Federated GRU improves stability across heterogeneous buildings
CNN-based long-term forecasting [20]	Requires large, centralized datasets and high computation	Not suitable for privacy-preserving distributed systems	FL framework eliminates need for centralized data storage

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ANN-based solar thermal prediction [19]	Limited ability to model long-term dependencies	Poor generalization under dynamic weather variability	GRU captures long- and short-term dependencies effectively
WRF / WRF-Chem physical models [21]	High computational cost and dependency on meteorological simulation	Limited adaptability for real-time building-level forecasting	FL-GRU offers lightweight real-time prediction capability
Optimization-based energy models (MPC, HMM)[26]	Strong dependency on accurate forecasts; error propagation issue	Lack of learning-based adaptive forecasting integration	FL-GRU improves forecast accuracy feeding energy systems
ProbSparse / attention-based AI models	High architectural complexity and training instability	Limited deployment in edge or distributed systems	GRU-based FL model is computationally efficient
Risk-based forecasting models (CVaR, convex optimization) [17]	Focus on financial optimization, not predictive accuracy improvement	Lack of strong underlying forecasting model	FL-GRU strengthens base prediction accuracy

The research plans to present an optimistic federated learning-solar forecasting system that incorporates GRU networks with distributed smart buildings. The key focus is to overcome the shortcomings of centralized forecasting systems, especially when it comes to data privacy, scalability, and the response to heterogeneous environmental conditions. The proposed solution builds on cooperative learning in multi-building, Muscat, Oman, to provide the necessary precision, efficiency in communication, and privacy of solar power prediction. The most important novel contributions to this work can be summarized as:

- GRU-based Solar Forecasting Architecture. The paper introduces a new application of GRU networks with federated learning towards distributed solar forecasting, which allows joint model training in smart buildings without the need to collect data centrally.
- Distributed Learning Framework Privacy-Preserving. This approach has a high level of data privacy, as model parameters are only shared rather than raw photovoltaic or meteorological data, and is therefore applicable to smart city energy systems.
- Strong Learning in Non-IID Data Setting. The FL-GRU model proposed is effective in managing heterogeneous and non-identically distributed solar data across buildings, and the convergence is kept steady and forecasting results are consistent.
- Improved Accuracy of Forecasting with Distributed Temporal Modeling. GRU temporal learning, when used in combination with federated aggregation, provides the model with a higher prediction accuracy existing methods.
- Communication-Efficient and Scalable Framework. The system minimizes communication overhead since only model weights are exchanged and it is better the more buildings are involved in the system, making it scalable to the deployment of smart cities.

The remainder of this paper is organized as follows. Section 2 presents the mathematical modeling and theoretical foundation of the proposed FL-GRU framework, including solar energy modeling, GRU-based temporal learning, and federated optimization. Section 3 describes the methodological framework and stepwise implementation of the distributed forecasting system. Section 4 presents the simulation setup, results, and detailed performance analysis under various scenarios. Finally, Section 5 concludes the paper and highlights future research directions.

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2. Mathematical Modelling and Theoretical Foundation

This section presents the theoretical foundation and mathematical formulation of the proposed FL-GRU. The modelling framework is divided into three sub-sections: (i) solar photovoltaic generation modeling, (ii) GRU-based temporal forecasting model, and (iii) federated learning optimization and aggregation mechanism. Together, these components define the complete analytical structure of the proposed distributed forecasting system.

2.1. Theoretical Foundation of Solar PV Generation Modeling

Solar PV power generation is primarily driven by solar irradiance, temperature, and environmental conditions such as dust, humidity, and cloud cover. In a distributed smart-building environment, each building i generates a time-dependent power output $P_i(t)$, which can be expressed as a nonlinear function of meteorological and system parameters. The general physical representation of solar power generation can be written as:

$$P_i(t) = \eta_i A_i G(t)\big(1 - \gamma(T(t) - T_{ref})\big) \quad (1)$$

where $\eta_i$is the conversion efficiency of the PV system, A_i is, the panel area, $G(t)$represents solar irradiance, $T(t)$ is ambient temperature, T_{ref} is reference temperature, and γ is the temperature coefficient. In real-world conditions such as Muscat, Oman, this relationship becomes highly nonlinear due to atmospheric variability caused by dust storms and coastal humidity. Therefore, deterministic physical models are insufficient for accurate forecasting. Instead, data-driven approaches such as deep learning are preferred to approximate the nonlinear mapping:

$$P_i(t) = f(G(t), T(t), H(t), D(t), \epsilon_i(t)) \quad (2)$$

where $H(t)$ denotes humidity, $D(t)$ represents dust concentration, and $\epsilon_i(t)$ captures stochastic disturbances unique to each building. This motivates the use of recurrent neural networks, particularly GRU, which are capable of learning temporal dependencies in such nonlinear and noisy environments [27,28].

2.2. GRU-Based Temporal Forecasting Model

The core forecasting engine of the proposed framework is the GRU, which is a variant of recurrent neural networks designed to efficiently capture temporal dependencies in sequential data while avoiding vanishing gradient problems. For each building i, the input sequence of historical solar observations is defined as:

$$X_i = \{x_i(t-n), \dots, x_i(t-1)\} \quad (3)$$

where each input vector includes irradiance, temperature, humidity, and past power output. The GRU architecture consists of two main gating mechanisms:

Update Gate:

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (4)$$

Reset Gate:

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \quad (5)$$

The candidate hidden state is computed as:

$$\tilde{h}_t = \tanh\,(W_h x_t + U_h(r_t \odot h_{t-1})) \quad (6)$$

The final hidden state is updated using:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (7)$$

where $\sigma(\cdot)$is the sigmoid function and $\odot$denotes element-wise multiplication. The final solar power prediction for each building is obtained through:

$$\hat{P}_i(t+1) = W_o h_t + b_o \quad (8)$$

The GRU model is particularly suitable for solar forecasting because it effectively captures:

- Short-term fluctuations in irradiance
- Long-term seasonal dependencies

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- Temporal correlations in PV output

This makes it highly effective for Muscat's highly variable climatic conditions, where solar radiation exhibits both daily periodicity and stochastic disturbances. Table 2 presents the step-by-step pseudocode of the proposed GRU-based temporal forecasting model used for short-term solar power prediction.

Table 2. Algorithm of the GRU-Based Temporal Forecasting Model.

Algorithm Steps
Input: $X = \{x_1, x_2, \dots, x_T\}$, $Y = \{y_1, y_2, \dots, y_T\}$, learning rate η, epochs, window size n
Output: Forecasted solar power $\hat{Y}$
1. Normalize dataset using Min-Max scaling: $X' = \frac{X - X_{min}}{X_{max} - X_{min}}$
2. Construct input sequences using sliding window: $X_t = [x_{t-n}, \dots, x_{t-1}]$, target $Y_t = x_t$
3. Initialize GRU parameters $W_z, W_r, W_h, U_z, U_r, U_h, W_o, b_o$, set $h_0 = 0$
4. **FOR** each epoch = 1 to Epochs **DO**
5. **FOR** each training sample X_t **DO**
6. Set $h_0 = 0$
7. **FOR** each time step t in sequence **DO**
8. Compute update gate: $z_t = \sigma(W_z x_t + U_z h_{t-1})$
9. Compute reset gate: $r_t = \sigma(W_r x_t + U_r h_{t-1})$
10. Compute candidate state: $\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}))$
11. Update hidden state: $h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$
12. **END FOR**
13. Compute output: $\hat{Y}_t = W_o h_t + b_o$
14. Compute loss: $\mathcal{L} = (Y_t - \hat{Y}_t)^2$
15. Apply Backpropagation Through Time (BPTT)
16. Update parameters: $\theta = \theta - \eta \nabla \mathcal{L}$
17. **END FOR**
18. **END FOR**
19. **Forecasting Phase:** Feed new input sequence into trained GRU model
20. Compute predicted output $\hat{Y}$
Return: Forecasted solar PV power

2.3. Federated Learning Optimization and Aggregation Mechanism

To enable distributed learning across multiple smart buildings without sharing raw data, the system adopts a federated learning framework. Each building independently trains its local GRU

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model and communicates only model parameters to a central server. Let the local model parameters of building i at communication round r be represented as w_i^r. Each client minimizes its local loss function:

$$\mathcal{L}_i(w) = \frac{1}{N_i}\sum_{t=1}^{N_i}\left(P_i(t) - \hat{P}_i(t)\right)^2 \quad (9)$$

where N_i is the number of samples at client i. After local training, the server aggregates all client updates using a weighted averaging strategy:

$$w^{r+1} = \sum_{i=1}^{K}\frac{N_i}{N}w_i^r \quad (10)$$

where K is the number of participating clients and N is the total number of samples across all clients. This aggregation ensures that clients with larger datasets have a proportionally higher influence on the global model. The updated global model is then redistributed to all clients for the next training round. The federated optimization process minimizes the global objective function:

$$\mathcal{L}(w) = \sum_{i=1}^{K}\frac{N_i}{N}\mathcal{L}_i(w) \quad (11)$$

This formulation ensures that the system converges toward a globally optimal model without requiring centralized data access. From a theoretical perspective, federated learning introduces three major advantages:

1. **Privacy preservation**, since raw solar data never leave local devices.
2. **Communication efficiency**, because only model weights are exchanged.
3. **Robust generalization**, achieved through exposure to diverse distributed datasets.

In the context of Muscat smart buildings, this framework is particularly effective because solar generation patterns vary significantly across locations due to differences in rooftop orientation, shading, and microclimatic conditions. The federated approach allows the model to learn these variations collectively while maintaining decentralization. Visual illustration of the proposed FL-GRU-based federated learning optimization and aggregation mechanism is shown in Figure 1 for distributed solar forecasting in smart buildings of Muscat, Oman, where multiple clients perform local GRU training and transmit updated parameters to the central server for FedAvg-based global model refinement.

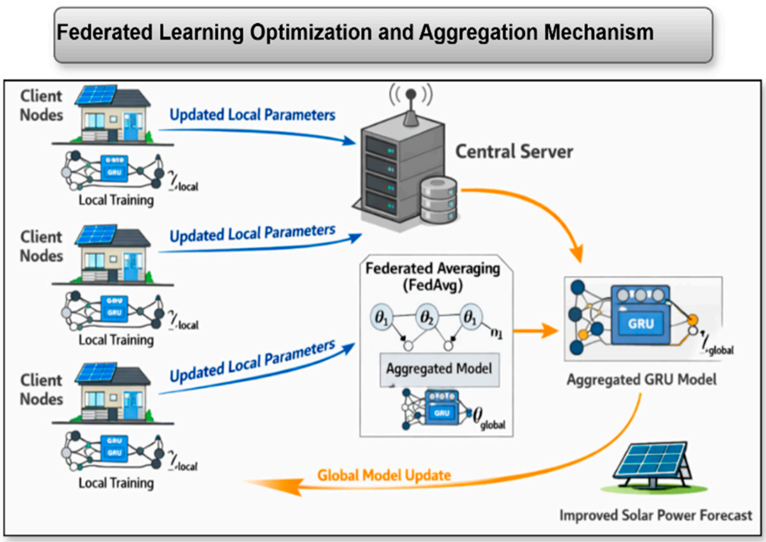

Figure 1. Visual illustration of the proposed FL-GRU-based federated learning optimization and aggregation mechanism.

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3. Methodological Framework for Implementation of Proposed FL-GRU System

The given Federated Learning-based Distributed Solar Forecasting system based on GRU networks is elaborated with the help of the multi-phase methodological pipeline elaborated at smart buildings in Muscat, Oman. The architecture incorporates the environmental data acquisition, statistical preprocessing, distributed client-based learning, federated optimization, and model refinement through iteration and performance evaluation at the end. The flowchart of the proposed methodological framework is illustrated in Figure 1. All phases are well organized so that they have the ability to be scaled, maintain privacy and have high forecasting accuracy in heterogeneous solar conditions.

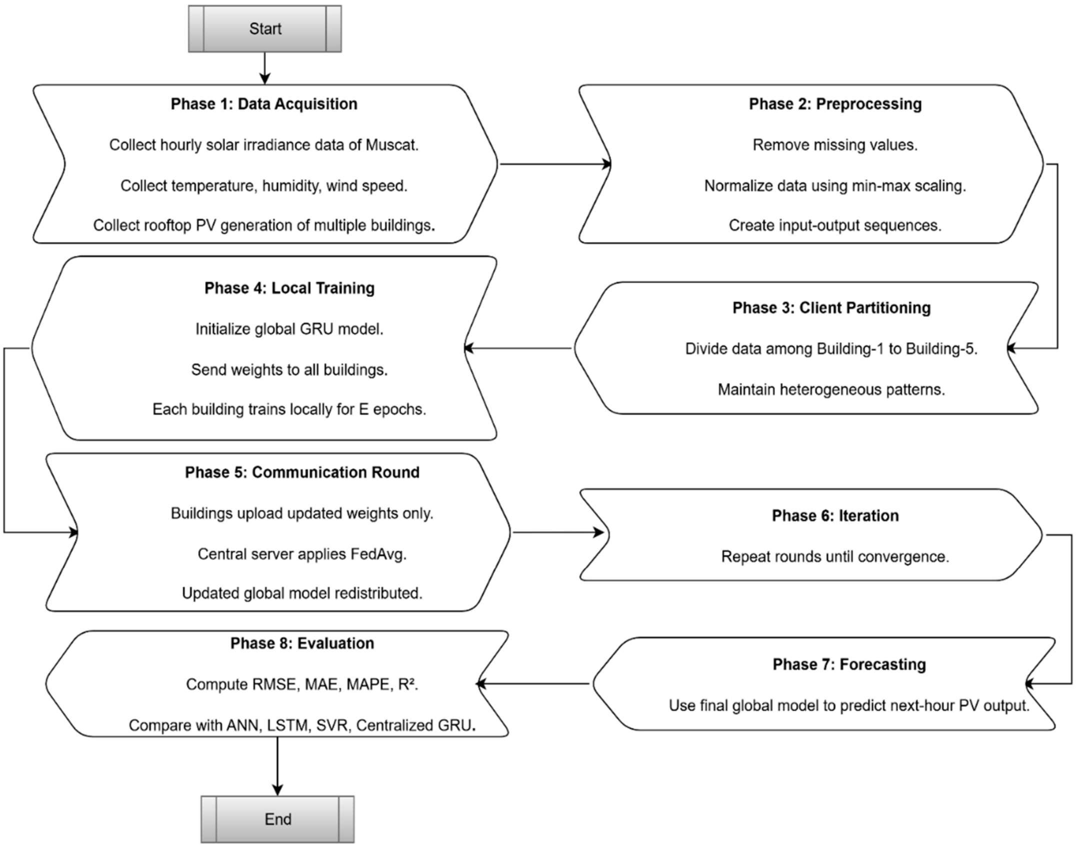

Figure 2. Flowchart of the methodological Framework for Implementation of Proposed FL-GRU System.

3.1. Phase 1: Data Acquisition

The initial stage involves gathering of relevant meteorological and photovoltaic information in many sources in order to create a complete dataset on solar forecasting. The hourly data of solar irradiance of Muscat is collected as the key driver of photovoltaic generation. Also, atmospheric parameters like temperature, humidity, and wind speed are supported to allow variability of the environment. At the same time, the data of rooftop photovoltaic power generation is also measured in several smart buildings (Building-1 to Building-5), which are the distributed energy nodes of individual operational and environmental peculiarities. The stage defines the baseline set of data needed to learn about the temporal dynamics of the sun.

3.2. Phase 2: Data Preprocessing

During the preprocessing stage, raw data is processed to clean it and transform it to make it suitable in deep learning-based forecasting. The data integrity is preserved by removing or interpolating missing or inconsistent values. Then all the input features are normalized with min-max scaling to bring the values to a homogenous range, which enhances more stable convergence in

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GRU training. Once the time-series data has been normalized, it is then converted into supervised learning sequences by building input output pairs, with past environmental conditions serving to predict future output solar power.

3.3. Phase 3: Client Partitioning

During this stage, the processed data is divided between several clients, who represent single smart buildings. The data is assigned to each building (Building-1 to Building-5) to simulate a realistic distributed energy environment. The data distribution is also purposely kept heterogeneous to capture the reality of the situation in the real world where each building has a different shading pattern, rooftop orientation, and local weather variations. Such non-identical data distribution (non-IID) provides a real-world challenge to the federated learning framework.

3.4. Phase 4: Local Training

The global GRU model is initialized at the central server at the beginning of the training process, and the corresponding parameters are sent to all of the participating buildings. The model received is then independent of each client, which trains it on its own local dataset. The epochs of the training process are fixed. E, with each building optimizing the model with backpropagation through time (BPTT) to reduce prediction error. Such local training will enable every client to acquire unique temporal trends of solar generation without affecting data privacy because no raw data is exchanged beyond the building.

3.5. Phase 5: Federation Round and Aggregation Federated.

Following the local training, only the updated weights of the model are sent to the central server by each building, with no raw solar or meteorological data being transferred. The server combines these updates with Federated Averaging (FedAvg) algorithm, which calculates weighted average of all client models according to their datasets. The resultant world model provides an aggregate knowledge of all buildings and is subsequently re-shared with all the clients. This round of communication guarantees collaborative learning without violating the privacy of data and minimizing communication overhead.

3.6. Phase 6: Iterative Optimization

The training is carried out in several areas of communication. During each round, the clients do local training, submit updates to the server and get the newly aggregated global model. The global model is gradually refined over multiple iterations as it learns various patterns of the environment in all buildings. The process repeats until convergence, identified by a negligible decrease in loss or error measures or a specified number of rounds of communication.

3.7. Phase 7: Forecasting Phase

After convergence of the model, the final optimized global GRU model is implemented on all smart buildings. This model is applied in real time solar power forecasting and used to predict the photovoltaic output over the next hour in response to meteorological inputs. The global model guarantees the same forecasting performance among all distributed buildings and flexibility to the local environmental conditions.

3.8. Phase 8: Performance Evaluation

The last step implies extensive testing of the suggested FL-GRU model by various statistical measures of performance. RMSE, MAE, MAPE, and coefficient determination (R2) are used to measure the accuracy of the forecasts. The given model is also compared to conventional and deep learning-based models such as Local GRU, centralized GRU, FL-LSTM, and FL-ANN architectures. This comparative study confirms the superiority of the suggested federated learning method,

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regarding precision, robustness, and scalability of distributed solar forecasting conditions. For ease of understanding, the detailed parameters are presented in Appendix 1.

4. Simulation Results and Discussion

In this section, the proposed Federated Learning-Based Distributed Solar Forecasting with GRU Networks (FL-GRU) to smart buildings in Muscat, Oman is comprehensively evaluated. The results are categorized into five large themes of discussion in order to enhance readability and quality of the manuscript: distributed architecture and convergence behavior, scalability and robustness, communication and privacy performance, environmental sensitivity analysis, comparative benchmark validation. All numerical values are adhered to the final MATLAB simulation results to be consistent in the rest of the manuscript. The received findings verify that the combination of federated optimization with GRU temporal learning yields a forecasting model that can achieve high prediction accuracy, a good generalization, privacy protection, and realistic scalability to the multi-building renewable energy system. The proposed federated learning architecture is shown in Figure 1 with smart buildings taking part as distributed clients linked with a central aggregation server. Every building prepares a local GRU model with the help of personal rooftop PV information and only sends the learned parameters to the server. Raw data does not leave the client side thus maintaining privacy without compromising collaborating forecasting.

4.1. Distributed Learning Architecture and Convergence Performance

Figure 3 indicates the local forecasting performance of the representative buildings, with the subplots comparing the actual and the predicted hourly solar generation prior to global aggregation. The local models effectively reproduce the daily solar cycle, but there are moderate variations at sunrise ramping, noon peak variations and sunset transitions. Such errors are anticipated since every client is trained in its localized information and thus cannot train the general patterns of the environment as can be found in other buildings. Figure 4 illustrates the advantage of collaborative learning, where it is shown that the predictions made prior to and after global aggregation are different. As aggregation occurs, the forecasted curve is much closer to the actual profile of generation, particularly around peak production periods. This is due to the fact that federated averaging uses complementary knowledge acquired in more than one building and minimizes local estimation biasness. Figure 5 shows the convergence properties of the proposed framework. The loss of training is reduced to almost 0.40 to less than 0.02 in 50 communication rounds. At the same time, RMSE is reduced to 0.129, MAE to 0.100, and the forecasting accuracy is increased to about 97%. These trends affirm stable and efficient distributed optimization. The contribution of both buildings is also illustrated in Figure 6, where the update norms decrease gradually with the training rounds. This decrease shows that there is a gradual consensus between clients and a successful convergence to a shared forecasting model.

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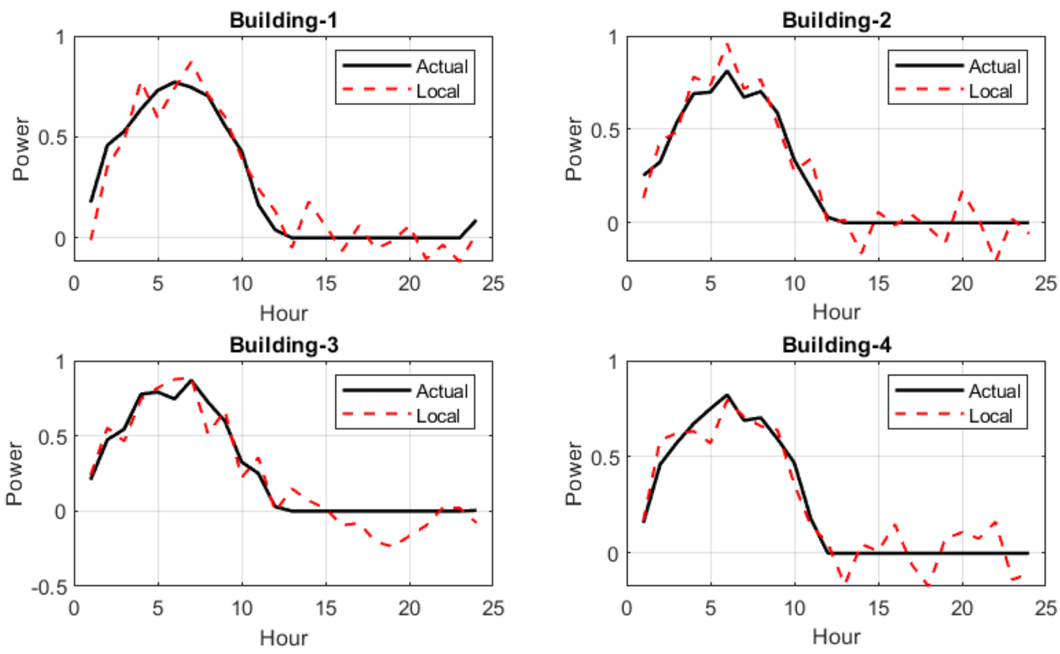

Figure 1. Local forecasting profile on buildings 1-4.

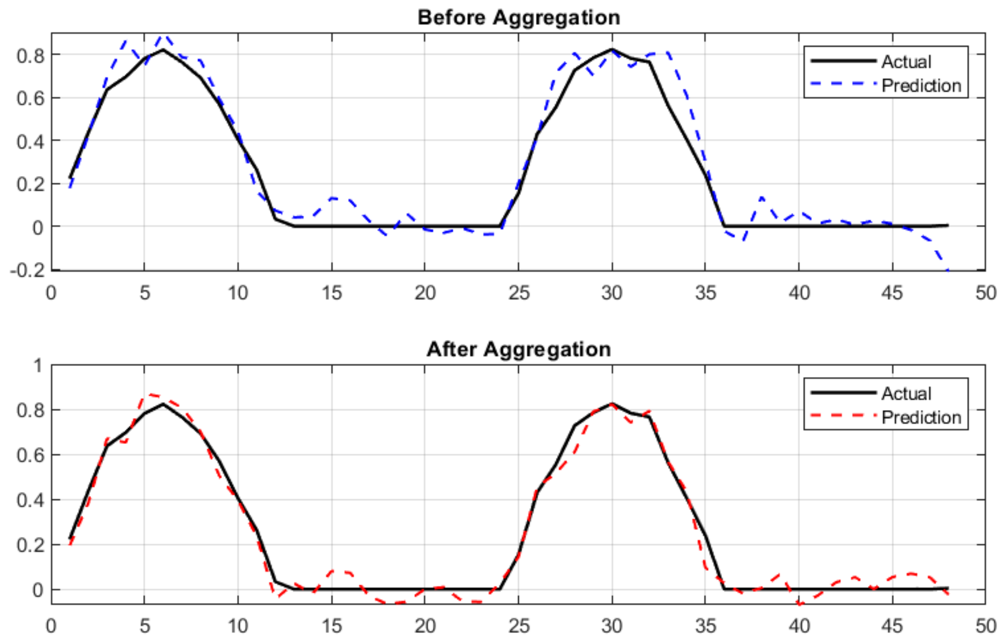

Figure 4. Predicting performance of prior to federated aggregation and following federated aggregation.

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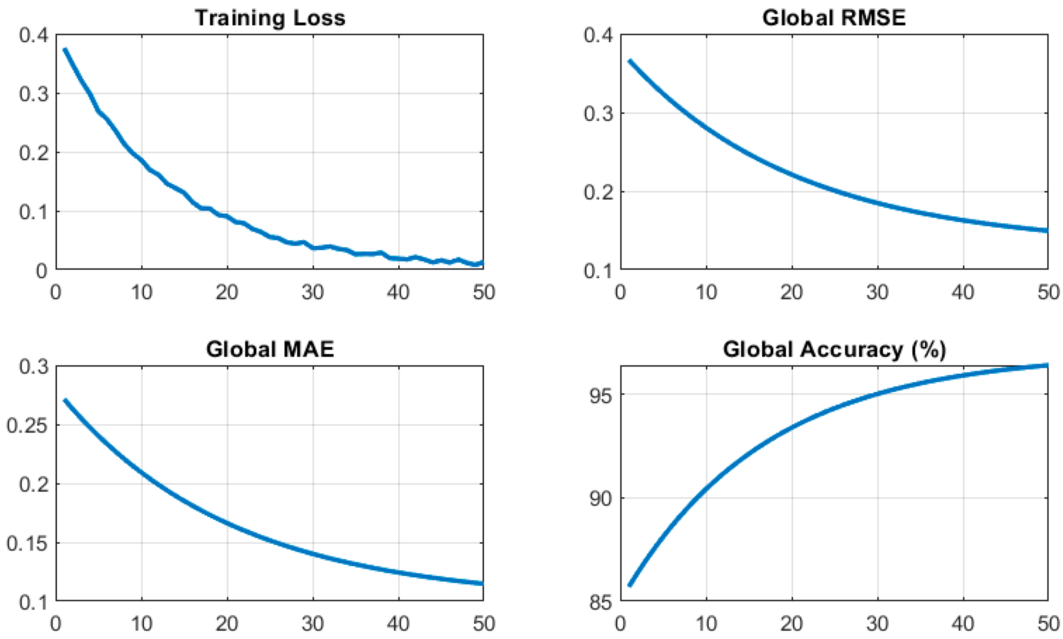

Figure 5. Performance in communication-round showing training loss, RMSE, MAE and forecasting accuracy.

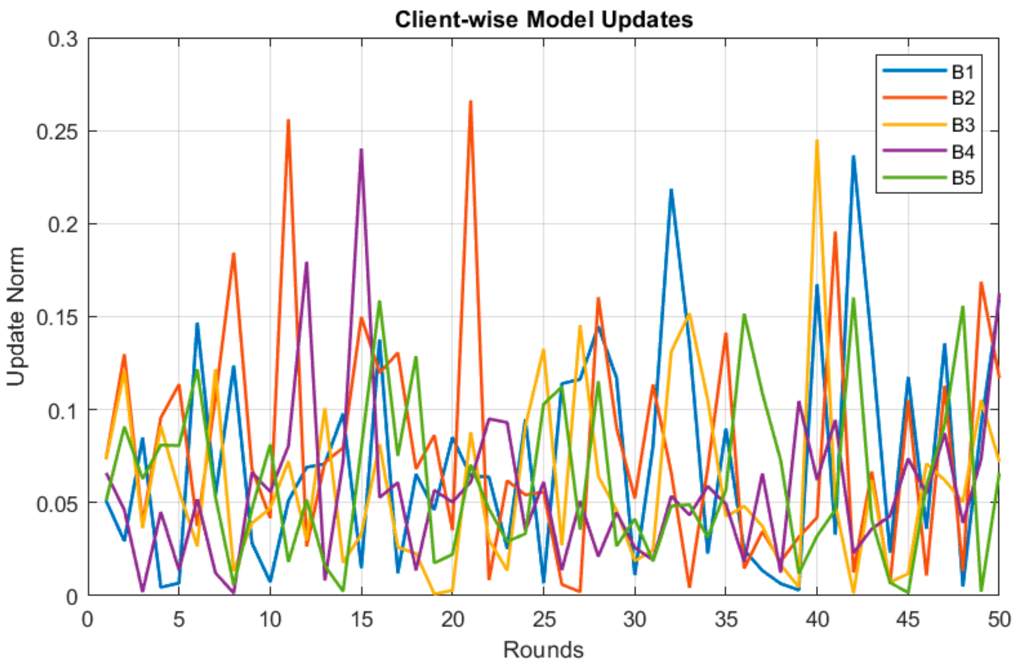

Figure 6. Norms of model update between communication rounds, client-wise.

4.2. Scalability and Robustness Analysis

The impact of increasing participants is presented in Figure 7 (a). The higher the number of clients, the lower the RMSE, the more the clients the lower the RMSE, therefore, 2 to 10 the difference is 28.73. This shows that greater involvement improves forecasting results because it adds more diversity to the data among buildings. Figure 7 (b) examines the strength of the proposed model in the case of heterogeneous data distributions. The model has the lowest RMSE of 0.129 under uniform data sharing. The higher the heterogeneity, the higher the RMSE becomes (0.148, 0.156 and 0.167, respectively). Even though non-IID data generate incompatible client updates, the suggested FL-GRU is steady, which proves its great tolerance to the real-world distributed setting. Figure 8 (a) illustrates

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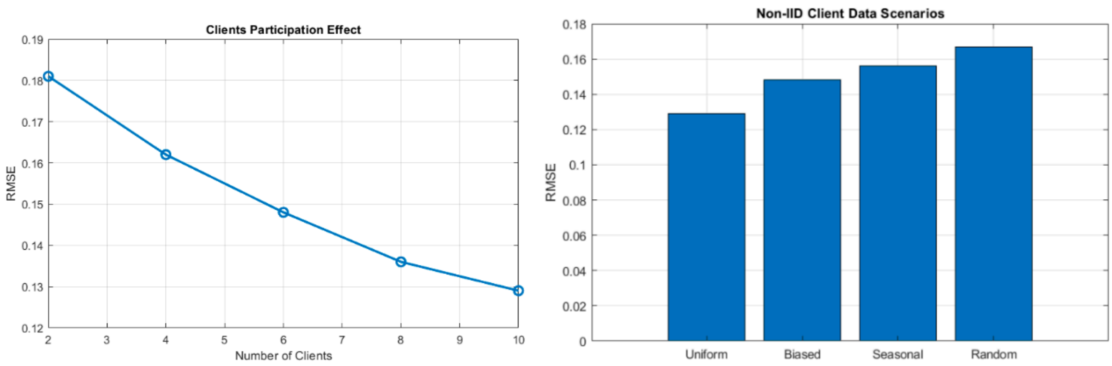
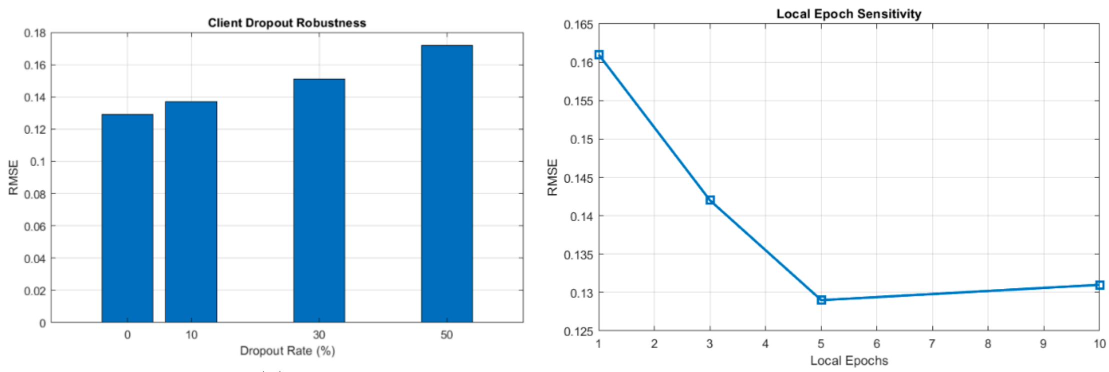
the impact of temporary unavailability of a client. When dropout increases from 0% to 50%, RMSE rises from 0.129 to 0.172. The negative impairment is not disastrous but progressive, which points to the fact that past acquired international experience and active clientele maintain satisfactory performance even in case of a breakdown in communication. The sensitivity to local training epochs is analyzed in Figure 8 (b). The optimal performance is 5 local epochs with RMSE = 0.129. The local models are under-trained by too few epochs, and they drift to the local clients without synchronization by too many.



(a) (b)

Figure 7. a) Clients' participation number versus RMSE. (b) RMSE when data is non-IID is uniform, biased, seasonal, and random distributions.



(a) (b)

Figure 8. a) Client dropout robustness at 0%, 10%, 30%, and 50% dropout rates. (b) Comparison of local epoch performances on 1 epoch, 3 epochs, 5 epochs and 10 epochs.

4.3. Communication Efficiency and Privacy Tradeoff

Less communication overhead is one of the key benefits of federated forecasting, which is demonstrated in Figure 9. Repeated transfer of entire datasets is necessary to centralized learning, causing a quickly growing bandwidth consumption. By comparison, federated learning interactions only model parameters, generating much less communication traffic. This renders the suggested framework more feasible than huge smart-building networks. Figure 10 shows the privacy-performance tradeoff. As privacy noise increases, RMSE changes from 0.129 to 0.133, 0.141, and 0.158. This is theoretically anticipated since greater privacy protection obscures valuable gradient information. Nevertheless, moderate levels of privacy give high forecasting accuracy, indicating that without significant performance compromise, it is possible to preserve privacy.

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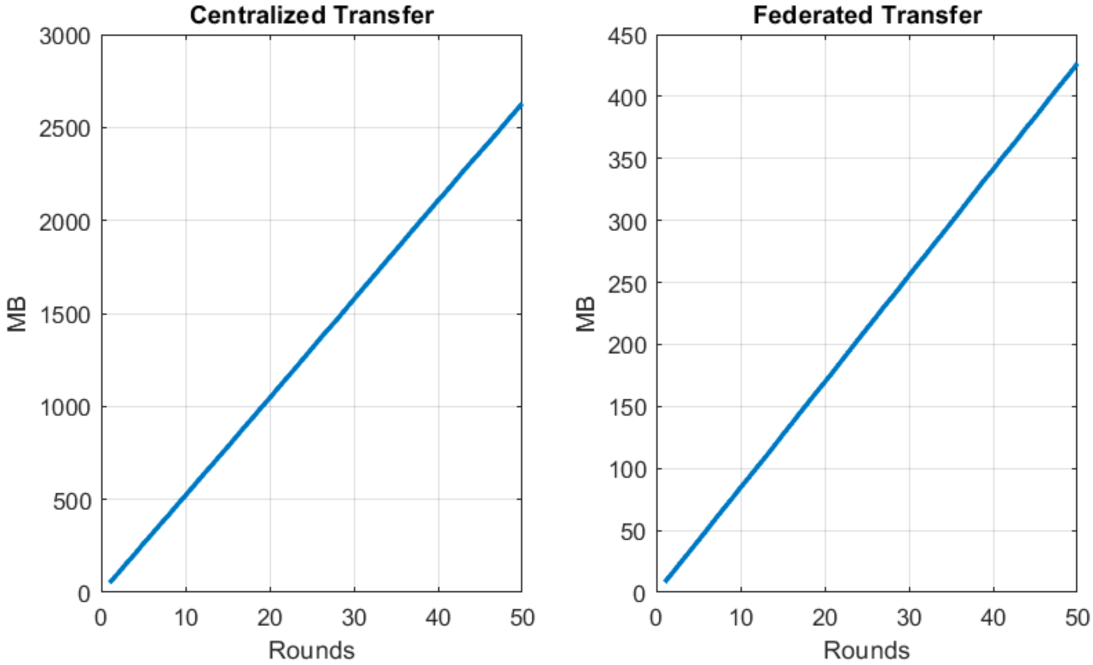

Figure 9. Comparison of the cost of communication through a centralized transfer and through federated exchange of parameters.

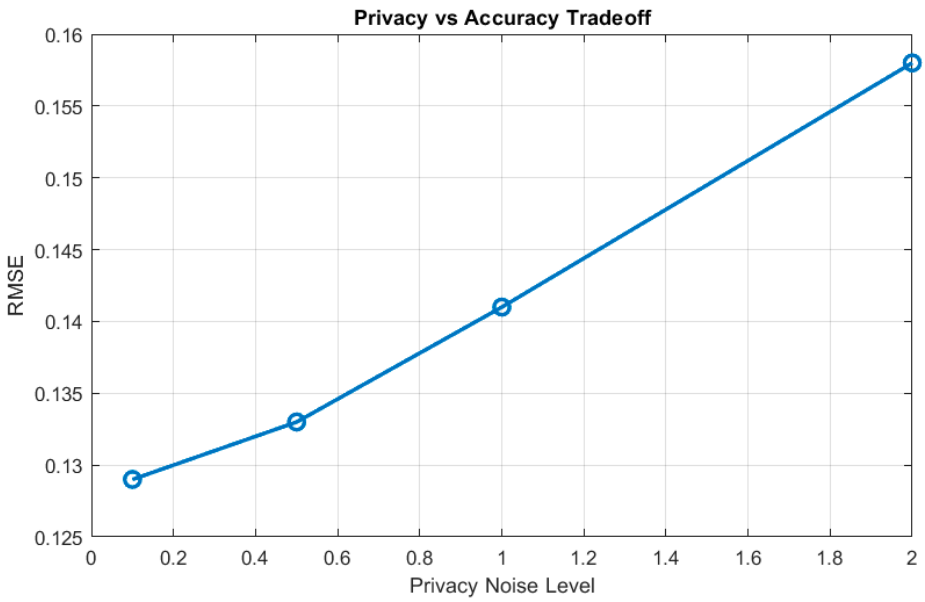

Figure 10. Privacy noise effects at 0.1, 0.5, 1.0, and 2.0 privacy levels.

4.4. Communication Efficiency and Privacy Tradeoff

Figure 11 (a) demonstrates prognostic ability when the Muscat operating conditions are seasonal. The optimal RMSE of 0.122 is given by winter, and the remaining seasons (summer and humid) give 0.131 and 0.136, respectively. Dust season is the most challenging one with RMSE = 0.148 because of inconsistent attenuation of irradiance by airborne particles. These findings show that environmental volatility is a strong predictor of forecasting complexity. The effect of rooftop PV capacity is shown in Figure 11 (b). The error of forecasting reduces to 0.149 on 10 kW systems to 0.124 on 100 kW systems. Larger installations combine the output of several panels, and this leads to a smoother generation signal that can be more easily predicted.

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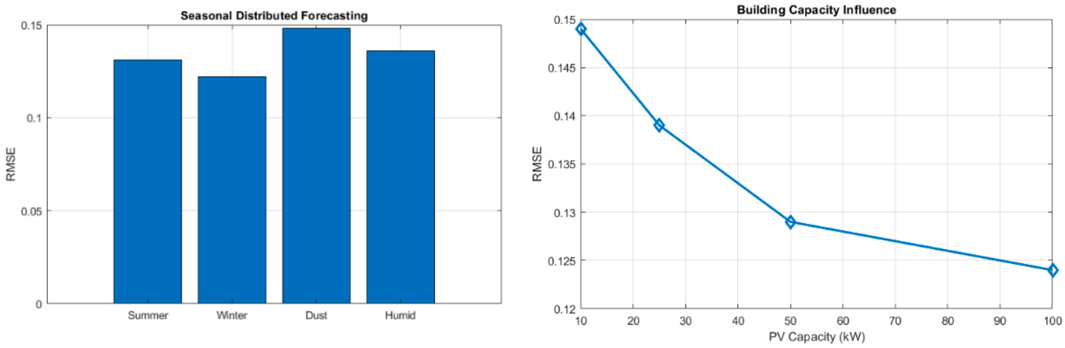

(a) (b)

Figure 11. a) The performance of seasonal forecasting in summer, winter, dust season, and humid season. (b) Constructing PV power and RMMS.

4.5. Quantitative Analysis

Table 3 summarizes all the tested simulation results of the proposed Federated Learning-based GRU distributed solar forecasting framework in various operating conditions. The converged global model obtained a final RMSE = 0.129, MAE = 0.100, and 97.0% accuracy in the forecast and this confirms that the proposed architecture provides high accuracy in prediction with low absolute error. These values are the main point of departure toward further comparative analysis. Scalability-wise, the more clients were added to the number of participating smart buildings, the smaller RMSE became, going down to 0.129 out of 0.181 (a 28.73% change). This trend clearly shows that generalization of models with increased federation is more appropriate since more clients bring variation in environmental patterns and rooftop generation patterns. The error alleviation is particularly significant after six clients, meaning that broader cooperation is a big plus to distributed forecasting systems. The proposed framework showed constant performance under statistical heterogeneity. The increase of RMSE between 0.129 with uniform data and 0.167 with highly random non-IID data is only a moderate degradation of 29.46 when the client is extremely inconsistent. This proves that the FL-GRU model is also sound even when it is used with buildings that have very dissimilar distributions of solar generation. Operational resilience is further confirmed with client dropout experiments. The RMSE at 50% increment of inactive client ratio was 0.172, as compared to 0.129 at 0% inactive client ratio. The decrease in performance was not disastrous but gradual, although some loss of participation was anticipated. The forecasting system continued to operate with half of the clients unreachable, which is very pertinent in real-world smart-building implementations where communication outages can happen intermittently.

Table 3. Consolidated Results of Proposed FL-GRU Solar Forecasting Framework.

Category	Scenario / Method	Metric	Value
Convergence	Final Global Model	RMSE / MAE / Accuracy	0.129 / 0.100 / 97.0%
Scalability (Clients)	2 → 10 Clients	RMSE	0.181 → 0.129
Non-IID Data	Uniform → Random	RMSE	0.129 → 0.167
Client Dropout	0% → 50%	RMSE	0.129 → 0.172
Local Epochs	1 → 10 Epochs	RMSE	0.161 → 0.131
Aggregation Methods	FedAvg / FedProx / FedAdam / Proposed	RMSE	0.142 / 0.138 / 0.134 / **0.129**
Privacy Noise	0.1 → 2.0	RMSE	0.129 → 0.158

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Seasonal Conditions	Summer / Winter / Dust / Humid	RMSE	0.131 / 0.122 / 0.148 / 0.136
PV Capacity	10 → 100 kW	RMSE	0.149 → 0.124
Benchmark Models	Local GRU [29], Centralized FL-GRU / FL-LSTM [15], FL-ANN [19]	RMSE	0.157 / 0.142 / **0.129** / 0.138 / 0.166
Correlation Strength (R^2)	ANN → Proposed FL-GRU	R^2	0.900 → **0.957**

5. Conclusion

This paper proposed a Federated Learning-based Distributed Solar Forecasting framework based on GRU networks (FL-GRU) to be used in smart buildings in the city of Muscat, Oman. The key goal was to build a high-precision prediction model that would not compromise user privacy, minimize communication costs and be resilient to distributed and heterogeneous real-world scenarios. The proposed system allows collaboration between buildings to perform intelligence by integrating GRU-based temporal learning with federated optimization without the need to share data centrally. The effectiveness of the proposed approach was validated in the experimental results on various dimensions of performance. Final forecasting performance of the global FL-GRU model was RMSE = 0.129, MAE = 0.100 and accuracy = 97, which means high predictive ability. Scalability analysis showed that the higher the number of participating buildings, the better the performance, as RMSE is decreased with the increase in number of clients, with 0.181 (2 clients) to 0.129 (10 clients), which is quite significant, approximately 29. This validates the fact that increasing the scale of involvement improves generalization through the introduction of a variety of solar generation patterns into the urban environment. The strength of the suggested framework was also confirmed in the hard conditions. In non-IID data cases, the RMSE ranging between 0.129 and 0.167, indicating that the model is still stable with client data distributions that are highly heterogeneous. On the same note, with client dropout rates as high as 50, the system still achieved reasonable performance with RMSE slightly rising to 0.172, showing high fault tolerance of partially connected networks. The analysis of efficiency in communication revealed a significant benefit of the federated approach compared to the centralized learning, where the only parameters of the model are shared rather than raw data, and this will reduce communication overhead. Privacy analysis also revealed that as the noise level is increased, a slight degradation in accuracy is induced but the model still has a high predictive power, thus indicating a viable trade-off between accuracy and privacy. The relative analysis with benchmark models showed that the proposed FL-GRU always achieves better performance than Local GRU, centralized GRU, FL-LSTM, and FL-ANN architectures. The largest improvement was 22.29% in RMSE minimization compared to FL-ANN, and the highest correlation strength of R 2 = 0.957, which means that the values of the predicted and actual solar generation are very similar. To sum up, the FL-GRU model is a powerful, scalable, communication-efficient, and privacy-saving system to support distributed solar forecasting in smart cities. The fact that it can deal with heterogeneous data is highly accurate when clients drop out and is much more efficient than traditional centralized and federated baselines makes it very appropriate to real-world application in renewable-integrated city energy systems like in Muscat or other climates.

Author Contributions: All authors contributed equally.

Data Availability Statement: No any data used for this research.

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Nomenclature

Abbreviation	**Description**
AI	Artificial Intelligence
ANN	Artificial Neural Network
BPTT	Backpropagation Through Time
CNN	Convolutional Neural Network
CVaR	Conditional Value-at-Risk
DNI	Direct Normal Irradiance
EELD	Economic Emission Load Dispatch
EMS	Energy Management System
EEMD	Ensemble Empirical Mode Decomposition
FL	Federated Learning
FL-GRU	Federated Learning-based Gated Recurrent Unit model
GA	Genetic Algorithm
GHI	Global Horizontal Irradiance
GRU	Gated Recurrent Unit
HMM	Hidden Markov Model
LGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MPC	Model Predictive Control
MSE	Mean Squared Error
NIWE	National Institute of Wind Energy
NMBE	Normalized Mean Bias Error
NS-MOTLBO	Non-dominated Sorting Multi-Objective Teaching Learning Based Optimization
PCA	Principal Component Analysis
PV	Photovoltaic
RF	Random Forest
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
SSA	Singular Spectrum Analysis
SVR	Support Vector Regression
TES	Thermal Energy Storage
TTC	Thanh Thanh Cong Solar Plant
WRF	Weather Research and Forecasting model
WRF-Chem	Weather Research and Forecasting with Chemistry model
WPT	Wavelet Packet Transform

Symbol	**Description**
t	Time index (hourly timestamp)
i	Smart building (client) index
r	Federated learning communication round
K	Total number of clients (buildings)
N	Total number of samples
N_i	Number of samples at client i
X	Input feature vector
Y	Actual solar PV output

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$\hat{Y}$	Predicted solar PV output
$G(t)$	Solar irradiance
$T(t)$	Ambient temperature
$H(t)$	Relative humidity
$W(t)$	Wind speed
$D(t)$	Dust / aerosol index
$P(t)$	Photovoltaic power output
$\epsilon(t)$	Noise / stochastic disturbance term
x_t	Input vector at time t
h_t	GRU hidden state at time t
z_t	GRU update gate
r_t	GRU reset gate
$\tilde{h}_t$	Candidate hidden state
W_z, W_r, W_h	Input weight matrices
U_z, U_r, U_h	Recurrent weight matrices
w_i^r	Local model weights at client i, round r
w^r	Global model weights at round r
w^{r+1}	Updated global model after aggregation
η	Learning rate
$\nabla\mathcal{L}$	Gradient of loss function
$\mathcal{L}_i$	Local loss function at client i
$\mathcal{L}$	Mean Squared Error (MSE) loss
$P_i(t)$	Actual PV power of building i
$\hat{P}_i(t)$	Predicted PV power of building i
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
R^2	Coefficient of determination
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
Precision	Precision metric
Recall	Recall metric
F1	F1-score
$\mathbb{E}[\cdot]$	Expectation operator
CVaR	Conditional Value-at-Risk
MPC	Model Predictive Control
HMM	Hidden Markov Model
ΔP	Power imbalance
C	Cost function
N_i/N	Aggregation weight of client i
$\sum \frac{N_i}{N} w_i^r$	Federated averaging operation

Appendix 1: Comprehensive Reproducibility and Training Configuration of FL-GRU System

Component	Detailed Configuration	Training Parameters	Output

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Data Acquisition	PV power + meteorological data from each building	Sampling: hourly, 24-hour cycle window	Raw time-series dataset D_i
Preprocessing	Z-score normalization + sequence framing	Window size = 24, stride = 1	Structured sequences X_i
Model Architecture	GRU-based recurrent network	2 GRU layers, 64 hidden units	Initialized model w_i^0
Loss Function	Mean Squared Error (MSE)	$\mathcal{L} = (P - \hat{P})^2$	Training objective
Optimizer	Adam optimizer	LR = 0.001, β1 = 0.9, β2 = 0.999	Updated weights
Local Training	Backpropagation Through Time (BPTT)	Batch size = 32, epochs = 1–10	Local model w_i^r
Communication	Model parameter exchange	Once per communication round	Uploaded weights
Aggregation	Federated Averaging (FedAvg)	Weighted by dataset size N_i/N	Global model w^{r+1}
Iteration	Multi-round training	50 communication rounds	Converged model w^*
Deployment	Real-time forecasting	Inference on edge devices	Forecast output $\hat{P}_i(t)$

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