An Ensemble Forecasting Method based on optimized LSTM and GRU for Temperature and Humidity Forecasting

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ABSTRACT

Temperature and humidity predictions play a crucial role in various sectors such as energy management, agriculture, and climate science. Accurate forecasting of these meteorological parameters is essential for optimizing crop yields, managing energy consumption, and effectively mitigating the impact of climate change. In this context, this paper proposes an enhanced ensemble forecasting method for day-ahead temperature and humidity predictions. The proposed method integrates a Long Short-Term Memory (LSTM) network, a Gated Recurrent Unit (GRU), Particle Swarm Optimization (PSO) and Bayesian Model Averaging (BMA). PSO is employed to optimize the parameters of the LSTM and GRU, thereby improving forecasting accuracy. The method is implemented using Python 3.10 with TensorFlow. Additionally, the proposed approach is compared with ensemble-1, LSTM, and GRU models to demonstrate its effectiveness. The simulation results confirm the superior performance of the proposed method over existing competitive approaches.

Keywords-forecasting; gated recurrent unit; humidity; long short-term memory; temperature

I. INTRODUCTION

In recent times, weather forecasting has become crucial for mitigating the effects of climate change, especially due to the dramatic shifts in natural patterns. Accurate weather predictions are essential for decision-making across various fields, including agriculture, tourism planning, energy management, and traffic management in large cities [1-3]. Among the different meteorological variables, temperature and humidity are considered the most significant for accurately forecasting to manage the impact of climate change effectively. Consequently, a substantial amount of research has been conducted to forecast various weather parameters to help minimize the effects of climate change. Statistical and machine learning-based approaches have been widely used in the literature to forecast weather parameters, including temperature and humidity. Authors in [4, 5], used autoregressive moving average (ARIMA) and Artificial Neural Networks (ANNs) to predict the temperature in Tehran, Iran and Delhi, India. Both studies highlight that the ANN provides higher accuracy than ARIMA. A transductive Long Short-Term Memory (LSTM)-based approach was proposed in [6] to predict 14 different weather parameters, including temperature and humidity, for Canada and the USA. In [7], a deep Convolutional Neural Network (CNN)-based approach was introduced to forecast various weather parameters in Denmark. The forecasting methods in [6] and [7] were compared with existing competitive approaches to demonstrate the efficiency of the proposed methods. In [8], five different machine learning approaches i.e., CNN, multiple linear regression, multiple polynomial regression, multilayer perceptron (MLP), and K-Nearest Neighbors (KNN) were utilized to forecast weather parameters such as temperature, wind speed, and humidity. The weather data were collected from four different locations in Mauritius to analysis the performance these five approaches. A granular sigmoid extreme learning machine-based method was developed in [9] to predict multiple weather parameters across various locations in Australia. The proposed method was compared with several existing competitive approaches to demonstrate its effectiveness. Similarly, a sequence-to-sequence stacked LSTM-based method was employed in [10] to forecast different weather parameters for Indian weather. In [11], a PSO-LSTM-based method was proposed to forecast the temperature across different regions of China, where PSO was used to optimize the LSTM parameters, improving forecasting accuracy. The performance of the PSO-LSTM model was compared with three existing methods. In [12], the Generalized Regression Neural Network (GRNN), Feed-Forward Neural Network with Back-Propagation (FNN-BP), and Radial Basis Function Neural Network (RBFNN) were used to forecast temperature in Turkey, and these approaches were compared with traditional forecasting methods. A Convolutional Recurrent Neural Network (CRNN) model was designed in [13] to predict daily temperatures in China. The CRNN method, which combines CNNs and Recurrent Neural Networks (RNNs), demonstrated superior performance compared to existing competitive approaches.

Based on the existing literature, it can be concluded that there is still room for improvement in forecasting accuracy. Therefore, this paper proposes an ensemble forecasting method aimed to enhance accuracy. The main contributions of this paper can be summarized as follows:

- An ensemble forecasting method using optimized LSTM and GRU models to predict temperature and humidity is proposed.
- The parameters of the LSTM and GRU models are optimized using PSO to improve forecasting accuracy.
- Bayesian Model Averaging (BMA) is employed to combine the outputs of the PSO-LSTM and PSO-GRU models in the proposed method.
- The performance of the proposed method is compared with ensemble-1 (PSO-LSTM, PSO-GRU and equal weight combination), LSTM and GRU models, demonstrating its superior accuracy.

II. THE PROPOSED ENSEMBLE FORECASTING METHOD

In this research, an ensemble forecasting method combining PSO-LSTM, PSO-GRU, and BMA is proposed to forecast temperature and humidity, as illustrated in Figure 1. Four years of historical temperature and humidity data were provided as input to the proposed ensemble method, with hourly forecasting being performed. A detailed description of each component of the proposed method is provided in the following subsections.

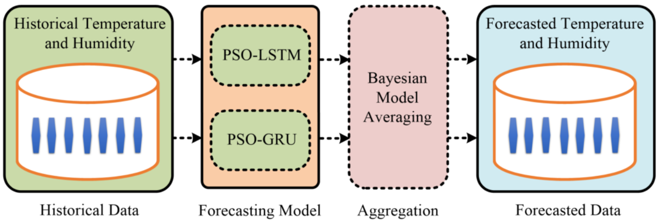

Fig. 1. The proposed ensemble forecasting method.

A. *Long Short-Term Memory Network*

The LSTM network is an enhancement of the RNN designed to address its inherent limitations [11]. LSTMs can capture temporal dependencies. The network operates through four primary gates: input, forget, update, and output, which are mathematically described below:

$$i_t = \sigma(W_i.[h_{t-1}.y_t] + b_i) \quad (1)$$

$$\tilde{c}_t = \tanh(W_c.[h_{t-1}.y_t] + b_c) \quad (2)$$

$$f_t = \sigma(W_f.[h_{t-1}.y_t] + b_f) \quad (3)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (4)$$

$$\mathrm{O}_t = \sigma(\mathrm{W_o}.[\mathrm{h}_{t-1}.\mathrm{y}_t] + \mathrm{b_o}) \quad (5)$$

$$h_t = O_t \odot .\tanh(c_t) \quad (6)$$

In (1)-(6), σ represents the sigmoid function, while W_i, W_c, W_f, and W_o are weight matrices, and b_i, b_c, b_f, and b_o are the corresponding bias terms associated with the input, forget, update, and output gates of the LSTM.

B. *Gated Recurrent Unit*

GRU, a simplified version of LSTM was proposed in 2014 [14]. Like LSMT, GRU resolves the vanishing gradient issue of RNNs while having a smaller number of parameters. The GRU architecture has only two gates, i.e. a reset gate and an update gate. The reset gate is used to determine how much information needs to be forgotten while the update gate is responsible to decide what information is needed to keep and what information is to delete. The GRU network is mathematically represented by:

$$z_t = \sigma(W_z.[h_{t-1}.y_t] + b_z) \quad (7)$$

$$r_t = \sigma(W_r.[h_{t-1}.y_t] + b_r) \quad (8)$$

$$\tilde{h}_t = \tanh(W_{\mathrm{h}}.[h_{t-1}.y_t] + b_{\mathrm{h}}) \quad (9)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (10)$$

where z_t represents the update gate at time step *t*, while r_t represents the rest gate. In addition, the term $\tilde{h}_t$ refers to the memory content that utilizes the reset gate to retain relevant information from previous time steps.

C. *Implementation of PSO-LSTM and PSO-GRU*

In this research, PSO is employed to optimize the parameters of both LSTM and GRU networks, enhancing their forecasting accuracy. PSO is a population-based swarm intelligence algorithm inspired by the movement of particles in search of an optimal solution. A detailed description of PSO can be found in [15]. The steps for implementing the PSO-LSTM and PSO-GRU models are outlined below:

- Define the key parameters of the LSTM and GRU networks, such as learning rate, dropout rate, and the number of neurons in the hidden layers.
- Set the control parameters of PSO, including population size and the maximum number of iterations.
- Calculate the Root Mean Square Error (RMSE) as the objective function to minimize, aiming for higher forecasting accuracy.
- Initiate the optimization process, updating each particle's position based on the objective function and continuously updating the archive of nondominated solutions at each iteration.
- Terminate the optimization process once the maximum number of iterations is reached, obtaining the final optimal solution.

D. Bayesian Model Averaging

This study employs the BMA technique to aggregate the outputs of swarm intelligence-based forecasting models to enhance the prediction accuracy. The BMA method allocates weights to each forecasting model according to their posterior probabilities, with higher weights assigned to models with better accuracy and lower weights given to less accurate models [16].

III. RESULTS AND DISCUSSION

A. Performance Measured Metrics

In this study, the Mean Absolute Error (MAE), RMSE, and Normalized RMSE (NRMSE) were employed to assess the performance of proposed ensemble forecasting method. The MAE, RMSE, and NRMSE are calculated by:

$$\text{MAE} = \frac{1}{M}\sum_{t=1}^{M}|P_A - P_F| \quad (11)$$

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(P_A - P_F)^2} \quad (12)$$

$$\text{NRMSE} = \left|\frac{\sqrt{\frac{1}{M}\sum_{t=1}^{M}(P_A-P_F)^2}}{P_{A-max}-P_{A-min}}\right| \quad (13)$$

where M represents the total number of samples, P_A and P_F are the actual and forecasted values of temperature and humidity, and P_{A-max} and P_{A-min} represent the maximum and minimum values of temperature and humidity.

B. Simulation Results and Discussion

In this study, temperature and humidity data, collected at half-hour intervals from January 2016 to December 2019 at the Queensland weather station, were used to evaluate the effectiveness of the proposed strategy. Data from January 2016 to December 2017 were utilized for training, while data from January 2018 to December 2019 were reserved for validation and testing. This results in a data distribution of approximately 50% for training, 25% for validation, and 25% for testing. Following the data partitioning, Python 3.10 was employed to simulate and analyze the performance of the proposed forecasting approach. The effectiveness of this strategy is further demonstrated by comparing it against ensemble-1, LSTM, and GRU models.

The forecasting results for temperature and humidity are shown in Figures 2-9 and Tables I-II. Figures 2-5 show the forecasting results of temperature for four different seasons, i.e. summer, autumn, spring, and winter. In summer, the proposed strategy achieves the lowest errors, with a MAE of 1.346, RMSE of 1.804, and NRMSE of 0.255 as shown in Table I. In comparison, the Ensemble-1 strategy follows closely with slightly higher errors, while GRU and LSTM exhibit significantly worse performance, with MAE values of 3.562 and 4.145, respectively, indicating their inability to capture the summer temperature patterns accurately.

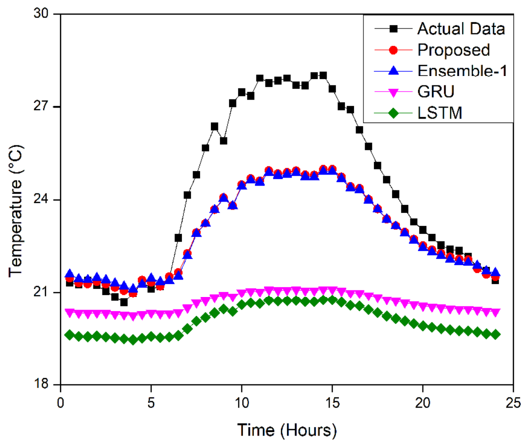

Fig. 2. Day-ahead temperature forecasting during a summer day.

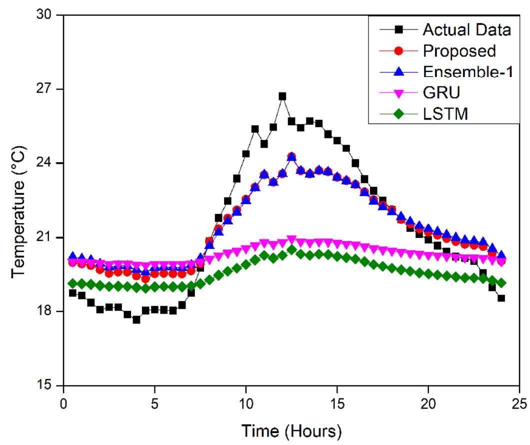

Fig. 3. Day-ahead temperature forecasting during an autumn day.

A similar trend is observed during autumn, with the proposed model showing superior predictive capability (MAE of 1.129, RMSE of 1.327, and NRMSE of 0.179). Ensemble-1 performs moderately well but falls behind the proposed strategy, while LSTM and GRU continue to struggle, with GRU recording an RMSE of 2.702 and LSTM showing slightly worse performance. The inability of these models to predict autumn temperatures effectively highlights their limitations in handling seasonal variability.

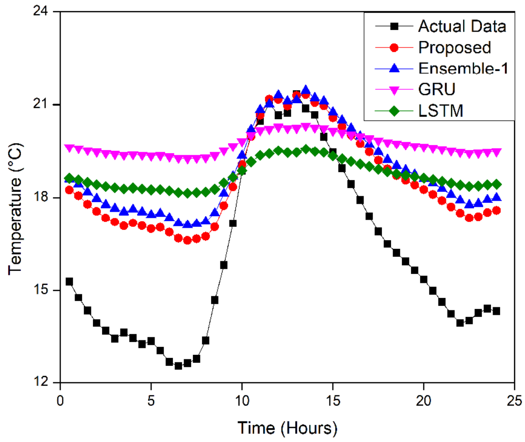

Fig. 4. Day-ahead temperature forecasting during a spring day.

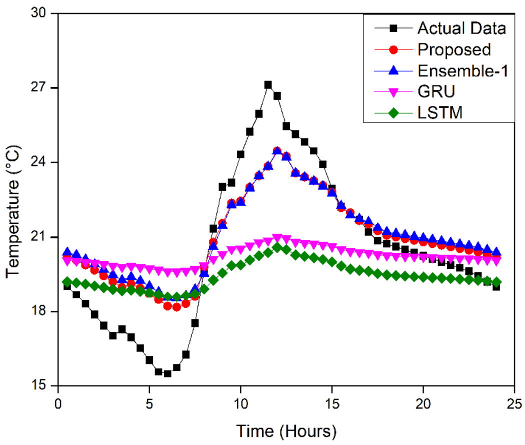

Fig. 5. Day-ahead temperature forecasting during a winter day.

In spring, the proposed strategy once again proves its efficiency, outperforming the other models with a low MAE of 1.281, RMSE of 1.544, and NRMSE of 0.172. Ensemble-1 remains competitive but shows slightly higher errors, while LSTM and GRU maintain their lower accuracy levels with RMSE values exceeding 2.7. This indicates that the proposed model is better suited for dealing with the unpredictable nature of spring temperatures compared to the deep learning-based models.

Winter presents the most challenging forecasting conditions, but the proposed strategy remains the best performer, despite its higher error rates (MAE of 2.450 and RMSE of 2.785) compared to other seasons. The performance gap between the proposed strategy and Ensemble-1 increases during winter, with Ensemble-1's NRMSE rising to 0.738. GRU, with an NRMSE of 2.101, performs particularly poorly in winter, while LSTM fares slightly better but still lags, further indicating the difficulties these models face in handling the extreme fluctuations in winter temperatures.

TABLE I. MAE, RMSE, AND NRMSE RESULTS FOR TEMPERATURE FORECASTING.

Season	Strategy	MAE (°C)	RMSE (°C)	NRMSE (%)
Summer	Proposed	1.346	1.804	0.255
	Ensemble-1	1.409	1.844	0.266
	GRU	3.562	4.260	0.547
	LSTM	4.145	4.684	0.546
Autumn	Proposed	1.129	1.327	0.179
	Ensemble-1	1.264	1.441	0.202
	GRU	2.215	2.702	0.395
	LSTM	2.315	2.948	0.379
Spring	Proposed	1.281	1.544	0.172
	Ensemble-1	1.437	1.702	0.198
	GRU	2.235	2.796	0.372
	LSTM	2.258	2.846	0.333
Winter	Proposed	2.450	2.785	0.588
	Ensemble-1	2.776	3.132	0.738
	GRU	3.787	4.372	2.101
	LSTM	3.094	3.525	1.101

Similarly, for humidity forecasting, the proposed method also shows superior performance across all seasons as shown in Figures 6-9 and Table II, though the gap between the proposed strategy and the other methods is narrower compared to the temperature results. During summer, the proposed method has an MAE of 6.792, while Ensemble-1 has a slightly higher MAE of 7.234. The performance gap widens significantly for GRU and LSTM models, which have MAE values of 12.033 and 11.650, respectively, indicating that the proposed model is far better at forecasting humidity during summer.

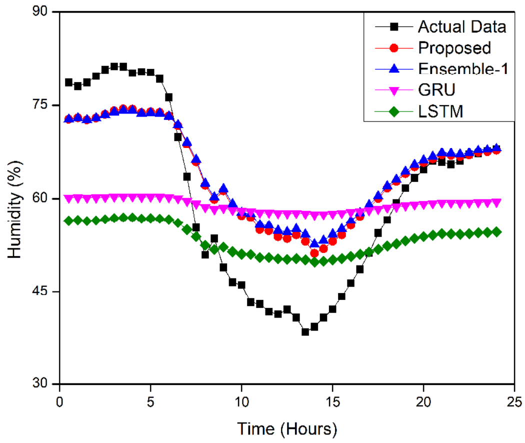

Fig. 6. Day-ahead humidity forecasting during a summer day.

In autumn, the proposed method again has the lowest error rates, with an MAE of 5.350 and an NRMSE of 0.255, outperforming Ensemble-1, LSTM, and GRU. This trend continues in spring and winter, with the proposed strategy consistently producing lower MAE, RMSE, and NRMSE values. In spring, for instance, the proposed model has an NRMSE of 0.199, while LSTM and GRU have much higher values, suggesting their limitations in predicting humidity accurately.

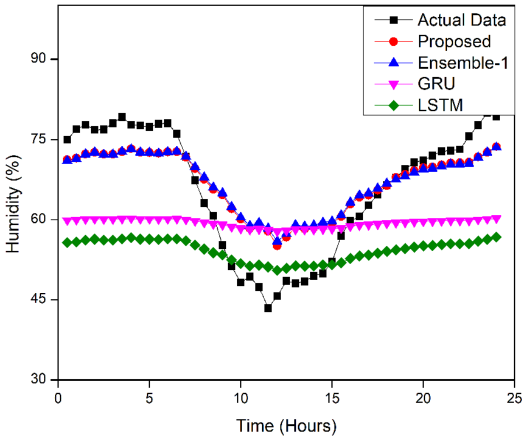

Fig. 7. Day-ahead humidity forecasting during an autumn day.

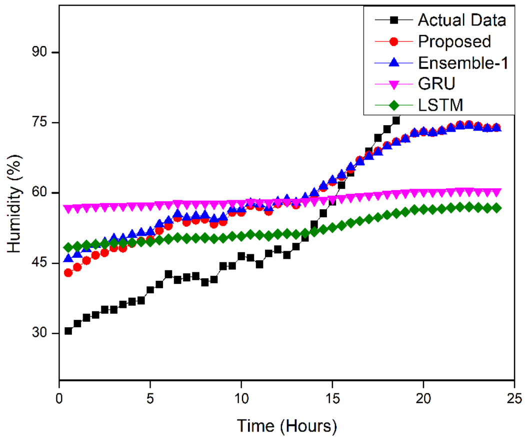

Fig. 8. Day-ahead humidity forecasting during a spring day.

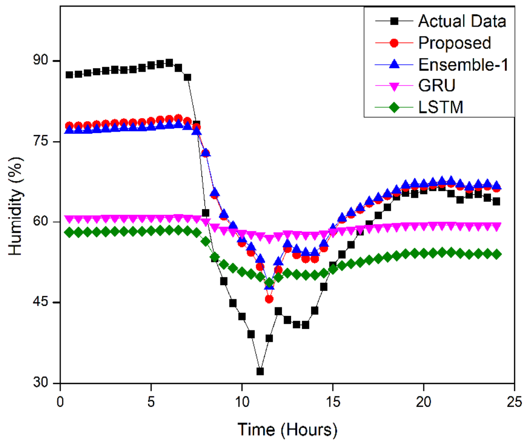

Fig. 9. Day-ahead humidity forecasting during a winter day.

However, it is worth noting that for winter, while the proposed method still outperforms the other models, the overall error rates increase, as seen with a higher MAE (8.513) compared to the other seasons. This could suggest that winter humidity patterns are harder to predict, which aligns with the increased complexity in temperature forecasting during the same season.

TABLE II. MAE, RMSE, AND NRMSE RESULTS FOR HUMIDITY FORECASTING

Season	Strategy	MAE (%)	RMSE (%)	NRMSE (%)
Summer	Proposed	6.792	8.089	0.268
	Ensemble-1	7.234	8.60	0.299
	GRU	12.033	13.487	0.565
	LSTM	11.650	13.768	0.436
Autumn	Proposed	5.350	6.352	0.255
	Ensemble-1	5.612	6.614	0.275
	GRU	11.543	12.740	0.575
	LSTM	13.029	15.156	0.515
Spring	Proposed	7.373	8.782	0.199
	Ensemble-1	8.084	9.502	0.228
	GRU	14.373	17.443	0.533
	LSTM	14.920	18.169	0.444
Winter	Proposed	8.513	9.277	0.240
	Ensemble-1	9.339	10.273	0.287
	GRU	15.400	16.575	0.666
	LSTM	12.781	14.738	0.443

IV. CONCLUSION

In this paper, an enhanced ensemble forecasting strategy, combining PSO-LSTM, PSO-GRU, and BMA, has been introduced for forecasting temperature and humidity. In this strategy, PSO was applied to optimize the parameters of both LSTM and GRU to achieve high forecasting accuracy, while BMA was employed to combine the outputs of PSO-LSTM and PSO-GRU for the final forecast results. The proposed strategy was implemented in Python and applied to forecast temperature and humidity across various seasons. The strategy's performance was validated using data collected from January 2016 to December 2019. Moreover, the effectiveness of the proposed approach was demonstrated by comparing it to standard LSTM and GRU models which is optimize with method, with the results confirming that the proposed strategy significantly outperforms both. The simulation results demonstrate that the proposed strategy provides 9.87%, 47.40%, and 47.46% more accurate temperature forecasts compared to ensemble-1, GRU, and LSTM, respectively, based on the MAE. Additionally, the proposed strategy offers 7.40%, 47.46%, and 46.49% better accuracy for humidity prediction when compared to ensemble-1, GRU, and LSTM, also measured by the MAE.

In the future, the proposed ensemble forecasting method could be utilized for long-term predictions of temperature and humidity. It could also be extended to forecast solar PV power, wind energy, and load demand. Another potential direction for this research would involve substituting the current algorithm used for hyperparameter tuning in GRU and LSTM models.

DATA AVAILABILITY

The utilized data are available upon request from the corresponding author.

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