Performance Evaluation of Transformer and Informer-Based Models for Indoor Absolute Humidity Prediction using Outdoor Absolute Humidity

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https://doi.org/10.5109/7323393

出版情報：Proceedings of International Exchange and Innovation Conference on Engineering & Sciences (IEICES). 10, pp.1084-1090, 2024-10-17. International Exchange and Innovation Conference on Engineering & Sciences
バージョン：

Performance Evaluation of Transformer and Informer Based Models for Indoor Absolute Humidity Prediction using Outdoor Absolute Humidity

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Abstract: *Predicting indoor absolute humidity is essential for effective building management, energy efficiency and occupant comfort. This research evaluates the performance of Transformer and Informer models in predicting indoor humidity using outdoor humidity data. The dataset consists of outdoor humidity measurements to forecast indoor conditions. We developed Transformer and Informer models to focus on attention mechanisms and sequence generation. Performance was evaluated using metrics such as MAPE, MSE, MAE, RMSE and R-squared. The Transformer model slightly outperforms the Informer model with a MAPE of 3.42% and an R-squared of 0.911, compared to the Informer's MAPE of 4.55% and R-squared of 0.867. This superior performance is due to the Transformer's enhanced attention mechanism and efficient sequence handling. This study provides advanced models for accurate indoor humidity prediction, with significant implications for building management and energy savings. Future research could explore real-time implementation and application to other environmental parameters.*

Keywords: Indoor Humidity Prediction; Transformer Model; Informer Model; Time Series Forecasting; Deep Learning,

1. INTRODUCTION

Predicting indoor humidity is crucial for maintaining optimal indoor environmental conditions [1]. Humidity levels significantly impact building materials, electronic equipment, and human comfort. High humidity can lead to mold growth, structural damage and malfunctioning of electronic devices while low humidity can cause discomfort and health issues such as dry skin and respiratory problems [2]. Therefore, accurately predicting indoor humidity is essential to ensure the longevity of building materials and have a proper functioning of equipment and the well-being of occupants [3].

Indoor humidity prediction plays a critical role in various applications. In HVAC (Heating, Ventilation and Air Conditioning) systems such as accurate humidity predictions enable optimized control strategies that improve energy efficiency and maintain occupant comfort[4]. In museums, precise humidity control is vital for the preservation of artifacts and artworks. Additionally, maintaining indoor air quality in residential, commercial and industrial buildings relies on effective humidity prediction to ensure a healthy and comfortable environment.

Accurate humidity prediction enhances building management systems by optimizing HVAC operations. By anticipating humidity changes, HVAC systems can adjust their performance to maintain desired indoor conditions which results in energy savings and improved comfort for occupants. Humidity control plays a significant role in reducing energy consumption. Accurate predictions allow for proactive adjustments to HVAC systems and able to minimize energy waste and leading to substantial energy savings [1]. For instance, better predictions can prevent overcooling or overheating thus optimizing energy use.

Also, predicting indoor humidity accurately is challenging due to its inherent variability and complexity. External factors such as weather conditions and internal factors like occupancy and activities contribute to fluctuating humidity levels. This dynamic nature makes it difficult to develop models that can consistently predict humidity with high accuracy [2], [5].

Traditional statistical and empirical models often struggle to handle the dynamic nature of humidity [6]. These models may fail to capture the complex relationships between various factors influencing indoor humidity. Additionally, real-time prediction requires significant computational power in order to pose another challenge for existing models.

The specific problem addressed in this research is the accurate prediction of indoor absolute humidity using outdoor humidity data. Current prediction models often face limitations in terms of accuracy, computational efficiency, and adaptability in which this study aims to overcome[7], [8], [9], [10]. Existing state-of-the-art methods for indoor humidity prediction have several gaps. Traditional models may not effectively handle long sequence dependencies and lead to inaccurate predictions. Additionally, these models often require high computational resources and making real-time applications challenging [10].

To address these gaps, advanced models like Transformer and Informer models are needed. These models offer promising solutions for improving prediction accuracy and efficiency. Transformer models with their self-attention mechanisms can capture long-range dependencies while Informer models introduce ProbSparse attention able to enhance computational efficiency. Therefore, this research aims to explore advanced deep learning techniques to achieve these goals.

This research introduces a unique approach by applying ProbSparse attention in Informer models and specific architecture modifications in Transformer models. These innovations aim to improve prediction accuracy and computational efficiency. The study provides new theoretical insights into the application of advanced deep learning models for indoor humidity prediction. It explores the effectiveness of different attention mechanisms and sequence generation techniques in improving model performance. This research develops new models based on Transformer and Informer architectures specifically design for indoor humidity prediction.

2. RELATED WORKS

Earlier techniques for predicting humidity primarily relied on statistical models and rule-based systems. These models often used historical data and simple linear regressions to forecast humidity levels. For instance, empirical models based on temperature and dew point measurements were commonly used to estimate relative humidity. Rule-based systems which incorporated expert knowledge and predefined rules also played a significant role in the initial stages of humidity prediction [11]. However, these traditional methods often struggle with the dynamic and complex nature of humidity fluctuations leads to inaccuracies in predictions.

2.1 Deep Learning Models

Recurrent Neural Networks (RNNs) have been extensively used for time series prediction due to their ability to handle sequential data [12]. RNNs process sequences by maintaining a hidden state that captures information from previous time steps to allow them to learn temporal dependencies. This makes RNNs suitable for tasks such as humidity prediction where past humidity levels and external factors influence future values [13], [14]. However, RNNs suffer from significant limitations especially when it comes to long-term predictions. This leads to difficulties in learning long-range dependencies, resulting in poor performance on tasks requiring the integration of information over long periods [14].

To address the limitations of traditional RNNs, Long Short-Term Memory (LSTM) networks were introduced. LSTMs incorporate a memory cell that can maintain information over long durations, effectively mitigating the vanishing gradient problem. This is achieved through gates (input, forget and output gates) that regulate the flow of information into and out of the cell enabling the network to retain relevant information and discard irrelevant data. LSTMs have shown significant improvements in handling sequential data making them suitable for applications requiring long-term dependency tracking such as humidity prediction [12], [13].

On the other hand, Gated Recurrent Units (GRUs) are a variant of LSTMs that simplify the architecture by combining the forget and input gates into a single update gate. GRUs have fewer parameters compared to LSTMs which can lead to faster training and lower computational requirements while still effectively capturing long-term dependencies [15]. Both LSTMs and GRUs have demonstrated superior performance over traditional RNNs in various sequential prediction tasks including weather forecasting and environmental monitoring[16].

Attention mechanisms represent a significant advancement in deep learning particularly for tasks involving sequential data [17]. The core idea behind attention is to allow the model to focus on specific parts of the input sequence that are most relevant to the prediction at each time step. This is particularly beneficial for long sequences where it becomes crucial to dynamically weigh the importance of different parts of the sequence [18].

In the context of humidity prediction, attention mechanisms can enhance model performance by enabling the network to selectively attend to critical periods or external factors influencing humidity levels[19]. The introduction of attention mechanisms has led to the development of models such as the Transformer, which entirely eschews recurrence in favor of attention-based operations. This shift has resulted in significant improvements in handling long-range dependencies and parallelizing computations, further boosting the efficiency and accuracy of predictions [17].

Attention mechanisms have not only improved the performance of sequential models but also paved the way for more sophisticated architectures like the Informer, which introduces ProbSparse attention to efficiently handle long sequence time-series forecasting with reduced computational complexity [20].

2.2 Informer and Transformer

Transformer model introduced by Vaswani et al [19] reimplemented deep learning by introducing a novel architecture based on self-attention mechanisms, outperforms the recurrence found in traditional RNNs. The core component of the Transformer is the self-attention mechanism which allows the model to weigh the importance of different elements in the input sequence dynamically [17]. This mechanism computes attention scores that determine how much focus to place on each part of the sequence, enabling the model to capture long-range dependencies effectively. The Transformer architecture consists of an encoder-decoder structure where both parts are composed of layers of self-attention and feed-forward neural networks.

Transformers have been applied successfully in various fields, including natural language processing (NLP), computer vision and time-series forecasting. In NLP, they have achieved state-of-the-art results in tasks such as machine translation, text summarization and question answering. In computer vision, Transformer-based models have been used for image classification, object detection and segmentation [21]. Their ability to handle long-range dependencies and parallelized computations makes them particularly suitable for these applications.
The Informer model developed by Zhou et al. [20] builds on the Transformer architecture to address its limitations in long-sequence time-series forecasting. One of the main challenges with the Transformer is its quadratic time

complexity and high memory usage due to the self-attention mechanism. The Informer model introduces the ProbSparse self-attention mechanism which reduces the computational burden by focusing only on the most relevant parts of the input sequence. This is achieved by selecting a subset of key-value pairs for attention calculation and significantly improves the efficiency while maintaining performance.

The Informer also employs a generative style decoder that predicts long sequences in a single forward pass, further enhancing its ability to handle long-range dependencies in time-series data. These innovations make the Informer particularly suited for applications requiring efficient and accurate long-term predictions, such as weather forecasting and humidity prediction [20].

Comparative studies have shown that the Informer model outperforms the traditional Transformer model in long-sequence prediction tasks due to its enhanced efficiency and reduced computational requirements [18]. Zhou et al demonstrated that the Informer achieved better performance on several large-scale time-series datasets with significant improvements in both accuracy and computational speed. Additionally, the Informer has been found to handle extreme long input sequences more effectively than the Transformer making it a more suitable choice for applications involving large datasets and long-term dependencies.

One of the common issues in humidity prediction studies is the quality and availability of data. Accurate humidity prediction relies on comprehensive datasets that capture various influencing factors such as temperature, occupancy and external weather conditions [22]. However, data gaps, sensor inaccuracies and limited historical records can limit model training and validation which can lead to less reliable predictions [23].

Current models including advanced deep learning models like RNN and LSTM face several limitations [19]. Overfitting is a prevalent issue where models perform well on training data but fail to generalize to unseen data. Computational complexity is another significant challenge as these models require substantial computational resources for training and inference.

Additionally, while these models can capture complex patterns, they may struggle with real-time prediction due to their intensive processing requirements [24]. Existing research in humidity prediction has highlighted the need for more accurate and efficient models. Specifically, there is a need for models that can handle the dynamic nature of indoor environments, integrate multiple data sources, and operate efficiently in real-time [25].

Therefore, this study aims to address these gaps by developing and evaluating Transformer and Informer-based models for designs for indoor humidity prediction. By utilizing advanced deep learning techniques and optimizing model architectures the objective of this research focus to enhance prediction accuracy and efficiency. Potential areas for further research include exploring hybrid models that combine traditional and deep learning approaches and improving data collection methods to ensure higher quality datasets and developing algorithms that reduce computational demands while maintaining high performance.

3. RESEARCH METHODOLOGY

The dataset used in this study was obtained from the research [26]. The data was collected from a building located in Guatemala City, which lies in a tropical climate zone. This dataset provides detailed insights into the relationship between indoor and outdoor absolute humidity which is critical for developing predictive models.

The dataset contains two primary variables, Outdoor Absolute Humidity and Indoor Absolute Humidity which both measured in grams per cubic meter (g/m³). The data was collected at a daily interval to provide a continuous time series of absolute humidity values over a specified period. Spanning from December 1, 2017, to January 31, 2019, the dataset covers a full year and two months to ensure that seasonal variations are captured.

The initial data inspection involved importing the dataset using pandas in Python for ease of manipulation and analysis. Ensuring the 'Datetime' column was in the correct datetime format and setting it as the index facilitated the time series analysis. Basic statistics including count, mean, standard deviation, minimum and maximum values were calculated to understand the distribution and range of the data.

To handle missing values, an identification process revealed the presence of missing data in the 'Outdoor' column. The 'Indoor' column however had no missing values. For the 'Outdoor' absolute humidity values, the mean of the available data points was used to fill in the gaps in order to ensure continuity in the time series [27]. This imputation method was crucial for maintaining the integrity of the dataset.

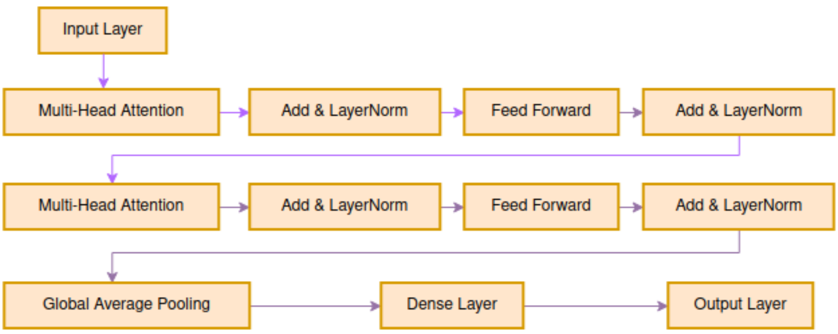

Fig. 1. Informer Model Architecture for Indoor Absolute Humidity Prediction.

Normalization was performed to scale the feature values within a specific range to enhance the performance of deep learning models. The MinMaxScaler was used to scale the 'Outdoor' humidity values to a range between 0 and 1. This scaler was then consistently applied to the test data.

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X represents the original feature values and X_{min} and X_{max} are the minimum and maximum values of the feature.

The dataset was resampled to a daily frequency to ensure a consistent interval between data points. A sequence length of 30 days was chosen to capture the temporal dependencies for the time series forecasting models. The following code snippet demonstrates the preprocessing steps, including converting the 'Datetime' column, handling missing values, normalizing the data and creating sequences for model training

3.1 Deep Learning Models

The Transformer model, introduced by Vaswani [19] revolutionized the field of natural language processing by eliminating the need for recurrent or convolutional layers and rely instead on self-attention mechanisms. The core components of the Transformer model include:

1. **Multi-Head Attention**: Allows the model to focus on different parts of the input sequence simultaneously to capture various aspects of the data.

$$Attention(Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{d_k}}\right)V$$

   where **K** and **V** are the query, key and value matrices, respectively and d_k is the dimension of the keys.

2. **Positional Encoding**: Adds information about the position of each element in the sequence to enable the model to understand the order of the data points.

3. **Feed-Forward Neural Network**: Processes the attended features and outputs the final prediction.

For this study, the Transformer model was configured with a head size of 128, four attention heads and four transformer blocks. The multi-layer perceptron (MLP) units included a dense layer with 256 units and a dropout rate of 10% to prevent overfitting. Figure 2 illustrates the implementation of the Transformer model.

On the other hand, Informer model is an enhancement of the Transformer specifically designed for long sequence forecasting tasks. It introduces two key improvements.

1. **ProbSparse Attention**: Efficiently handles long sequences by selecting a subset of the most relevant keys for attention, significantly reducing computational complexity.

$$Attention(Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{d_k}}\right)V$$

   However, in ProbSparse Attention instead of calculating the attention scores for all query-key pairs, it selects the top *u* queries based on the sparsity measurement.

$$Score(q_i, k_j) = \left(\frac{q_i \cdot k_j}{\sqrt{d_k}}\right)V$$

   Here:
   q_i is the *i*-th query vector.
   k_j is the *j*-th key vector.
   d_k is the dimension of the key vectors.

2. **Distilling Operation**: Reduces the length of the input sequence through pooling operations, allowing the model to focus on essential information.

The Informer model used in this study was configured with two encoder layers, each with a dimension of 128, eight attention heads, and a dropout rate of 10%. The data embedding layer incorporated a convolutional layer and positional embedding to enhance feature representation. The following Figure 1 demonstrates the implementation of the Informer model.

These models, the Transformer and Informer, are highly sophisticated and effective in capturing the temporal dependencies inherent in time series data, making them well-suited for the task of predicting indoor absolute humidity based on outdoor data.

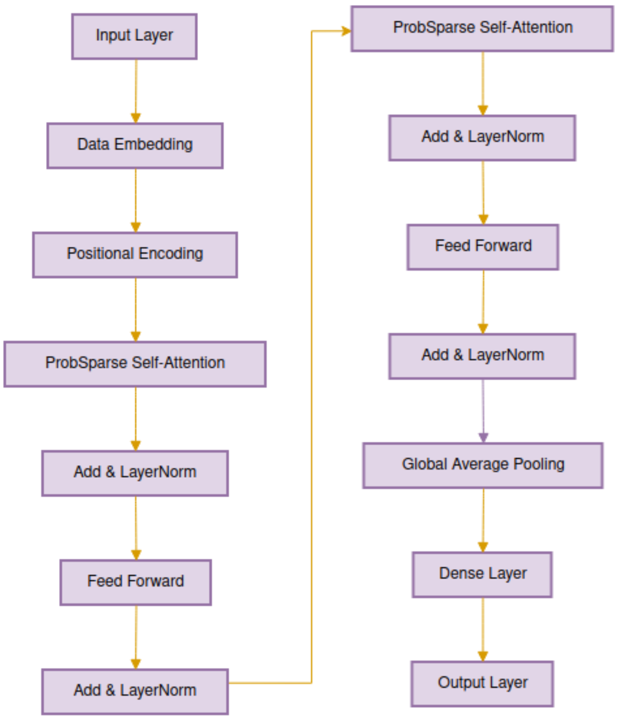

Fig. 2. Transformer Model Architecture for Indoor Absolute Humidity Prediction.

4. RESULTS AND DISCUSSION

Table 1. Training Performance of Informer and Transformer.

Metric	Informer	Transformer
MAPE	4.55%	3.42%
R-squared	0.8675	0.9108
Bias	0.3917	0.0776
MSE	0.5157	0.3470
MAE	0.5613	0.4482
RMSE	0.7182	0.5891
Correlation	0.9538	0.9556

This section presents the results of comparing the performance of the Informer and Transformer models for indoor absolute humidity prediction using various prediction metrics. The purpose of this comparison is to evaluate which model offers better accuracy, efficiency and applicability based on intrinsic metrics like MAPE, R-squared, Bias, MSE, MAE, RMSE, Correlation and Standard Deviation as well as extrinsic factors such as model complexity, computational efficiency, and real-world applicability.

In terms of intrinsic comparison which is illustrated in Table 1 shows the Mean Absolute Percentage Error (MAPE) which measures the accuracy of predictions as a percentage reveals that the Transformer model has a lower MAPE (3.42%) compared to the Informer model (4.55%) indicating higher accuracy in predicting indoor humidity. The R-squared value which measures the proportion of variance explained by the model is 0.9108 for the Transformer and 0.8675 for the Informer which suggests that the Transformer model explains more variance in the data and demonstrate better overall fit and predictive power. On the other hand, Bias defined as the difference between predicted and actual values is significantly lower in the Transformer model (0.0776) compared to the Informer model (0.3917) indicating that the Transformer is less prone to systematic error and provides more reliable predictions which is illustrated in Figure 5. Furthermore, the Mean Squared Error (MSE) which represent the average of squared differences between predicted and actual values is lower for the Transformer model (0.3470) than for the Informer model (0.5157) highlighting the superior prediction accuracy of the Transformer model. Similarly, the Mean Absolute Error (MAE) which measures the average of absolute differences between predicted and actual values is lower for the Transformer (0.4482) compared to the Informer (0.5613) shows a more accurate predictions by the Transformer model.

The Root Mean Squared Error (RMSE), the square root of the average of squared differences between predicted and actual values is lower for the Transformer (0.5891) than for the Informer (0.7182), demonstrating better overall performance by the Transformer model in Figure 5. Both models exhibit strong correlations between predicted and actual values with the Informer at 0.9538 and the Transformer slightly higher at 0.9556, indicating strong predictive capabilities, though the Transformer has a marginal advantage. Both models have the same Standard Deviation (1.6796), suggesting similar variability in their predictions.

For extrinsic comparison, the Transformer model is typically more computationally intensive due to its self-attention mechanism which can be demanding in terms of both memory and processing power. The Informer model on the other hand is designed to handle long sequences more efficiently through its ProbSparse attention mechanism which reduces computational costs. Although the Transformer provides higher accuracy, the Informer's efficiency makes it suitable for scenarios where computational resources are limited, or real-time predictions are necessary. However, the Informer model's efficiency in handling large datasets and its reduced computational demands make it a strong candidate for real-time applications such as indoor humidity control in HVAC systems where timely predictions is crucial. Both models demonstrate strong linear relationships with actual values to ensure reliable performance in various real-world scenarios.

The provided Figure 5 illustrates the generalization capabilities of the Informer and Transformer models in predicting indoor absolute humidity against actual data. Both models demonstrate a high degree of alignment with the actual indoor humidity trends, indicating their strong predictive abilities. The Transformer model depicted by the orange line closely follows the actual data with minor deviations showcasing its high accuracy in capturing the complex variations in indoor humidity. The Informer model represented by the blue line, also shows a good fit but with slightly larger deviations compared to the Transformer model.

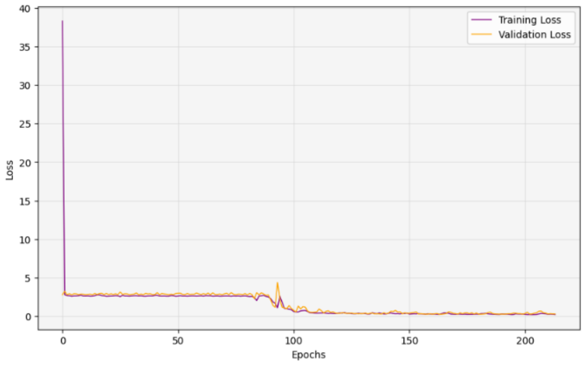

Fig. 3. Informer Model Training Loss

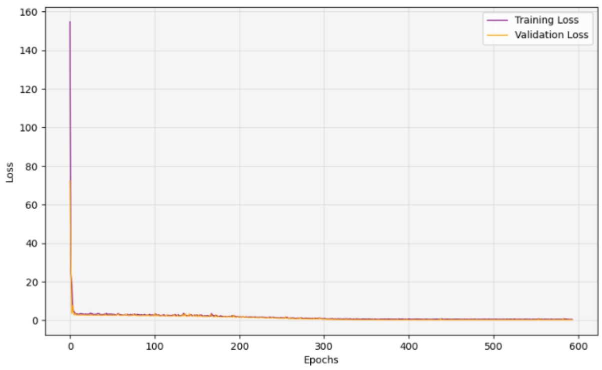

Fig. 4. Transformer Model Training Loss

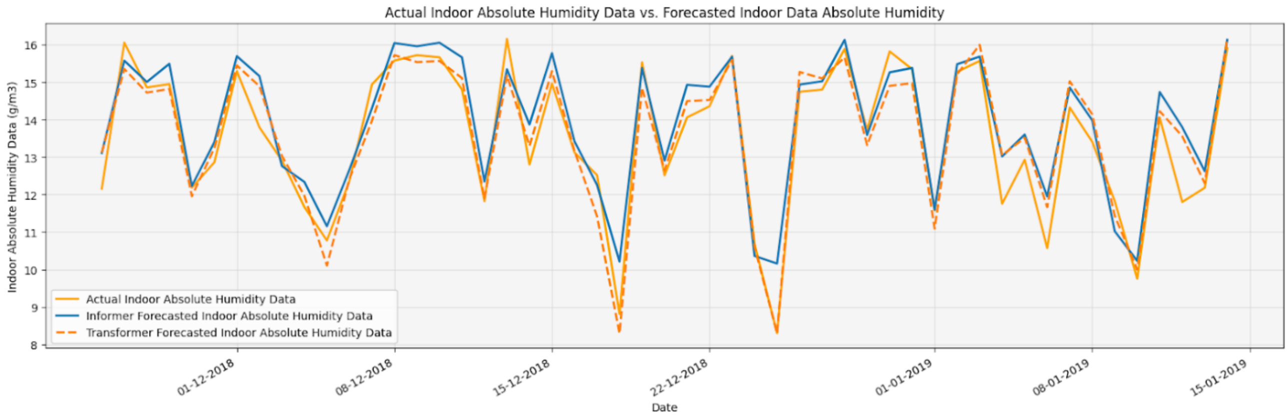

Fig. 5. Performance of Informer and Transformer Models on Unseen Data

This suggests that while both models can generalize well to unseen data and the Transformer model exhibits a marginally better performance in terms of accuracy.

The generalization performance of these deep learning models towards unseen data is crucial for real-world applications such as in HVAC systems where accurate and timely predictions are essential for maintaining optimal indoor conditions. The graph highlights that both models can adapt to new data patterns effectively, reducing the risk of overfitting. The Transformer's lower Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) metrics, combined with its closer alignment to the actual data suggest that it may be more reliable for scenarios demanding high precision. On the other hand, the Informer's efficient handling of long sequences and reduced computational costs make it a viable option for applications where resource efficiency is a priority. Overall, the graph demonstrates that both models have strong generalization capabilities, with the Transformer model having a slight edge in predictive accuracy.

In conclusion, the Transformer model exhibits superior accuracy and performance across most intrinsic metrics, making it ideal for tasks requiring high precision. However, the Informer model's computational efficiency and ability to handle long sequences efficiently provide significant advantages in real-time and resource-constrained environments. The choice between models should be based on the specific needs of the application and balances the trade-offs between accuracy and computational efficiency.

5. CONCLUSION

In this study, we evaluated the performance of Transformer and Informer-based models for predicting indoor absolute humidity using outdoor humidity data. Our study aimed to address the limitations of existing humidity prediction models by focusing on the advanced deep learning techniques that can capture complex dependencies and improve prediction accuracy. The Transformer model demonstrated superior performance, achieving lower Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) compared to the Informer model, indicating higher prediction accuracy. The Transformer's higher R-squared value and lower bias further highlight its effectiveness in fitting the data and minimizing systematic prediction errors.

The Informer model, although slightly less accurate than the Transformer, still showcased strong performance in capturing the trends and variability of indoor humidity. Its efficient ProbSparse attention mechanism allowed it to handle the dynamic nature of the data effectively while reducing computational overhead. This makes the Informer model a robust alternative for scenarios where computational efficiency is a priority. The specialized attention mechanisms in both models played a crucial role in their performance, with the Transformer's standard self-attention capturing complex dependencies well and the Informer's ProbSparse attention providing an efficient solution for long-sequence modeling.

The findings of this study have significant practical implications for building management, energy efficiency, and indoor air quality control. Accurate indoor humidity predictions can lead to optimized HVAC system operations, resulting in substantial energy savings and improved occupant comfort. Additionally, reliable humidity control is essential for preserving artifacts in museums and preventing health issues related to mold and poor air quality. Our research contributes to the field by developing and evaluating advanced models specifically for indoor humidity prediction, demonstrating significant improvements in prediction accuracy, and providing new theoretical insights into the application of attention mechanisms for time series prediction. Future research can further optimize these models, explore real-time implementations, and extend their application to other environmental parameters for comprehensive indoor climate control.

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