Improving Open Weather Prediction Data Accuracy Using Machine Learning Techniques

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***Abstract*—Weather prediction methods have evolved significantly over the past fifty years, including advances in numerical weather prediction, high-performance computing, mesoscale modeling, assimilation of observations from new sources, and ensemble prediction systems. In recent years, machine learning techniques, including Long Short-Term Memory (LSTM) models, have shown promise in improving the accuracy of weather predictions. In this paper, we aim at investigating the use of LSTM models to improve the accuracy of open weather datasets. Our work was conducted as part of the AUGEIAS research project, which aims at capitalizing on research results in the field of Internet of Things (IoT) and Low Power Wide Area Networks (LPWAN). More specifically, the project target is to create a smart ecosystem, utilizing machine learning techniques that will enable and optimize the use of treated wastewater reuse in agriculture. Our research indicates that, within the context of the AUGEIAS project, single-step LSTM models outperform multistep models in enhancing weather prediction accuracy.**

Keywords—Internet of Things, machine learning, open weather data, weather prediction accuracy enhancement

I. Introduction

Weather forecasting is the process of estimating atmospheric conditions, such as temperature, humidity, precipitation, wind speed, and direction based on the collection and analysis of meteorological observations, for a specific location and time in the future [1].

Accurate weather prediction is of utmost importance in various applications, including transportation, energy management, and disaster preparedness, to everyday planning for individuals and agriculture. Weather predictions are used in transportation planning [2], such as aviation, maritime, and road transportation, to optimize routes, schedule operations, and mitigate potential weather-related hazards. In energy management, accurate weather forecasting is essential for renewable energy sources [3], such as solar and wind power, as it helps in optimizing their generation and distribution. Precise weather forecasting has a pivotal role in disaster preparedness for severe weather events such as hurricanes, tornadoes, floods, and wildfires. Accurate weather forecasts enable the timely implementation of evacuation plans and preparedness measures, helping minimize these events' impact [4]. Furthermore, weather predictions are used by individuals in their daily planning, such as choosing appropriate clothing, scheduling outdoor activities, and making travel plans [5]. Finally, it plays a crucial role in agriculture as farmers need accurate weather information to make informed decisions about planting, harvesting, and irrigation of crops [6].

The AUGEIAS ecosystem utilizes treated wastewater from wastewater treatment plants (WWTP) for crop irrigation in a safe and cost-efficient way. By using weather forecasting to predict crop water needs, the system can optimize irrigation and save water resources while still ensuring that crops receive the necessary amount of water for healthy growth. Therefore, accurate weather forecasting is crucial to the AUGEIAS ecosystem to ensure that it can make informed decisions about irrigation and meet its goals of optimizing water usage and minimizing environmental impact.

Traditional methods for weather prediction often struggle to capture the complex and dynamic nature of weather patterns, leading to limited accuracy [7]. In recent years, machine learning techniques [8], including Long Short-Term Memory (LSTM) models, have shown promise in improving the accuracy of weather predictions. AUGEIAS ecosystem, to improve the accuracy of localized weather forecasting as regional forecasts could be inaccurate for local use, proposes a refinement procedure based on LSTM modeling.

The rest of this paper is organized as follows: the related work is presented in Section II. In Section III, the system architecture of AUGEIAS ecosystem is described. The open weather sources and the data preprocessing are analyzed in Section IV as well as the techniques and system implementation are described. Then, in Section V we present the evaluation of the proposed procedure. Finally, in section VI, we make some concluding remarks.

II. Related Work

Most weather forecasting operations rely on the Numerical Weather Prediction (NWP) method, which utilizes a complex set of non-linear equations. However, this forecasting approach encounters numerous challenges, such as errors in estimation caused by the inherent complexities of the atmosphere and the significant sensitivity of model results to even slight differences in initial weather conditions [8].

European Centre for Medium-Range Weather Forecasts (ECMWF) [9] and National Oceanic and Atmospheric Administration (NOAA) [10] which are deeply engaged in cutting-edge weather forecasting research, are planning the utilization of contemporary machine-learning techniques.

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Their comprehensive plans for the near future serve as a reliable indicator of the anticipated developments in the field.

Detailed evaluations of machine learning algorithms, specifically those used in atmospheric science which is a crucial subset of artificial intelligence techniques can be found in specialized articles [11]–[13]. Supervised and unsupervised techniques can be applied in machine learning.

Supervised machine learning techniques considered highly relevant in the field of atmospheric science, leverage labeled data, when accessible, to train a mapping function that establishes a relationship between input data and output predictions. This trained model can be tested on a separate dataset, referred to as the testing dataset, to evaluate its performance. Upon satisfactory results, the trained model can be utilized for tasks such as classification or regression in various applications.

Decision Trees [14], [15], Support Vector Machines [16], Artificial Neural Networks [17], including Long Short-Term Memory networks[18], [19], and Deep Learning [20] are popular methods used in this field. These techniques can handle complex data relationships, capture intricate patterns, and process large and complex datasets. By using these techniques, atmospheric scientists can improve their understanding and prediction of atmospheric processes and phenomena.

Unsupervised learning, as the second group of machine learning techniques, is a domain where algorithms do not have the luxury of labeled data for training. Instead, they must rely on alternative approaches to segment a given dataset or reduce its dimensions. In this context, atmospheric scientists have found certain methods to be particularly popular and relevant.

In atmospheric science, two commonly used unsupervised learning methods are K-means Clustering [21] and Principal Component Analysis (PCA) [22]. K-means is used to partition a dataset into clusters based on similarity or distance measures, while PCA is a dimensionality reduction technique that identifies important features or principal components in high-dimensional data.

Open weather datasets refer to publicly available datasets that provide information on weather conditions, such as temperature, humidity, wind speed, and precipitation. These datasets are often used by researchers, businesses, and individuals for a wide range of applications, including agriculture, transportation, energy management, and disaster preparedness. Examples of open weather datasets include OpenWeatherMap [23] and AccuWeather [24].

These datasets have limitations that can affect the accuracy of their predictions [25]. These limitations include the use of different data sources and collection methods, the inability to capture small-scale weather phenomena, and the reliance on historical data-based models that may not reflect current weather patterns or sudden changes in weather conditions. Additionally, open weather datasets may not provide complete and up-to-date information on weather conditions, limiting their accuracy and usefulness.

Weather stations can provide more accurate and localized weather data than open weather services. Incorporating data from weather stations into machine learning models can help address the limitations of open weather datasets and improve prediction accuracy by capturing the local variability and adapting to changing weather patterns.

Our approach builds upon existing research and knowledge and utilizes machine learning models in combination with weather station data to refine and adjust forecasts obtained from open weather services like OpenWeatherMap and AccuWeather. Our focus is not on weather forecasting, but rather on improving the accuracy and reliability of the forecasts obtained from these external services through fine-tuning, refinement and local adjustment using machine learning techniques.

III. System Architecture

The AUGEIAS ecosystem is designed to tackle the challenge of sustainable water management through the reduction of water wastage and the utilization of treated wastewater in agriculture. This smart ecosystem incorporates IoT and Low Power Wide Area Network (LPWAN) for real-time data collection from end devices installed in the Wastewater Treatment Plant (WWTP) and the field. Specifically, the field is equipped with a meteorological station, systems for measuring soil parameters, and the Normalized Difference Vegetation Index (NDVI). Additionally, a system for measuring the quality characteristics of treated wastewater has been installed at the output of the WWTP.

The IoT ecosystem [26] utilizes the Long Range Wide Area Network (LoRaWAN) and has the potential to support NB-IoT networks for transmitting IoT device data. In the context of the ecosystem, it has been developed an energy-efficient network protocol and a data management platform to gather, analyze, and process information from sensors deployed in the field and the WWTP. Additionally, the platform integrates data from external systems and open data, such as meteorological data, in the cloud and correlates it with IoT data.

The AUGEIAS IoT Data Platform constitutes a data management system that enables the real-time processing and analysis of collected data. The platform supports both push and pull mechanisms for data collection, and the collected data can be filtered and processed based on user-defined data models. The push mechanism is an HTTP endpoint that allows sources such as sensors to push their data to the platform, while the pull mechanism retrieves data from sources that expose their data through an API, such as open data. Finally, the IoT data platform provides several functionalities, including the ability to match and compare data to verify specific conditions or requirements, send notifications or perform actions, and forward data to other applications.

The primary goal of the AUGEIAS is to optimize the utilization of treated wastewater in agriculture for irrigation by fulfilling the crop's water needs, conserving the available water resources, and minimizing the environmental impact. This is accomplished through advanced machine learning techniques and data analytics that enable predictions for assessing crop water needs as well as the risk of using treated wastewater for irrigation based on its quality characteristics. It also determines the appropriate mixing ratio of freshwater and treated wastewater, as well as dynamic pricing of treated wastewater.

AUGEIAS calculates the crop water needs and utilizes them along with weather forecasts, obtained from open sources and their reliability, to implement predictive irrigation mechanisms that optimize the management of both conventional and treated wastewater for irrigation purposes.

Open meteorological data is being leveraged to enhance the accuracy of crop irrigation requirement predictions. Specifically, by utilizing open meteorological data, the irrigation plan and crop water needs prediction are optimized. This enables farmers to have better knowledge about the water requirements of their crops, allowing them to make informed decisions about the optimal use of water resources.

A. Open Weather Data

In the context of weather forecasting, there are several sources of open data that can be used for various purposes, including:

1) Global Forecast System (GFS) [27]: A numerical weather prediction model operated by NOAA, that offers open data in the form of weather model outputs, including forecasts of temperature, precipitation, wind, and other weather variables.

2) ECMWF [28]: An organization that offers access to a wide range of weather and climate data, including observations, forecasts, reanalysis data, and more.

3) OpenWeatherMap: A commercial weather service provider that also gives free access to a limited set of weather data, including current weather conditions, forecasts, and historical data through its OpenWeatherMap API.

4) AccuWeather: A commercial weather service provider that offers weather forecasts, radar maps, satellite imagery, and other weather-related content for global locations. They provide weather information through their website, mobile app, and other platforms.

Both OpenWeatherMap and AccuWeather use multiple data sources, including weather stations, satellites, and numerical weather prediction models, to gather weather data. OpenWeatherMap uses a combination of multiple data sources and numerical weather prediction (NWP) models to provide weather forecasts and publishes some limited information about accuracy and quality of the predictions. Accuweather uses real-time data, a combination of more than 190 forecast models and proprietary AI algorithms to provide forecasts.

AUGEIAS utilizes datasets from OpenWeatherMap and AccuWeather for weather forecasting purposes. These services were used because they provide data that are within the scope of the AUGEIAS requirements since the use of GFS or ECMWF would require regional models as MM5 [29] and WRF [30] to generate forecasts specific to a particular location.

Fig. 1 displays the varying values of temperature, humidity, and wind speed between the two open datasets. AUGEIAS assess their reliability by comparing them against the factual data obtained from the agrometeorological station situated in the field [31]. In order to address this issue, an algorithm was created to locally adjust the open weather data by incorporating data obtained from an agrometeorological station situated in the field of the pilot application.

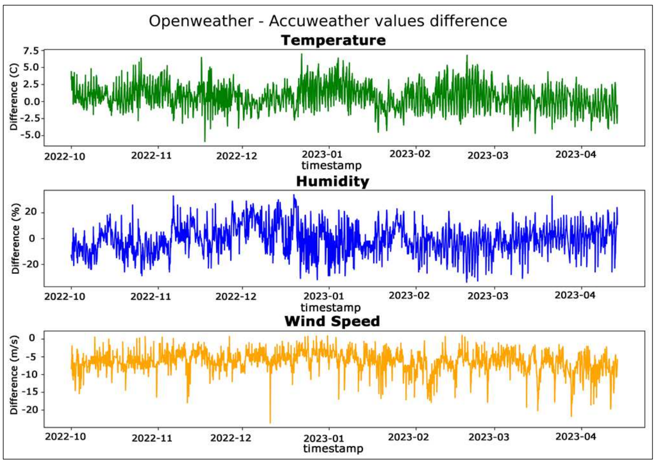

Fig. 1. OpenWeatherMap vs AccuWeather value differences.

Thus, a machine learning model based on LSTM networks is proposed, as shown in Fig. 2. The LSTM is executed to locally adjust forecasts of temperature, humidity, wind speed, precipitation, solar irradiance, and evapotranspiration. The differences for each target variable between the actual value from the agrometeorological station that is installed in the field and the value that the open weather source provides is used as input to train the model. The LSTM network, after the necessary training, outputs a set of difference forecasts for the next few hours. These differences are applied numerically to the open data forecasts, thereby allowing the Accuweather and OpenWeatherMap forecasts to be adapted to local conditions. The improved weather forecasts could be used by the irrigation optimization algorithm and by the farmers themselves.

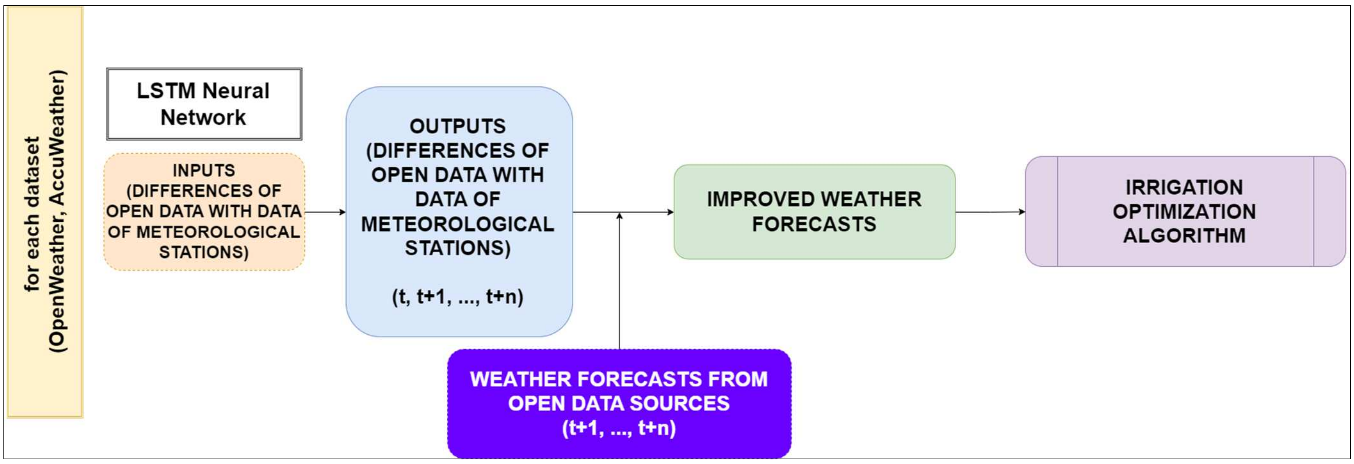

Fig. 2. LSTM Neural Network Architecture.

IV. Methodology

A. Data Preprocessing

In our approach we collected data from OpenWeatherMap and AccuWeather services, with a starting date of 22-09-2022 and 18-01-2022 respectively, provided at an hourly resolution. These datasets were used in conjunction with weather station data, as shown in Fig. 3 in our study, to adjust and refine forecasts using machine learning networks.

During the initial step of data preprocessing, the datasets from each source were carefully examined for any anomalies or inconsistencies. Any significant parts of data that were found to be anomalous were excluded to ensure the integrity and quality of the data used for training and evaluation. This step is crucial to ensure that the model is trained with reliable and accurate data, which is essential for generating accurate results.

Next, missing values and incomplete hourly data in the datasets were checked. Missing values can occur due to various reasons such as sensor failures, data transmission errors, or gaps in the data collection process. To address the missing hours, we employed resampling techniques in conjunction to forward and back filling methods, which are available in the popular data manipulation library, Python Pandas. Forward filling involves propagating the last known value forward to fill the missing values, while back filling involves propagating the next known value backward to fill the missing values. These techniques help to interpolate or fill in the gaps in the datasets, ensuring that the data is complete and suitable for training the machine learning model.

Fig. 4 showcases the cleaned and processed dataset from OpenWeatherMap, and Fig. 5 displays the cleaned and processed dataset from AccuWeather. These figures include plots or visualizations of various meteorological parameters such as temperature, humidity, precipitation, and wind speed depending on the specific data used in the study.

The resulting data created a smaller number of data points compared to the original datasets or the meteorological station data. This is acknowledged as a limitation of the modeling since the model may face challenges in capturing complex temporal patterns and making accurate predictions. Limited data points may result in reduced model performance, increased vulnerability to overfitting, or reduced generalization ability of the model.

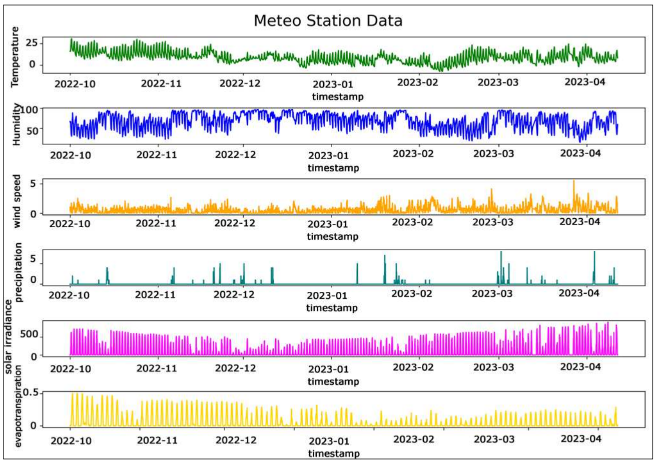

Fig. 3. Available Meteo Station Data

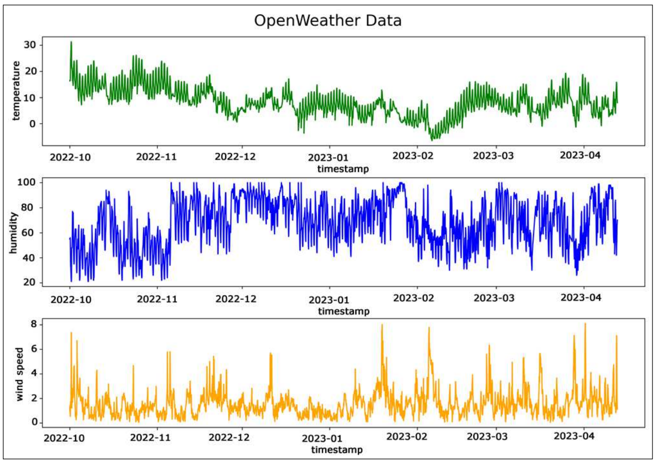

Fig. 4. Available OpenWeatherMap Data

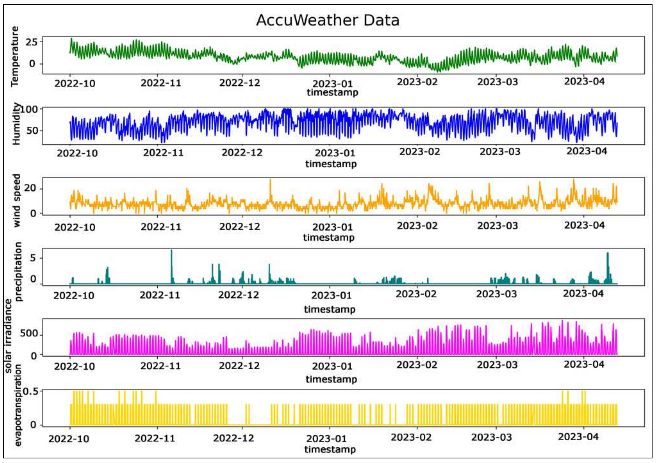

Fig. 5. Available AccuWeather Data

In the subsequent step, the mathematical difference between the open data and the corresponding meteorological station data was calculated for each variable. New datasets were then generated to incorporate the values from the open dataset, meteorological station data, and the calculated differences for each variable. An example of such a dataset is depicted in Fig. 6.

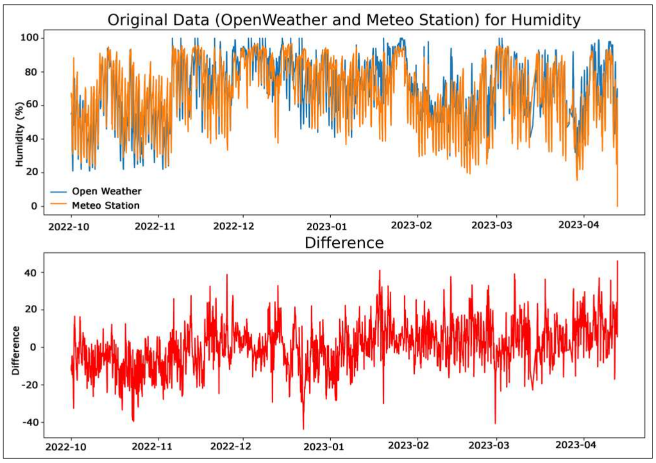

Fig. 6. Example of generated dataset (*Humidity*)

Table I presents the datasets created for each variable, which incorporate data obtained from both open data sources and available meteorological station data.

TABLE I. GENERATED DATASETS

Generated Datasets	OpenWeatherMap	Accuweather
Temperature	X	X
Humidity	X	X
Wind Speed	X	X
Precipitation		X
Solar Irradiance		X
Evapotranspiration		X

B. Techniques and System Implementation

The development of the LSTM model involved several steps. Firstly, the dataset containing the open data variable and meteorological station measurements, along with their differences, was prepared for training. The data was split into training and testing sets, with 80% of the data allocated for training and the remaining 20% for testing.

The purpose of splitting the data into training and testing sets is to ensure a reliable and unbiased evaluation of the LSTM model's performance. By allocating a significant portion of the data for training, the model can learn from the underlying patterns and relationships in the data, enabling it to make accurate predictions during the testing phase. This setup allows for robust evaluation of the model's performance and generalization of unseen data.

As part of the data preparation for LSTM modeling, the time series were transformed into sequential format to capture temporal dependencies and patterns and allowing the model to leverage its recurrent architecture and capture long-term dependencies in the data. This involved creating input-output pairs where the input represents the independent variables or features, and the output represents the dependent variable or target that the model aims to predict.

Before feeding the data into the LSTM model, they were scaled using the MinMax scaler from the popular scikit-learn library. The MinMax scaler transformed the data by scaling it to a specific range, typically between 0 and 1, ensuring consistency in the scale of the data. Importantly, the scaling parameters were calculated exclusively from the training data to prevent data leakage, as using information from the testing data could introduce bias into the model's performance evaluation.

The LSTM models were constructed using the TensorFlow library, a widely used deep learning framework. The architecture of the models, including the number of LSTM layers, number of hidden units, and activation functions, were carefully defined as critical hyperparameters. Experimentation and model evaluation were conducted to determine the optimal values for these hyperparameters. The number of LSTM layers and hidden units were chosen to strike a balance between capturing complex patterns in the data and mitigating the risk of overfitting, which occurs when the model becomes too complex and performs poorly on unseen data.

Activation functions, including sigmoid, tanh, and ReLU, were tested to capture complex patterns in the data, with the final choice depending on the nature of the data and problem. Other hyperparameters, including learning rate, batch size, and dropout rate, were fine-tuned through experimentation to optimize model performance for the specific dataset and problem.

Based on the analysis and comparison of different models, it was concluded that a model with a small number of layers, an input sequence length of 72 hours, and 50 hidden units resulted in superior accuracy and reliability in forecasting the target variable. A graphical representation of an example prediction for the temperature difference between the OpenWeatherMap data and meteorological station data can be observed in Fig. 7.

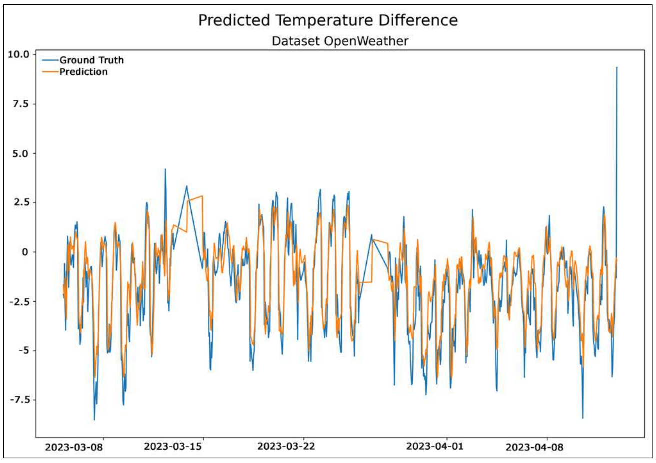

Fig. 7. Example prediction of Temperature Difference utilizing OpenWeatherMap and Meteorological Station Data.

Finally, the model was utilized to predict each target variable for the next hour. This forecasted value was then applied to the new incoming data from OpenWeatherMap or AccuWeather services to generate a corrected value. An example of the corrected values is presented in Fig. 8. This corrected value considers the model's prediction and the real-time data, providing an updated and refined estimate of the weather variable for the next hour.

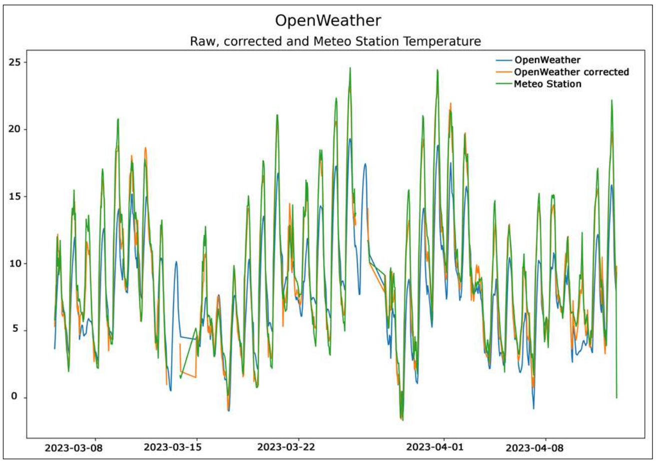

Fig. 8. Temperature. *(OpenWeatherMap raw, corrected and Meteorological Station values)*

The extension of the previous procedure involved training an LSTM model for multi-step forecasting [32], where the model was modified to predict the differences for multiple hours ahead, instead of just the next hour.

The data preprocessing steps, such as handling missing values, normalizing the data, and splitting into training and testing sets, remained similar to the single step forecast.

However, the target variable for training the model was adjusted to represent the differences for multiple hours ahead.

V. EVALUATION

The initial phase of the model evaluation involved the development of a baseline model utilizing the ARIMA methodology [33]. This was accomplished with the aid of the pmdarima package, which incorporates the auto-ARIMA function. The function efficiently determines the best parameters for an ARIMA model. It uses differencing tests to establish 'd' and fits models within specified ranges, aiming to minimize a chosen information criterion for optimal model efficiency [34].

The predicted variables, which as noted before is the calculated difference of the open dataset to the meteorological station value, were applied to each dataset and variable. The Root Mean Squared Error (RMSE) was calculated for each dataset to quantify the model's prediction accuracy. These values, shown in Table II, provide a numerical measure of the model's forecasting precision.

In the second step of LSTM model evaluation, we employed the available testing datasets for preliminary analysis. We used these datasets to evaluate the trained LSTM model's ability to accurately predict the target variable based on the input data. The evaluation process involved feeding the testing datasets into the LSTM model and comparing the model's predictions with the actual values from the testing datasets. Finally, we analyzed the results of this evaluation to determine the performance and effectiveness of the LSTM model in generating accurate predictions for the target variable. The RMSE for each predicted variable is presented in Fig. 9.

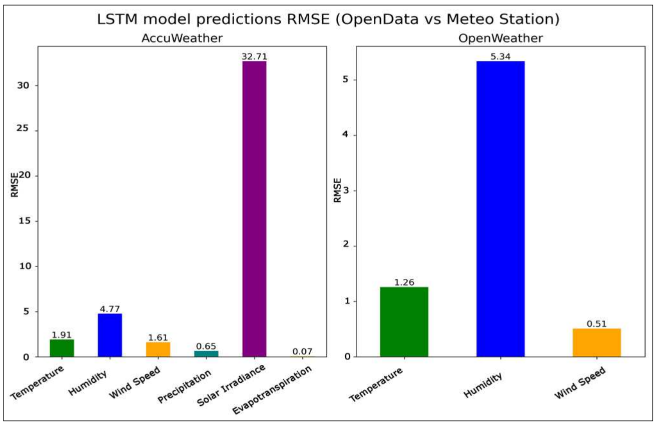

Fig. 9. RMSE for LSTM model predictions for each variable.

It was observed that while the RMSE value for precipitation prediction was low, indicating relatively accurate predictions in terms of magnitude, the model still failed to capture the actual trend correctly. This is indicated by the negative predictions Fig. 10, which suggest that the model was underestimating the precipitation values. This discrepancy between the RMSE value and the actual trend may indicate a limitation of the LSTM model in capturing the complex dynamics of precipitation, such as sudden changes or non-linearity in the data.

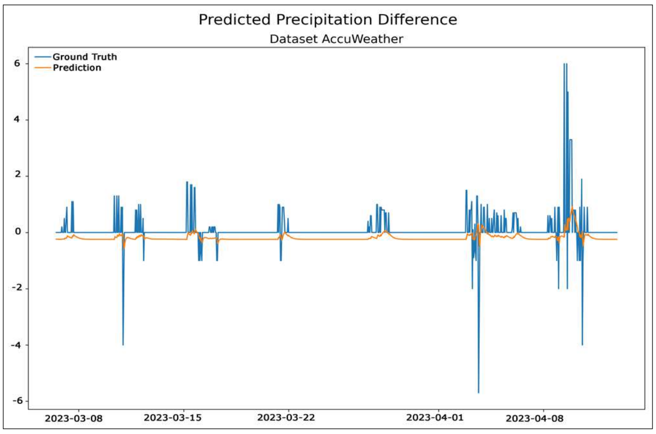

Fig. 10. Predicted Precipitation Difference. *(AccuWeather)*

After applying the predicted value differences to the corresponding datasets, the RMSE was calculated for both the original data, as well as the corrected data. The results of this evaluation are presented in Table II for the AccuWeather dataset and in Table III for the OpenWeatherMap dataset. This evaluation suggests that the single-step LSTM model improves upon the baseline model's performance. The last column of these tables presents the RMSE for the ARIMA baseline model after the application of corrections.

TABLE II. ACCUWEATHER VARIABLE RMSE BEFORE AND AFTER APPLIED CORRECTIONS

Accu Weather	**RMSE**			
	Before corrections	***After corrections***	***Difference***	***ARIMA***
Temperature	2.496	1.090	1.406	1.151
Humidity	10.679	4.927	5.752	5.379
Wind Speed	9.387	1.327	8.060	1.863
Precipitation	0.625	0.641	-0.016	0.978
Solar Irradiance	116.505	84.247	32.258	100.589
Evapo-transpiration	0.065	0.055	0.010	0.061

TABLE III. OPENWEATHERMAP VARIABLE RMSE BEFORE AND AFTER APPLIED CORRECTIONS

Open Weather Map	**RMSE**			
	Before corrections	***After corrections***	***Difference***	***ARIMA***
Temperature	2.903	1.303	1.600	1.456
Humidity	12.162	5.462	6.700	6.014
Wind Speed	1.433	0.488	0.945	0.592

The implementation of multistep one-shot LSTM in forecasting future time series data has been observed to exhibit reduced accuracy compared to single step forecasting as shown in Table IV and Table V. As previously mentioned, the final column in these tables displays the RMSE values for the ARIMA model, computed post-correction. Furthermore, the multistep model was found to be unsuccessful in enhancing the performance of the baseline model. Despite the potential advantages of predicting multiple time steps in a single prediction, such as increased efficiency, there were notable challenges associated with this approach.

One of the primary challenges was the potential compromise in prediction accuracy due to the absence of model updates between the predicted time steps. This limitation resulted in the model's inability to adapt to changing patterns in the data, leading to diminished accuracy in long-term predictions. Additionally, the complexity of capturing and modeling dependencies between multiple future time steps in a single prediction was heightened, further impacting the accuracy of the results. Further research and experimentation may be necessary to optimize the performance of this approach in diverse forecasting.

In our research, we evaluated the computational efficiency of the ARIMA, single-step LSTM, and multistep LSTM models, considering their training times and memory usage for each target variable. The ARIMA model, factoring in the time for identifying the optimal parameters, averaged 524377ms and 250 MB of memory. The single-step LSTM model, despite consuming more memory (400 MB), was faster, requiring only 73859ms on average. The multistep LSTM model was the most resource-intensive on average, requiring 721736ms and 550 MB of memory. Despite its higher memory usage, the single-step LSTM model exhibited superior computational efficiency. These computations were conducted without the use of a Graphics Processing Unit (GPU), which could potentially improve efficiency.

TABLE IV. ACCUWEATHER VARIABLE RMSE BEFORE AND AFTER APPLIED CORRECTIONS

Accu Weather	**RMSE**			
	Before corrections	***After corrections***	***Difference***	***ARIMA***
Temperature	2.861	2.625	0.236	1.151
Humidity	12.270	10.242	2.028	5.379
Wind Speed	8.847	5.107	3.740	1.863
Precipitation	0.419	1.117	-0.698	0.978
Solar Irradiance	100.400	100.400	0.000	100.589
Evapo-transpiration	2.861	2.625	0.236	0.061

TABLE V. OPENWEATHERMAP VARIABLE RMSE BEFORE AND AFTER APPLIED CORRECTIONS

Open WeatherMap	**RMSE**			
	Before corrections	***After corrections***	***Difference***	***ARIMA***
Temperature	2.963	2.933	0.030	1.456
Humidity	11.928	10.582	1.346	6.014
Wind Speed	1.325	0.869	0.456	0.592

VI. CONCLUSION AND DISCUSSION

Weather forecasting plays a critical role in various domains such as transportation, energy management, disaster preparedness, agriculture, and everyday planning. The AUGEIAS ecosystem leverages open weather data from trustworthy sources like OpenWeatherMap and AccuWeather to improve irrigation algorithms. However, disparities in data sources, data collection methods, data processing techniques, and forecast algorithms may result in divergent values for common weather variables as compared to meteorological station data.

Our approach builds upon existing research and knowledge, utilizing machine learning networks that incorporate weather station data to refine and adjust forecasts obtained from external weather services, aiming for enhanced accuracy and reliability. The data from OpenWeatherMap and AccuWeather services, along with meteorological station data, were curated and preprocessed to train and evaluate machine learning models.

The model exhibited satisfactory accuracy in predicting the next hour for most variables. However, it was observed that the model faced challenges in making accurate predictions for certain variables, such as precipitation difference. This suggests that the model may not be as reliable in forecasting certain variables compared to others, and further refinement and improvement may be necessary to enhance its accuracy for precipitation predictions.

The multi-step forecasts and subsequent corrections were found to be less accurate compared to single-step forecasts. This implies that the model's performance in predicting multiple time steps ahead may not be as reliable as its performance in predicting just one time step ahead. The accuracy could have been influenced by various factors, including changes in weather patterns, spatial and temporal variability of weather variables, and the influence of local topography or microscale weather phenomena. Additionally, limitations in data quality or availability, model architecture, and training techniques may have impacted the accuracy of the multi-step forecast. It's crucial to consider these factors when interpreting the results of the multi-step forecast.

It's worth noting that weather forecasting, particularly for variables like precipitation, is inherently complex and challenging due to the dynamic and unpredictable nature of weather systems. It's common for models to have limitations and encounter difficulties in accurately forecasting certain weather variables, especially over longer time horizons.

To enhance the accuracy of the model, future work could involve exploring alternative algorithms, further adjusting hyperparameters, and incorporating additional features or data sources. Variable-specific forecasting approaches or ensemble methods, along with considering external factors such as climate change, could also be explored. Thorough evaluations, sensitivity analyses, and cross-validation can aid in identifying model strengths and weaknesses for further refinement.

Finally, the use of GPUs could be explored for potential computational efficiency gains and larger datasets could offer deeper insights into computational costs, thereby enhancing model robustness and generalizability.

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