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VARIMA and the RNN weather predictions Comparison in Irbid city

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This research aims to compare two weather forecasting models: the Autoregressive Integrated Moving Average Model and the Recurrent Neural Network model. Analysis and forecasting of boundary layer variables in the city of Irbid is performed based on historical data for many weather variables. The performance of both models is evaluated using the root mean square prediction error (normalized RMSPE) to predict each variable separately. The results showed that the Recurrent Neural Network model was superior to the Autoregressive Integrated Moving Average Model in predicting five variables out of the six variables used in the study.

keywords: Weather prediction, LSTM, Time Series, deep learning, Machine learning .

1 Introduction

Meteorology is the science that studies weather patterns and events in the Earth's atmosphere over short periods of time, monitors and analyzes changes in the atmosphere, and predicts various weather variables such as rainfall, humidity, humidity, and others. Meteorology is concerned with monitoring and understanding weather phenomena that occur during short-term periods, such as thunderstorms, atmospheric instability, and the movement of cold and hot air fronts. Meteorology uses a set of tools and techniques to collect data about different weather variables, such as weather stations distributed in different places in the world, weather balloons that collect data at different altitudes, and satellites.This data is used for short-term forecasts involving a few hours or days (Ackerman and Knox, 2011).

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The boundary layer is the layer of the atmosphere in which humans live, interact and are affected by and in direct contact with the Earth's surface. This layer extends from the Earth's surface to certain heights ranging from a few hundred meters to a few Kilometers, depending on various factors such as terrain and weather conditions (Monin, 1970). The boundary layer is an important layer for various atmospheric and physical processes that occur on the Earth's surface. The boundary layer helps us understand atmospheric changes, the effect of wind speed and direction on the Earth's surface, the formation of clouds and fog, and the effect of sunlight on temperature, as well as many other phenomena (Garratt, 1994).

A limited number of research can be found in literature that discusses forecasting weather conditions in Jordan. Aksoy and Dahamsheh (2009) discussed predicting precipitation in semi-arid and arid regions in Jordan using an artificial neural network (ANN) models. The authors compared the performance of ANN with multiple linear regression (MLR) model, the radial basis function (RBF), and the feed forward back propagation (FFBP). The models were tested on monthly Precipitation data at three monitoring stations affiliated with the Meteorological Department in Al-Safawi, Amman, and Al-Baqoura.

Momani and Naill (2009) dealt with forecasting precipitation at Queen Alia Airport in Amman using time series analysis through the autoregressive integrated moving average (ARIMA) model. The model was tested on monthly precipitation data from 1922 to 1999. In this study, the ARIMA(1, 0, 0) $(0,1,1)^{12}$ model was used. Khaled and Abandah (2023) dealt with forecasting weather variables (precipitation and temperature) in Jordan using machine learning techniques. Precipitation and temperature data were analyzed in the Jordanian governorates over the past 13 years.

Matouq et al. (2013) analyzed of meteorological data such as maximum and minimum temperature, and precipitation in Jordan during the period 1979-2009 using the artificial neural network model (ANN). Arabeyyat (2018) discusses the prediction of some weather conditions in the arid regions of Jordan using the Adaptive Neuro-Fuzzy Inference System (ANFIS). Yearly time series data were used for the period 1985-2015.

Sharadqah et al. (2021) studied the prediction of precipitation in central Jordan using the Nonlinear Autoregressive Artificial Neural Networks (NAR-ANN) model using the Levenberg-Marquardt algorithm. Precipitation data were obtained at five stations affiliated with the Ministry of Water and Irrigation in the period 1938-2018. Freiwan and Kadioglu (2008) analyzed various weather variables such as relative humidity, precipitation, and temperatures in Jordan using the Kriging statistical model. Data on various weather variables were tested during the period (1971-2000) in 16 locations.

Alhusban and Makhamreh (2013) analyzed the general trends of temperature and frost in the eastern desert in Jordan using linear regression, t-tests, and moving averages. Temperature and frost data were tested during the period 1980 - 2010, which were obtained from stations affiliated with the Meteorological Department in the region.

This study extends the available literature in different ways. First, most of the above mentioned work has been done on data collected on monthly or yearly basis. However in this research we uses hourly detailed data. Second, most of the work focuses on the arid or semi-arid zones of Jordan and discussed precipitation only. In this research we will focus in the northern Governarate, Irbid, and we will study six weather variables: wind, 2 meter dew temperature , 2 meter temperature, skin temperature, surface pressure, and total precipitation. See Appendix A for more details on variables. This hourly data set increases the accuracy and information value of the results we can get from this valuable data as aggregating weather variables on monthly or yearly basis will distort the information available in the data.

The focus of this research is the city of Irbid which lies in the north of Jordan. Irbid belong to the mountainous (hilly) zone. The climate of this zone is rather mild in summer and cold in winter. The amount of rainfall ranges from 300-600 mm year, snowfall occurs over the mountains. Irbid was chosen because it is the most affected city of the immigration that happened during the past decade by Syrian, Lebanese, and Iraqis. This immigration caused a high increase in the demand of water, and hence water shortage became a terrible crises, as the main source of of water for Irbid is the precipitation. This work will be extended later to cover major cities and to cover all the meteorological zones of Jordan.

Recently, autoregressive integrated moving average (VARIMA) and recurrent neural networks (RNN) models have been used to analyze multivariate time series data. This research will consider both VARIMA and RNN to analyze the multivariate time series of the six weather conditions in Irbid because they are the most common and flexible models for such data. These two models can be used without any specific characteristics or assumptions on the data under study other than the stationary of the time series when applying the VARIMA model. The aim is to compare the performance of the classical model, VARIMA, with the modern one, RNN.

This paper discusses the following themes. In Section 2, we will introduce and examine the (VARIMA) model. Section 3, discusses the RNN model. In Section 4 we discussed the data preparation. In Section 5, we will present short-term predictions and long-term predictions for the different variables of the VARIMA and RNN models. The results are compared between the two models for each variable separately. Section 6 concludes the paper with discussion and future work.

2 Moving Average of Integrated Vector Autoregression model

Time series analysis is one of the branches of statistics that is concerned with understanding and analyzing the change in data over time. The ARIMA model is one of the statistical models used to analyze single time series (Öller, 1985), but in various scientific applications we deal with multiple variables and thus we need to analyze multivariate time series. In multivariate time series, we are interested in studying changes in temporal variables over time so that these variables are related to each other and influenced by each other (Rusyana et al., 2020). The VARIMA model appears as one of the important statistical models for analyzing and forecasting multivariate time series, and it is an extension of the ARIMA model (Khusna et al., 2017). The VARIMA model deals with stationary time series, so the concept of integration appears as one of the important components in the VARIMA model, which is removing the trend and seasonality to make the time series stationary (Dickey and Pantula, 1987).

The general equation for the VARIMA model is given by (Hariningrum et al., 2018):

$$\Phi_p(\boldsymbol{B})\nabla^d \boldsymbol{y}_t = \boldsymbol{\theta}_q(\boldsymbol{B})\boldsymbol{a}_t,$$

where $\Phi_P(\boldsymbol{B})$ is the autoregressive coefficient matrix, which reflects the effect of previous values on current values. The operator B is employed as a lag operator within the autoregressive terms. In contrast, $\nabla^d \boldsymbol{y}_t$ denotes the variable that has undergone integration to the degree of d, resulting in a time series after the application of appropriate integration operations. Concurrently, $\boldsymbol{\theta}_q(\boldsymbol{B})$ pertains to the matrix containing the coefficients of the moving average, characterizing the impact of past errors on the present value. a_t is independent, identically distributed (iid) random variables each with zero mean and variance.

The VARIMA model is represented as follows: VARIMA(p, d, q) where p, d, q are the model parameters that we want to estimate. Where p represents the order of the autoregression (AR), q is the order of the moving average (MA), and d is the order of the differences (Zhang, 2018). We always strive to choose the parameters that best fit our data to obtain the best predictions and solve the "NaN" problem that appears when the matrix is not solved. The parameters in this model were chosen through careful testing and experimenting with different values for these parameters to obtain the best predictions. Experimental results showed that p=2, d=1, q=0 were the most appropriate estimated values for our data. Based on the previous results, we used the VARIMA(2, 1, 0) model to analyze and predict our time series data.

The equation for a VARIMA(2, 1, 0) model :

$$Y_t = c + \phi_1 \cdot Y_{t-1} + \phi_2 \cdot Y_{t-2} + a_t \tag{1}$$

We improved the performance of the model by using MTS::refVARMA(model), which is called to enhance the VARIMA model. The refVARMA function resolves (improves) the base VARIMA model. Settings can be modified or optimized in the model parameters based on the performance of the model in the training data. Configuration can help improve the performance of the model on experimental data or improve its predictions (Tsay, 2013).

3 Recurrent Neural Network model

The RNN model represents the "Recurrent Neural Network" which is a type of deep learning technique used in data based analysis such as time series. RNN can be used to estimate time series and predict future values (Sak et al., 2014b).

The mathematical equation for a simple RNN model, (Gao and Glowacka, 2016)

$$h_t = \mathrm{g}(w_{hh} * h_{t-1} + w_{hx} * x_t + b_h)$$

where h_t represents the hidden state at time t, and g represents the activation function.w_{hh} is the weight that links the memory that contains private information to the current and previous data (hidden state) at times $t-1$, t. h_{t-1} is the memory that includes current and previous data information at the previous time t-1. x_t is the input value at time t. w_{hx} is the weight that connects the memory that contains the previous and current data with the entered value x_t. b_h is the bias in the memory that contains information about the previous and current data and knowing the effect of the entered values on the memory.

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) used in deep learning. It was developed to handle time series that are long-term in nature, making it suitable for predicting time series such as weather data. The main goal of developing the LSTM is to solve the problem of missing gradients that we encounter in the traditional RNN.The unique characteristic of LSTM is its ability to independently process data sequences by storing and recalling long and short-term information This feature provides good skills in data sequences with long-term relationships across data points various, Sak et al. (2014a).Two layers of LSTM were used in the recurrent neural network.

In the process of building a model, we divide the time-series data into a series of time windows. The length of this window, called the sequence length, determines the amount of forecast time. Input and output data are generated based on appropriate time windows. There are three components of the model. The first layer is the LSTM layer, which is used to extract features from time-series data. The number of LSTM units is set to 50, and we will need an output sequence to use in the second layer. The second layer is another LSTM layer, which is used to process the objects removed from the first layer. Here again we use 50 LSTM units. The last layer is the Dense layer, which is used to make predictions. The number of units in this position corresponds to the number of changes in the time series data.

During the model training process, the model weights are optimized to improve its ability to make good forecast at the new data using the "Adam" optimization algorithm and the (mean squared error) loss function.The process begins with data preparation, where the time series data are divided into successive windows by sequence length, and the input and output data are fine-tuned.

Subsequently, several epochs are generated, during which the loss is estimated by a loss function between the forecast and actual results. The "adam" algorithm is used to update the model weights and standard deviations based on this loss. Throughout the training process, the model learns specific time series references, increasing its predictive power. The model is periodically evaluated to evaluate its performance and monitor training progress. After a fixed number of times have elapsed, the trained model can be used to predict new events.

4 Data Preparation

The data considered here consist of hourly observations of the six weather conditions from January 1^{st} to August 1^{st}, 2023. This data are obtained from the European Center for Medium-Range Weather Forecasts (ECMWF) through so-called ERA5-Land. ERA5-Land provides detailed, hourly data of weather variables for almost any site on earth from 1950 to the present, allowing researchers to understand climate and environmental conditions over time. The ERA5-Land data source is based on atmospheric observations and observational data from many sources around the world (Muñoz-Sabater et al., 2021)

Before starting to use the VARIMA model for time series data analysis, we need to check whether or not our data are stationary. The Kwiatkowski-Phillips-Schmidt-Shin(KPSS) test stands out as one of the main tests used for this purpose. The test aims to check whether the time series is stationary around a fixed level or not. When we say that the time series is stationary around a fixed level, we mean that it does not follow a continuous descending fluctuation, or that its fluctuations are finite and stable with respect to a fixed value as opposed to the time series is not stable enough to track significant changes and move to different values with time (Kočenda and Černỳ, 2015).

If the time series is non- Stationary, a solution uses a Integrated difference of the possible steps to make it more stationary. Integrated difference is an important concept in time series analysis, Integrated difference is used to stabilize the time series by applying differentiation to the data If we are talking about Integrated difference is differences in successive values in time series (Yang and Shahabi, 2005). One other hand, the RNN model can handle both stationary and non-stationary time series.

The null hypothesis to be tested in KPSS test is that the time series are stationary against the alternative it is not. Using KPSS test at significant level 0.05, the time series for six variable show non-stationary with p-value=0.01. After applying the first-order differentiating, the p-value of KPSS test for the six variable time series are 0.1 which is not significant at α=0.05. Thus, the data are stationary and we can use VARTMA model.

On other hand, for the RNN model we have entered non-stationary time series. But, the data are standardized using the Z-score normalization. This helps standardize data metrics and make them spread around zero with one standard deviation, facilitating analysis and processing (Hasanah et al., 2020).

When developing a time series prediction models, it is essential to divide the data into two main parts: training data and test data. In the context of time series, training data represents a pre-existing period that is used to educate the models about patterns and behaviors, while testing data are used to evaluate the models performance and test its ability to predict future values. This portion of the data corresponds to a period that the models has not been trained on, and it is used to assess accuracy and overall models performance. After dividing the data into training and testing sets, we input the training set into the models to obtain predictions, which are then compared with the testing set.

5 Model performance comparison

In this section, we will use the Normalized Root Mean Squared Prediction Error (Normalized RMSPE) metric to compare the prediction performance of the two models over 7 days a low value of the metric close to zero indicates good performance of the model. Normalized RMSPE is a form of correction for RMSPE measurements in which the RMSPE value is divided by the average of the actual values. This helps to improve error measurement for variables with different averages (Chai and Draxler, 2014). Where

$$RMSPE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_i - \hat{x}_i)^2}, \tag{2}$$

where m is the number of observation to be predicted, x_i is a actual values (Test Values), and $\hat{x}_i$ is the predicted values. This metric allows you to accurately compare predictive power between variables, regardless of their actual average (Li et al., 2016).

Figures (1) to (4) show the short-term and the long-term forecasts along with the actual values of the variables for both models. Short term representing one day (24 observations) while long term representing 7 days (168 observations).

Based on Figure (1) and Figure (2), it is evident that the VARIMA model has exhibited a good efficiency in predicting the surface pressure variable. However, it appears that this model was not effective in forecasting the precipitation variable accurately. Precipitation is considered one of the sensitive variables in this study. The study relied on hourly data collected over a period ranging from January to August. This time frame encompasses both winter and summer seasons. Consequently, the precipitation variable exhibits nonzero values during the winter season, whereas its value is zero during the summer. The likely reason for the VARIMA model's inability to comprehend the relationship in the precipitation variable is the significant variability in the data between the winter and summer seasons. We also observe that the VARIMA model showed relatively good performance in predicting wind and temperature variables. Lastly, we have noted that the VARIMA model alwyas underestimated the six variables.

Based on Figure (3) and Figure (4), we observed that the RNN model demonstrated high efficiency in predicting wind variables and the 2m temperature, as well as Skin temperature. Additionally, it showed relatively promising results in predicting 2m dewpoint temperature and surface pressure variables. However, it is evident from the graph that the model struggles to fully comprehend the precipitation variable, which we think is due to precipitation variable sensitivity, as previously mentioned. However, its performance in predicting the precipitation is better than VARIMA.

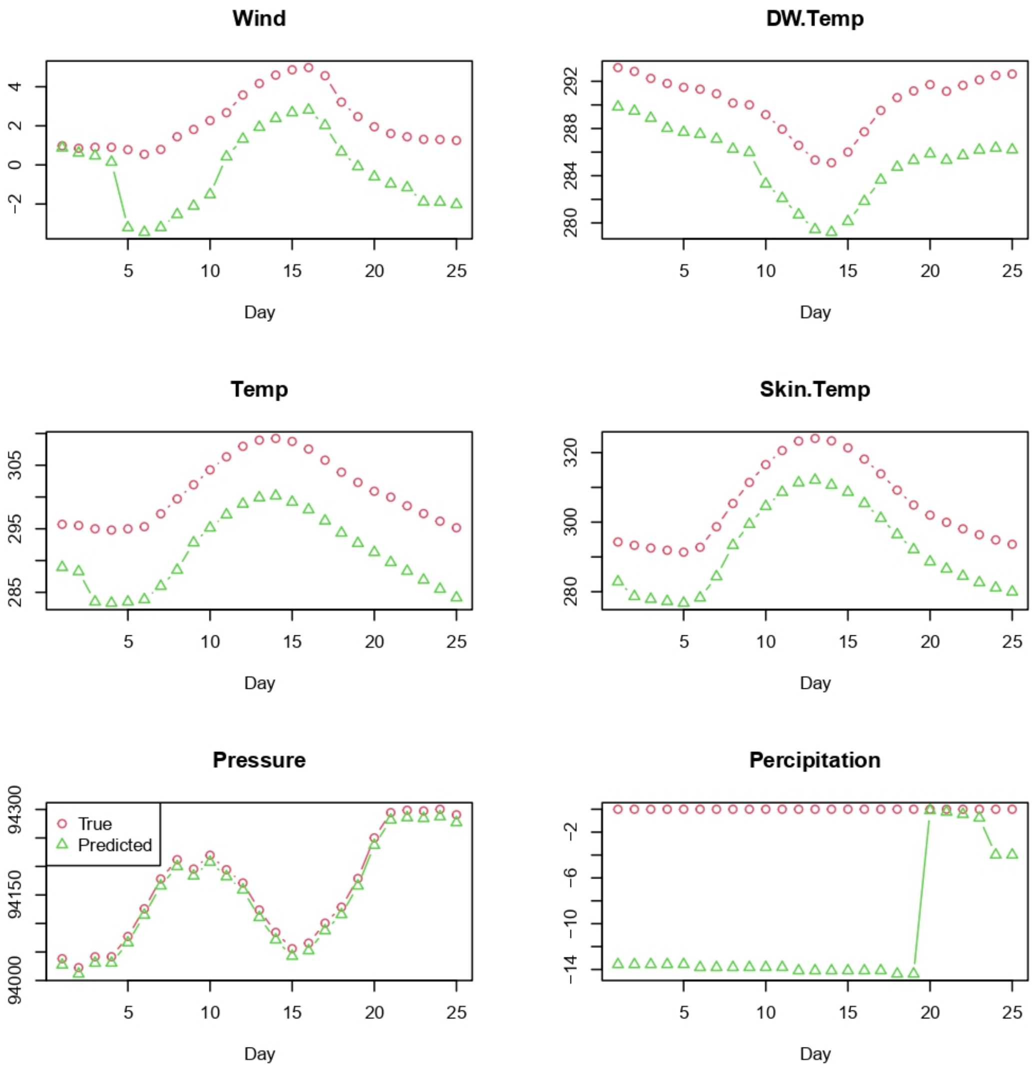

Figure 1: 24-hour prediction in VARIMA

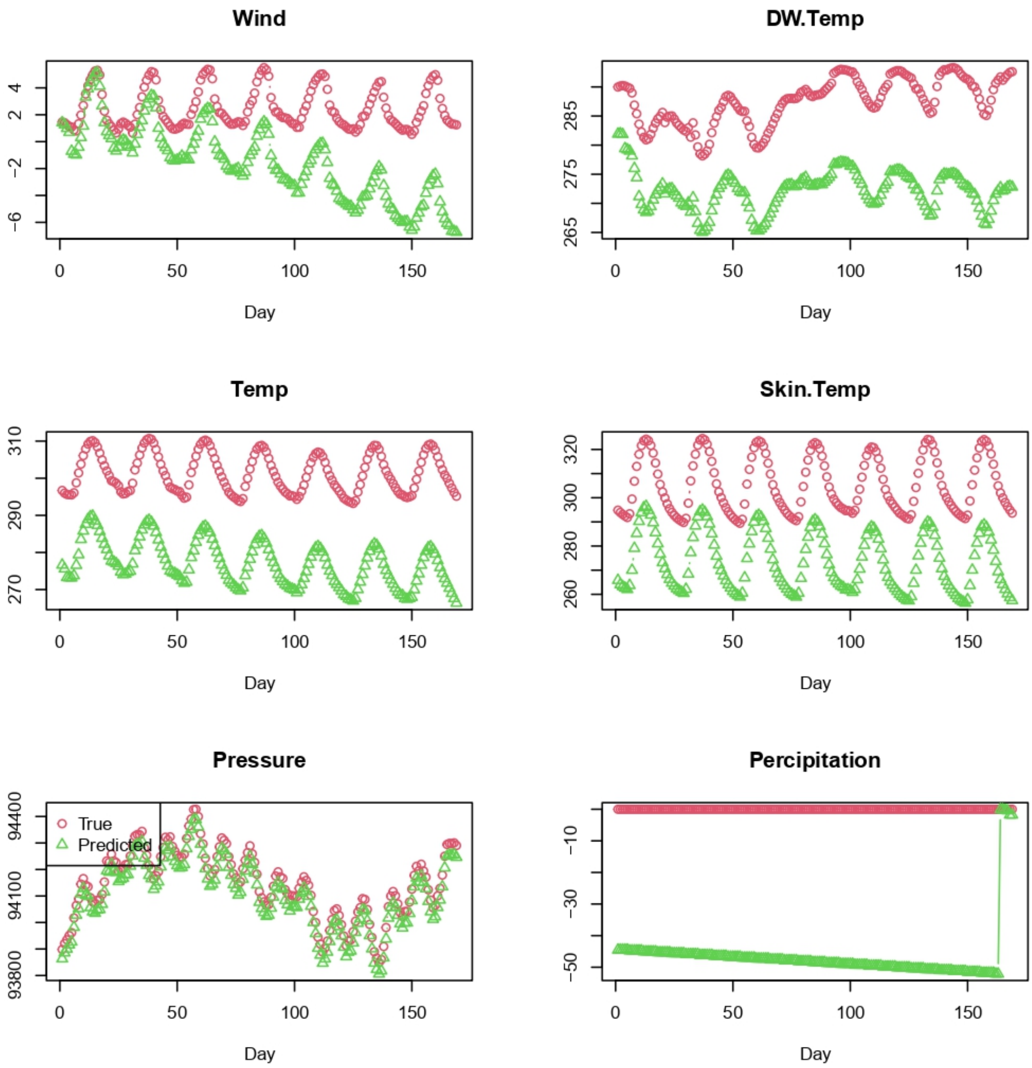

Figure 2: 168-hour prediction in VARIMA

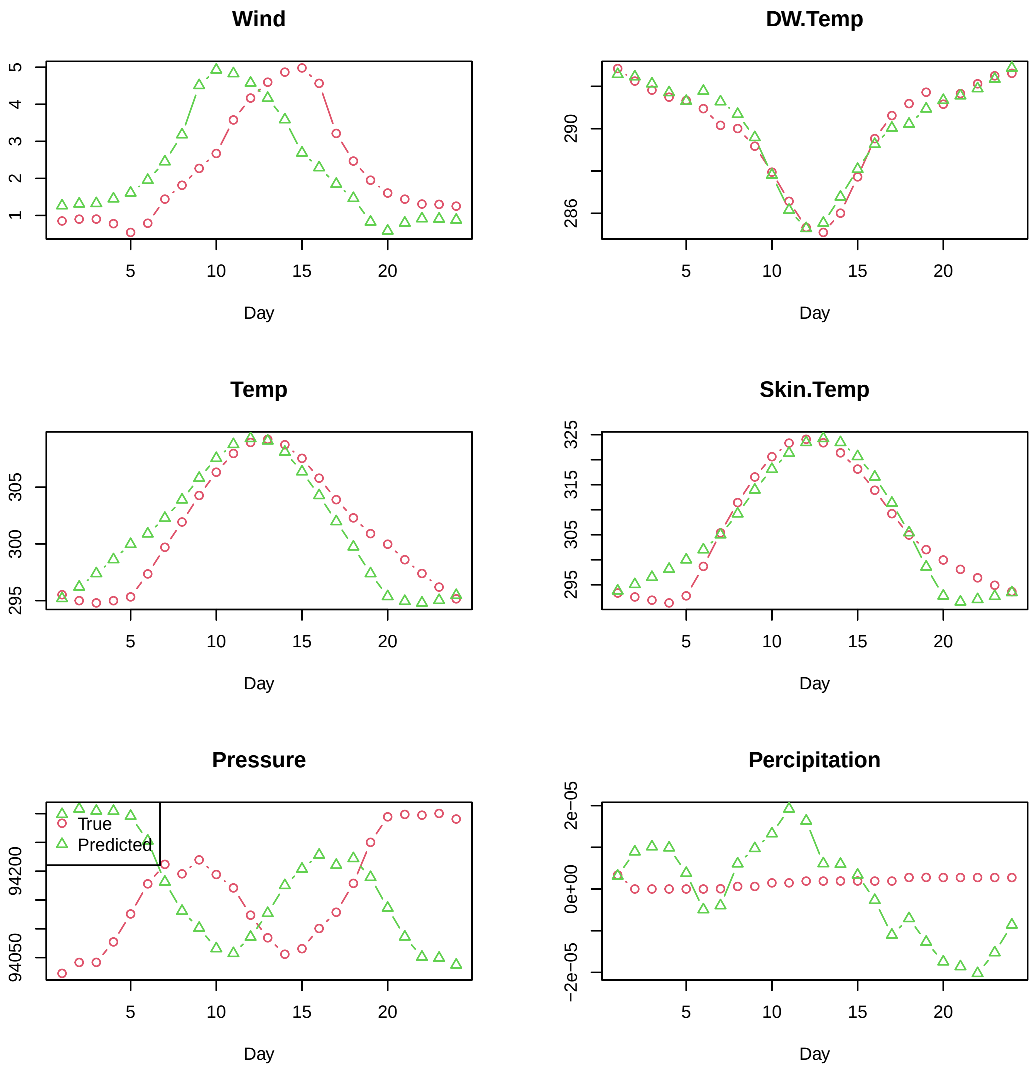

Figure 3: 24-hour prediction in RNN

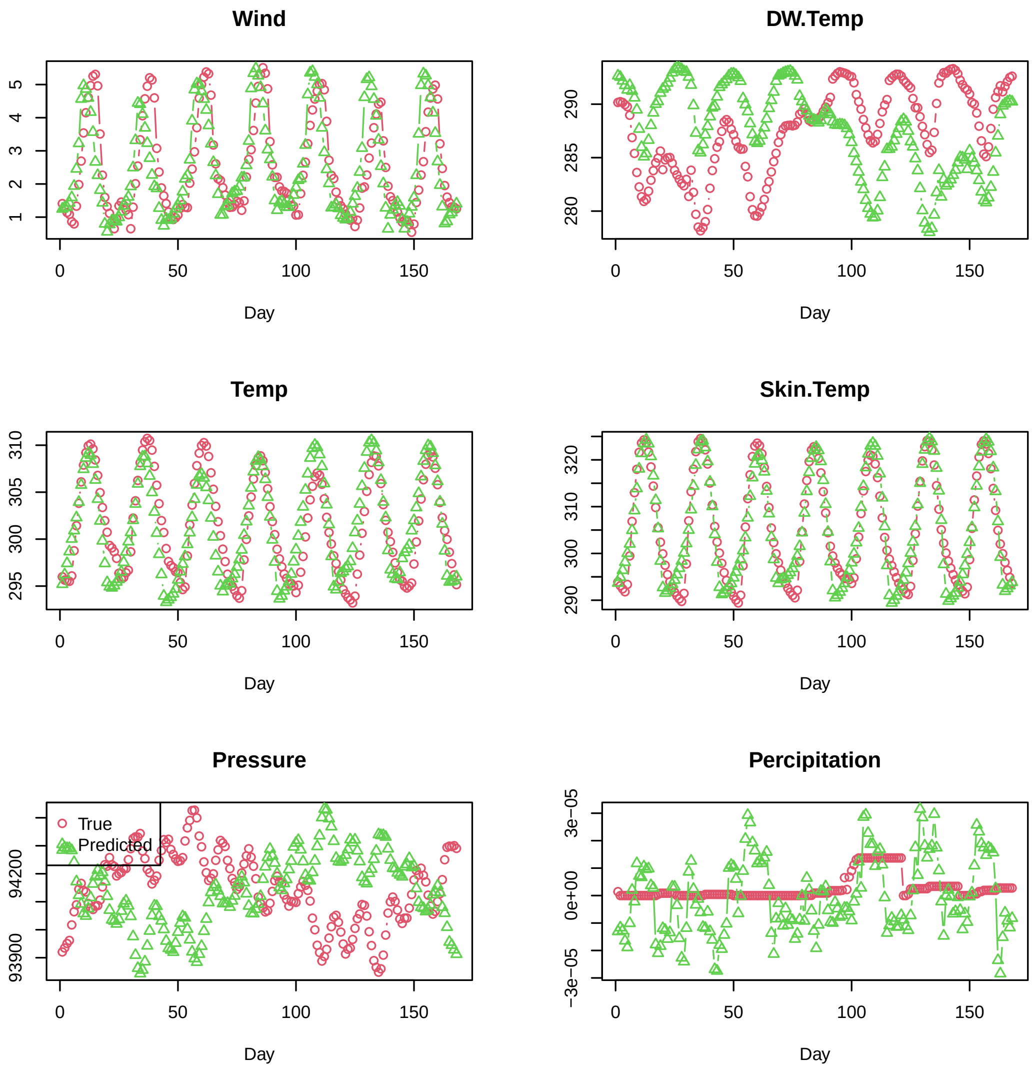

Figure 4: 168-hour prediction in RNN

The following are six tables that show the comparisons results between the two models for each variable separately over a 7-day period using the Normalized RMSPE metric to determine the superior one. Based on these results we observe that the RNN model outperforms the VARIMA model in predicting the wind variable, 2m dewpoint temperature, 2m temperature, skin temperature, total precipitation. See Table(1) to Table(4), and Table(6). On the other hand, the VARIMA model outperform the RNN in predicting surface pressure, see (5)

Table 1: Normalized RMSPE scale for Wind Variable

Day	VARIMA	RNN
24-hour	1.2613	0.5453
48-hour	2.2993	0.6019
72-hour	0.6556	0.5050
96-hour	2.6845	0.5058
120-hour	3.6343	0.4801
144-hour	2.7169	0.4596
168-hour	1.8620	0.4453

Table 2: Normalized RMSPE scale for 2m dewpoint temperature Variable

Day	VARIMA	RNN
24-hour	0.0180	0.0017
48-hour	0.0287	0.0039
72-hour	0.0233	0.0038
96-hour	0.0373	0.0061
120-hour	0.0414	0.0148
144-hour	0.0521	0.0200
168-hour	0.0539	0.0212

Table 3: Normalized RMSPE scale for 2m temperature Variable

Day	VARIMA	RNN
24-hour	0.0330	0.0080
48-hour	0.0558	0.0101
72-hour	0.0337	0.0098
96-hour	0.0710	0.0084
120-hour	0.0824	0.0089
144-hour	0.0872	0.0095
168-hour	0.0813	0.0101

Table 4: Normalized RMSPE scale for Skin temperature Variable

Day	VARIMA	RNN
24-hour	0.0432	0.0117
48-hour	0.0770	0.0117
72-hour	0.0429	0.0111
96-hour	0.1002	0.0116
120-hour	0.1180	0.0121
144-hour	0.1167	0.01269
168-hour	0.1052	0.0127

Table 5: Normalized RMSPE scale for Surface pressure Variable

Day	VARIMA	RNN
24-hour	0.0001	0.0017
48-hour	0.0002	0.0024
72-hour	0.0001	0.0016
96-hour	0.0003	0.0012
120-hour	0.0003	0.0019
144-hour	0.0004	0.0024
168-hour	0.0004	0.0026

Table 6: Normalized RMSPE scale for Total precipitation Variable

Day	VARIMA	RNN
24-hour	07303446	7.5819
48-hour	09529512	9.9008
72-hour	03650807	3.0753
96-hour	08061839	3.3201
120-hour	10823901	5.0389
144-hour	14829810	4.4646
168-hour	18217042	4.4646

6 Conclusion

This research studied and compared the effectiveness of RNN and VARIMA models in predicting 6 weather conditions that are measured on hourly basis in the city of Irbid, Jordan, during the time period from January to August, 2023. The models were compared through the prediction power by calculating the normalized RMSPE. The results showed the superiority of the RNN model over the VARIMA model in predicting five out of the six weather variables studied in this research. This leads us to the possibility of using deep learning models such as the RNN model effectively in meteorological science. This research will be extended in the future in different ways. First, covariates will be added to the models to improve the prediction. Second, different sites and cities will studied to cover all metrological zones in Jordan. Finally, a third model, the Bayesian Gaussian process model, will be studied and compared with the discussed models.

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Appendix A

Definitions of Study Variables:

2 Meter Dew Point Temperature: This is the dew point temperature (in Kelvin) measured at 2 meters above the ground. It refers to a temperature that must be cooled before the air begins to freeze and become dewy or foggy and is used to calculate air humidity (Muñoz-Sabater et al., 2021).

Skin temperature: This refers to the surface earth temperature. It is used in studies of the effect of solar radiation and environmental factors on surface temperature measured in Kelvin (Jin and Dickinson, 2010).

10m u-Wind component: it shows the wind speed and direction 10 m above the ground in an east west direction, measured in "(m/s)" units (Hu et al., 2023).

10m v-Wind component (wind component horizontal 10m above in a north-south direction): represents the wind speed and direction horizontal 10m above the ground in a north-south direction, with "(m/s)" unit (Hu et al., 2023).

To calculate wind magnitude using wind components "10m u-component of wind" and "10m v-component of wind" each time using equation:

$Wind = SQRT((\textit{10m u-wind component})^2 + (\textit{10m v-wind component})^2)$ Calculating this equation for each time period yields the amount of wind at that point. These quantities can be used in forecasting to get a better estimate of the change in wind energy over time (Bell et al., 2021).

2 meter temperature: This is the temperature above 2 meters above the ground. It is used to define human temperature and its effect on the environment, measured in units of Kelvin (Muñoz-Sabater et al., 2021).

Surface Pressure: This is the atmospheric pressure exerted by wind on the surface of the earth. It is usually measured in pascals (Pa) (Muñoz-Sabater et al., 2021).

Total Precipitation: Represents the cumulative amount of water that reaches the Earth's surface from clouds, including all types of precipitation such as rain, snow, hail and is measured in meters (Muñoz-Sabater et al., 2021).