Air Temperature Forecasting

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The accurate forecast of air temperature plays an important role in water resources management, land–atmosphere interaction, and agriculture. However, it is difficult to accurately predict air temperature due to its non-linear and chaotic nature. Several deep learning techniques have been proposed over the last few decades to forecast air temperature.

Keywords: Air Temperature Forecasting

1. Introduction

Global warming has recently drawn scientists' attention since it is correlated with the rise in air temperature. Increasing air temperature leads to changes in climatic conditions, such as sea-level rise, growth of extreme events, and global warming, ultimately negatively impacting humans' lives [1]. Air temperature is the state variable of the atmosphere and affects atmospheric and land surface processes [2][3][4]. Forecasting air temperature is an important part of weather prediction because it is used to protect human lives and properties. People may suffer potential health problems when the air temperature is not in a suitable range [5][6]. Extreme changes in air temperature may cause damage to plants and animals. The accurate forecast of air temperature is essential due to its significant effect on various sectors, such as industry, energy, and agriculture [7][8]. Reliable air temperature predictions increase the accuracy of energy consumption [9]. Air temperature is also one of the key factors in predicting other meteorological variables, such as streamflow [10], evapotranspiration [11], and solar radiation [12]. Therefore, finding an appropriate approach for the prediction of air temperature is vital and may mitigate the consequences of global warming and climate change. Furthermore, the accurate prediction of air temperature plays an important role in establishing a plan for human activities, energy policy, and business development [13].

Recently, models based on artificial neural networks (ANNs) have attracted scientists' attention in various disciplines, such as meteorology, water resources, and hydrology, because of their capability in capturing nonlinear relationships between inputs and outputs. Various ANNs-based approaches performed successfully in many hydrologic problems, such as flood [14], rainfall [15], water quality [16], and air temperature [17] predictions. Inspired by the biological nervous systems, ANNs are powerful tools for modeling nonlinear relations between dependent and independent variables. Generalization is one of the capabilities of ANNs, allowing them to predict patterns that were not provided to them during training. As a result, ANN forecasting models are able to provide a more promising performance than physical and statistical approaches. They are also easily accessible in commonly used programming environments (e.g., Matlab, Python, etc.) as a toolbox.

Different types of ANNs (e.g., multi-layer perceptron (MLP), recurrent neural network (RNN), long short-term memory (LSTM), convolutional neural network (CNN), etc.) have been utilized to forecast air temperature [18]. Each type has its unique structure to learn the air temperature patterns and forecast them. However, accurate air temperature forecasting has remained a major challenge (especially when the forecast time horizon increases) for many decades due to the chaotic and complex nature of air temperature data.

This paper provides a review of neural network (NN) models for air temperature forecasting. We focused on the recent studies during the last 15 years. This review paper also identifies new research problems arising from the published literature. To the best of our knowledge, this is the first review paper on the application of neural network-based techniques in predicting air temperature. In total, 26 studies that used different kinds of neural networks, such as MLP, generalized feed forward neural network (GFFNN), modular neural network (MNN), RNN, and LSTM, to predict air temperature are discussed. The review of neural network methodologies and their performance will encourage researchers to utilize these techniques to forecast air temperature.

2. ANN Inputs

This work focuses on the widely used neural network approaches (e.g., MLP, RNN, and LSTM) in air temperature prediction. Different studies have used various input variables as they can significantly impact the performance of models. In a number of studies (e.g., Chattopadhyay et al. [19], Ustaoglu et al. [20]), air temperature was predicted based on the historical air temperature data by accounting for time lags (the so-called univariate model). Another common approach is to use other relevant climatic variables (e.g., rainfall, air humidity, wind speed, air pressure, etc.) as inputs to forecast air temperature (the so-called multivariate model) [21][22]. Therefore, the ANN models can be categorized into two groupings: the first group uses only the historical air temperature measurements as inputs, and the second group employs air temperature and other relevant hydrologic variables.

3. Artificial Neural Networks (ANNs)

ANNs are a class of artificial intelligence, which work by imitating the biological structure of the human brain. In this section, three commonly used types of ANNs (i.e., MLP, RNN, and LSTM) are described. For a detailed description of radial basis function (RBF), modular neural network (MNN), ward-style ANN, convolutional recurrent neural network (CRNN), convolutional long short-term memory (ConvLSTM), generalized regression neural network (GRNN), and convolution neural network (CNN), the readers are referred to Ustaoglu et al. [20], Chattopadhyay et al. [19], Smith et al. [22], Zhang et al. [23], Kreuzer et al. [24], Kreuzer et al. [24], and Lee et al. [25], respectively.

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