Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 04, April-2023

A Study of Artificial Intelligence Methods for Forecasting Natural Resources

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***Abstract*:- Big Data's intrinsic size, speed, and complexity are too much for conventional forecasting methods to manage which is caused by the scale and lack of organization in large data sets. Traditional methods are therefore rarely selected for dealing with Big Data. They also lack models that can forecast big data. An example is the abundance of earthquake data, but the absence of a trustworthy model that can reliably forecast earthquakes. TBig data dimensions are primarily characterized by three concepts: volume, velocity, and variety. As contrast to time series, static data has been the primary target of data mining approaches in big data. Although identifying the absence of theory to support big data is an additional worry, some current challenges are connected to hypotheses, testing, and models used for forecasting. One of the biggest issues is finding people with the abilities needed to handle the problem of predicting with big data and their availability.**

Wind energy, a clean and sustainable energy source, is produced by wind turbines. The movement of water via streams and other channels is known as streamflow or channel runoff, and it is a crucial part of the water cycle. In situations where there are no physical barriers preventing surface flow, runoff occurs when the amount of rain falls exceeds the soil's capacity for infiltration. The review article examines and analyzes the AI-based forecasting techniques used to forecast diverse natural resources such as wind, stream flow and rainfall runoff.

INTRODUCTION

Big Data is a brand-new phenomenon that has quickly emerged as one of the most contentious issues of the modern period and will continue to do so for the foreseeable future. It is necessary to use strong tools, such as data mining techniques, which may help simulate the intricate relationships present in big data. Furthermore, it is important to note that the recent financial crisis has increased the widespread importance of risk management in organizations. According to, businesses are now attempting to use risk management as a tool for maximizing their opportunities while minimizing the associated threats. Herein lies the potential since big data forecasting may boost organizational performance while facilitating improved risk management. Big Data and predictive analysis work hand in hand in the present day, as stated by, with businesses focusing on generating real-time projections utilizing the data that is becoming more and more readily available.

The use of big data to produce accurate weather forecasts is currently the subject of further research, and preliminary findings suggest that this trend will significantly improve weather forecasts. In reality, one of the primary uses of Big Data has been for weather forecasting, although the predictions are still unreliable after a week. The fashion industry utilizes big data to anticipate the future of fashion as seen in companies like EDITD, the aviation industry as well as the film industry where Netflix is using big data to make decisions prior to the beginning production of its own TV show.

One of the issues with big data forecasting of natural resources such as wind speed and oil is that the research on AI and big data in natural resource forecasting lacks a systematic literature review. Despite papers being written on these topics, the topic remains poorly understood by prospective researchers. For instance, it is currently unclear what kind of big data is employed in the wind speed market and how to use this new data. Contrarily, when big data is contrasted with conventional data, the former may include a vast quantity of information and a more complicated structure, resulting in distinct data characteristics, concentrating on different study concerns, and necessitating different analytic methodologies.

The next sections discuss several natural resources, including wind energy, stream flow, and rainfall-runoff, as well as the corresponding Artificial Intelligence-based forecasting techniques. The conclusion discusses the problems with the forecasting techniques and provides guidance on the future directions for study considering the problems with the present forecasting techniques.

WIND ENERGY

Wind energy is a clean and sustainable energy source that is produced by wind turbines. The wind power sector is expanding quickly, increasing installed capacity. The installed wind power capacity worldwide in 2020 was 93 GW, a considerable increase of 52.96% over the installed capacity in 2019. They just installed 86.9 GW of onshore wind power and 6.1 GW of offshore wind power, respectively. Once the wind speed changes by just 1 m/s for a wind farm with a big installed capacity, the electricity output varies wildly. The nonlinear link between wind speed and wind power generation is to blame for this variation. To ensure sustainable energy growth and to maximize the choice of wind farm sites, fast and accurate wind energy forecasting is essential. Additionally, wind speed is affected by many forces that are uncertain and complex such as wind direction and atmospheric pressure. Also, Wind power is a process of converting air kinetic energy to electrical energy and the air kinetic energy reaching the wind farm is affected in many ways contributing to the randomness and volatility of the wind power generation making wind power forecasting difficult.

There are primarily two categories of data: internal data, such as photographs or data created by the equipment, and external data, such as weather satellite data, related time series, environmental change data, etc. Big data pertaining to wind can offer sufficient information free from sample bias to assist researchers in creating new knowledge and reshaping their understanding of wind speed forecasts.

The development of wind energy prediction algorithms has received a lot of recent scientific attention. These techniques are divided into four groups: statistical, physical, intelligent, and hybrid approaches. The physical methods predicted wind energy using meteorological data, such as topographic features, atmospheric pressure, and ambient temperature; the intelligent methods use AI models to process and maximize the integration of external and internal big data to estimate future wind energy; and the hybrid methods combine the advantages of multiple prediction methods. In the realm of wind energy, it is important to note that intelligent approaches and AI-based hybrid methods may more effectively investigate the complex linkages in large data and are crucial for enhancing energy efficiency, lowering energy consumption, and real-time decision-making.

One of the issues with big data forecasting of wind speed is that the research on AI and big data in wind energy forecasting lacks a systematic literature review. Despite papers being written on the topic, the topic remains poorly understood by prospective researchers. For instance, it is currently unclear what kind of big data is employed in the wind speed market and how to use this new data. Contrarily, when big data is contrasted with conventional data, the former may include a vast quantity of information and a more complicated structure, resulting in distinct data characteristics, concentrating on different study concerns, and necessitating different analytic methodologies. The expansion of the wind energy industry and the provision of invaluable insights for future possibilities necessitate the urgent need for a thorough assessment of the research on AI and big data-based wind energy forecasting.

This essay examines the use of big data in studies on wind energy. The literature review discovered that among the four approaches mentioned above, the intelligent and hybrid AI-based methods are most often utilized in the field of data-driven wind energy forecasting.

Also, based on the predicted time horizon, wind energy forecasting may be broken down into four categories: extremely short-term, short-term, medium-term, and long-term. The four different time horizon types are dependent on the predicted time range, which might be anything from a few seconds to a lengthy duration of more than a day. The position of the application varies for each anticipated time period. In general, the reaction is faster when the prediction period is shorter and slower when the forecast period is longer. For instance, relatively short-term applications are employed in the control of turbines and the clearing of the energy market, whilst long-term projections are utilized in the planning of associated equipment maintenance.

Depending on the situation, the implications of long-term and short-term wind energy forecasts vary. Both short-term and long-term projections have benefits, which are mostly shown in anticipated outcomes and applications. More specifically, a shorter forecast time period can deliver more precise and thorough data but less time for the installation of wind power. Long-term information on potential wind energy is provided through extended forecast time frames, although accuracy is typically poor. Because of this, the application situation typically plays a role in choosing the right data granularity projection for actual applications.

How to compare the predicting findings with the actual values is extremely important once the forecasting results have been obtained. The use of the model depends on selecting an appropriate assessment metric. We categorize the assessment metrics into three groups based on the relevant scenarios: metrics for accuracy, volatility, and zero index evaluation. The most popular measures for measuring accuracy among them are accuracy evaluation metrics which consist of Mean square error, mean absolute error and mean bias error among others. The difference between expected and actual performance can be measured through volatility evaluation criteria. In order to prevent the prediction from including a lot of points very near to zero, which might introduce biases into the evaluation, the zero index evaluation measures were altered.

The majority of big data research being conducted focuses on investigating structured data, including wind speed. Due to their extreme volatility and non-stationarity, wind speed time series are difficult to model with a single model.

When it comes to forecasting techniques, the majority of the currently used techniques employ hybrid techniques that provide outstanding predicting performance from a single model. Hybrid approaches, however, call for a thorough comprehension of diverse decomposition and prediction techniques, which necessitates extensive fundamental study. Moreover, the interpretability of such methodologies is generally poor, making it challenging to uncover the underlying truth revealed by the data. Future studies on wind energy prediction could concentrate on investigating interpretable deep learning techniques.

In reality, the expansion of data and the development of AI help to boost the precision of wind energy forecasts. Yet, the complexity of wind speed and the discrepancy between the uncertainty of forecasting models and the uncertainty that applies to preprocessed models place restrictions on data processing techniques. Accurate wind speed forecasting may be successfully increased by the development and use of big data and AI-based wind energy forecasting models.

STREAM FLOW

The phenomena and characteristic pattern of stream-flow are not easily predictable. This is due to the fact that stream-flow is characterized by high complexity, non-stationarity, dynamism and non-linearity.

Planning and management of water resources greatly benefit from stream-flow modeling and forecasting. Similar to wind energy, there are two basic temporal divisions for stream-flow forecasting, fundamentally. First, short-term (real-time) forecasting, which is essential for the efficient functioning of flood and mitigation systems (e.g., hourly and daily). Secondly, long-term forecasting (e.g., weekly, monthly, and yearly), which is crucial for many applications, including reservoir operation and planning, hydropower production, sediment transport, irrigation management choices, and release timing.

Since 1970, stream-flow forecasting has used the traditional black box time series models such as auto regression (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with exogenous input (ARIMAX), linear regression (LR), and multiple linear regression (MLR). The non-stationarity and non-linearity of the hydrological application cannot be captured by standard linear models. Researchers have thus focused on creating models that may overcome the shortcomings of the traditional models.

The most often used artificial intelligence (AI) techniques in the hydrologic research field include ANN, SVM, Fuzzy set, EC, and Wavelet-Artificial Intelligence (W-AI) models.

Much research, particularly in the field of streamflow forecasting, have shown how well ANN models perform. ANN models have established themselves as one of the primary hydrological forecasting tools and have been enthusiastically embraced by water resource professionals due to their ability to overcome several challenges associated with conventional models, such as those associated with autoregressive integrated moving average models (ARIMA) and other linear and nonlinear models.

The use of ANNs for streamflow forecasting still faces certain challenges, though. Cleaner signals utilized as model inputs will increase the performance of the ANN model. Noise often found in streamflow series may impact the prediction quality. The significant correlation in the data in daily flow modeling tends to introduce lag predictions in ANN models. Some researchers have brought up the problem of lagging predictions in the ANN model. Non-stationary data commonly presents challenges for ANNs and other techniques. The use of techniques to pre-process input data has been emphasized as a practical solution to address these problems and enhance the performance of ANN models. Wavelet analysis is one such approach, and it has recently drawn a lot of interest. The original time series may be usefully divided into high- and low-frequency components using wavelet analysis, and wavelet-transformed data can help forecasting models by collecting important information at different resolution levels.

In recent years, there have been a substantial number of studies considering the use of hybrid wavelet and ANN models in the context of streamflow forecasting. Anctil and Tape assess the performance of multiple-layer artificial neurons and a neuro-wavelet hybrid system at two sites for 1-day ahead streamflow forecasting. created a hybrid model for predicting monthly rainfall and runoff in Italy. Adamowski created a brand-new approach to wavelet- and cross-wavelet-based flood forecasting. created a wavelet neural network model to predict the inflow of the Yangtze River's Three Gorges Dam. In order to anticipate monthly river flows in Turkey, Partal used a wavelet neural network structure and evaluated the effectiveness of WA approaches to traditional ANN methods.

In order to anticipate the daily flow of intermittent rivers, Kisi investigated the use of WA models. To enhance the estimation of daily flows, three data pre-processing methods—moving average, single spectrum analysis, and wavelet multi-resolution analysis—were combined with an ANN. For the purpose of forecasting flow in non-perennial rivers in semi-arid watersheds with lead periods of 1 and 3 days, Adamowski and Sun suggested an approach based on coupling discrete wavelet transforms and ANNs. In each of these investigations, the WA models were found to perform better than the other models (such as multiple linear regression and conventional ANNs that were investigated for hydrological forecasting applications).

Despite the growing number of inquiries into this matter, there are currently extremely few and regionally constrained studies that specifically evaluate the efficacy of WA models in forecasting daily streamflow for periods longer than three days. For this reason, it is thought that more study on the subject may help to broaden and supplement the findings and conclusions drawn from earlier studies. In this regard, the major goals of this study are to evaluate the effectiveness of WA models in the forecasting of daily streamflows for 1, 3, and 5 days in advance, and to compare the outcomes with models based on conventional ANNs.

The high-frequency components (details) retrieved from the wavelet analysis served as the primary input variable for the vast majority of applications employing WA models that have been reported to far. The use of solely low-frequency sub-series (approximations) as model input is unique to the current study.

The fact that hydroelectric systems supply 90% of the electricity used in Brazil served as the primary impetus for this research. Because of this, accurate streamflow forecasting is necessary for both the optimisation of short-term generation planning as well as for effective mid- and long-term generation planning. The National Electricity System Operator now forecasts streamflow using stochastic models, although their precision is restricted. In order to enhance the planning process and operation programming of the National Interlinked System, it is necessary to test, develop, and improve different forecasting approaches.

In this study, the accuracy of ANN models and wavelet-ANN hybrid models for forecasting daily streamflows over the next 1, 3, 5, and 7 days was compared. For every scenario examined, the WA models outperformed the ANN models in terms of outcomes. To guarantee that the model performed well for 1-day-ahead forecasting, knowledge of the high-frequency content of the signal was crucial.

The most practical input for WA hybrid models was found to be higher-order approximations with fewer high-frequency information for days to come. These models were also shown to be effective in eliminating the delays often seen in daily flow forecasts using ANN models.

The findings produced here, albeit being restricted to a particular application, show and quantify the advantages of using wavelet transforms in ANN-based daily streamflow forecasting. The success of this hybrid technique is encouraging for the growth of fresh studies on this subject. Investigations in the sense of assessing the impact of various mother-wavelet usage in the construction of WA models and the creation of techniques to choose ANN input approximations are thought to considerably enhance this approach.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 04, April-2023

RAINFALL-RUNOFF

An important distinction between rainfall and runoff is that the phrase base flow, or fair-weather runoff, refers to streamflow that is fully made up of groundwater and occurs where a stream channel contacts the water table. Groundwater that is discharged into a stream is also considered runoff. This research discusses the creation and use of Artificial Neural Networks (ANNs) for flow forecasting in two UK catchments that are prone to flooding using actual hydrometric data. It was feasible to build reliable models of 15-min flows with six-hour lead periods for the Rivers Amber and Mole using very short calibration data sets. The effectiveness of the ANN's performance was compared to that of traditional flood forecasting techniques. The outcomes for the River Amber validation predictions were of an equivalent caliber to the outcomes from the operating systems. An interesting alternative to traditional lumped or semi-distributed flood forecasting models is the ANN's capacity to deal with missing data and "learn" from the event now being predicted in real time.

This paper specifically researched two physical locations, namely river mole and river Amber at Kinnerley manor and the river Amber at Wingfield Park is an upland tributary of the Derbyshire Derwent.

The trained ANNs may be sensitive to the selection of the calibration season, as was noted above. Seasonal variations in catchment features will be less important for the ANN for the River Amber because it was trained and validated on winter data. The River Mole ANN, which was validated in the winter and early spring after being trained in the autumn and early winter, is expected to be less sensitive to rainfall than it would be if training had been done using data from the wetter winter period. Similar to this, it would also be essential to consider other catchment processes, such as urbanization, changes in land use, or patterns in seasonal abstraction/effluent returns, if the ANNs were to be employed operationally in the long run.

In order to address these problems, an ANN was calibrated using the current rainfall and discharge as inputs to anticipate flows 3, 6, 9,..., 21 and 24 h in the future. This allowed the sensitivity of the models to the training season and forecast lead time to be examined. The River Mole ANN was initially trained using rainfall-runoff data from winter and spring and then verified using data from autumn and winter. The data from the calibration and validation periods were then swapped out in a subsequent series of simulations. The RMSEs obtained by the ANNs trained utilizing several seasons with progressively longer prediction lead times are shown in Figure 11. The RMSE grew gradually as the anticipated lead time lengthened, as would be expected.

Yet it is clear that the performance of the ANN that was trained using autumn/winter rainfall-runoff data and verified against winter/spring flows was better than the ANN that was trained for winter/spring. As a result, the choice of the calibration and validation periods does have a discernible impact on the ANN's capacity for predicting. The ANN should ideally be calibrated and verified using data from a similar season; alternatively, other input variables (such as temperature or evaporation) could be included to reflect the major flood producing mechanisms or seasonally dependent antecedent circumstances.

In that different properties of the hydrograph are simulated to variable degrees of success, ANNs are similar to traditional hydrological models in this regard. An I?2 statistics or the RMSE would have accurately predicted peaks over low flows, however the optimisation criteria utilized here are impartial. In order to better train the flood magnitudes, times to peak, or low flows reported here, depending on whatever attribute is in question, an appropriate optimisation criterion should have been used. In a similar vein, it was shown that the choice of standardization method (sum of squares or range) has an impact on how well an ANN simulates peak as compared to low flows.

As a result, knowledge gained from rainfall-runoff modeling of the Rivers Amber and Mole suggests that accurate flood forecasting using ANNs necessitates (a) training the ANN against selected elements (i.e., individual flood hydrographs) within the total flow data set; (b) the use of sum of squares standardization of ANN output; and (c) an optimisation criterion such as the RMSE which is biased towards peak flow.

The RMSEs previously mentioned for the River Amber and Mole validation simulations are well within the parameters specified for the WMO (1992) simulated real-time flood forecasting intercomparison experiment. The eleven models in the WMO research produced RMSEs of 2.5-8.5 m3 s"1 for 6-h predictions for the similar 100 km2 Orgeval catchment in France. The findings of the current pilot research, when combined with the Severn-Trent FFS model comparisons, indicate that there is ample room for the creation of a fully functional ANN flood forecasting system.

An interesting alternative to traditional lumped or semi-distributed flood forecasting models is the ANN's capacity to handle missing data and to update predictions in real time.

However, more investigation is needed to find the ideal training duration for certain catchment and climatic situations, which may be determined by a second ANN in a real-time system. Also, rather than training ANNs on absolute runoff values, gains may be made by training them on the rate of change of flow from one time period to the next. Yet, this can cause networks to "snowball" inaccurate estimations into subsequent projections.

The ANN has the potential to turn into a "prisoner of its training data," as Minns & Hall (1996) noted. The specificity of the resulting model weights to the provided calibration data will depend on the number of hidden nodes and training epochs. According to French et al. (1992), increasing the number of training iterations without altering the ANN structure enhances performance on training data but may not always do so on independent data. Hence, a balance must be struck between building an ANN that accurately replicates the essential components of the flow series during the calibration phase and is sufficiently resilient in the face of novel data.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 04, April-2023

For operational reasons, the moving training period must also give enough data for model calibration and a suitable amount of time for antecedent behavior memory. In contrast, the training period should be brief enough, taking into account the hardware and software limitations imposed by real-time forecasting and model update.

The findings of the pilot research reported here have shown that ANN development in the areas of rainfall-runoff modeling and flood forecasting is possible. It has proven feasible to build reliable models of 15-min flows with 6-h lead periods for two flood-prone catchments using very short calibration data sets. Future studies should apply the methods to forecasting lead times and other catchments. A detailed examination is also required into the connection between the duration of the training period (or information content) and the hydrological realism of the ANN forecasts.

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ANALYSIS

This section consists of important points regarding the similarities and the differences of the AI based forecasting methods used in the three natural resources discussed.

As mentioned earlier, Wind energy and Stream flow have complexity and uncertainty in categorizing them. Similar to Wind energy, Stream flow forecasting uses a temporal division of short and long term.

Wavelets provide simultaneous temporal and frequency localisation. The use of rapid wavelet transform makes wavelets computationally very quick, which is their second major benefit. Both wind energy and stream flow forecasting have wavelet decomposition or wavelet transforms (Continuous and Discrete) as the methodology for forecasting.

A neural network can carry out operations that a linear programme cannot, and it can make judgments without needing to be programmed once again.

The parallel properties of the neural network allow it to continue operating even when one of its components falters. It is capable of being used in any application. Both Rainfall-Runoff and Stream flow use ANN models for forecasting.

CONCLUSION

Today's forecasting systems, for the most part, employ hybrid techniques, which produce remarkable prediction accuracy from a single model. Yet, hybrid techniques need a comprehensive comprehension of several decomposition and prediction strategies, necessitating a solid grasp of the basics. Moreover, the interpretability of these methodologies is often poor, making it challenging to uncover the true nature of the reality that the data are pointing to. Future studies on wind energy forecasting could examine interpretable deep learning techniques.

Indeed, the expansion of data and the development of AI help to increase the precision of wind energy predictions. The intricacy of wind speed and the distinction between the uncertainty associated with forecasting models and the uncertainty associated with preprocessed models, however, place limitations on data processing techniques. The development and use of big data and AI-based wind energy forecasting models may successfully improve the precision of wind speed forecasts.

When using ANNs to predict streamflow, challenges include a lack of cleaner signals, noise reduction, latency reduction, and the use of non-stationary data, where cleaner signals as model inputs could improve the ANN model's performance, among others. When streamflow series are modeled daily, noise, which is commonly present, may have an impact on prediction accuracy and the limitation of data correlations, which introduces lag forecasts in ANN models. Non-stationary data is typically difficult for ANNs and other methods to handle.

FUTURE DIRECTIONS

Yet, as wind power plant technology develops, a rising amount of unstructured data, such as motor temperature data and satellite image data, is becoming accessible. These data have received little research, yet they offer a wide variety of potential uses for precise and timely wind speed forecasts. Due to the challenges posed by many data sources, research into forecasting utilizing multi-modal data is very crucial. Moreover, there is no assurance that one data preparation method is superior to another. An extensive amount lacks research in AI based forecasting methods for natural resources other than the ones mentioned such as in sustainability such as biomass fuels and energy, into geographic systems information in the use of renewable energy conservation. These topics would be effective areas for the future research of AI based methods for forecasting.

The results of the pilot study, which are presented here, have demonstrated that ANN development in the fields of flood forecasting and rainfall-runoff modeling is feasible. Using extremely small calibration data sets, it has been demonstrated that it is possible to create trustworthy models of 15-min flows with 6-h lead times for two flood-prone catchments. The methodology should be used in future research to anticipate lead times and other catchments.

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