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"Monitoring data quality using ANN-based Hybrid Exponentially Weighted Moving Average control charts"

R. Sasikumar and M.Sujatha

Department of Statistics, Manonmaniam Sundaranar University, Tirunelveli – 627012, Tamil Nadu, India

sasikumarmsu@gmail.com, sujathaa11091998@gmail.com

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ABSTRACT

Background: Quality is essential to determining public health and is required for the healthcare industry to sustain itself. An important component of public health is air quality. This research endeavour aims to monitor and enhance air quality by creating control charts with Artificial Neural Networks (ANN), a machine-learning technology based on the human brain. **Objective:** The objective of this paper is to evaluate the effectiveness of the Shewhart individual X bar chart, the ANN-based Hybrid Exponentially Weighted moving average (HEWMA), and the ANN-based Exponentially Weighted Moving Average (EWMA) for Delhi's air quality index data from January to December 2023. **Methods:** According to the most current studies, only very few studies used the hybrid EWMA charts with ANNs. One of the most effective ways to activate a new hybrid EWMA (HEWMA) control chart and monitor the process mean is to combine two EWMA control charts. ANN-based HEWMA system was one approach that demonstrated potential for air quality index variable detection. After that ANN-based EWMA control charts and Shewhart X bar control charts are developed. The Average Run Length (ARL) and number of outliers were determined for all three charts. **Findings:** When comparing ARL values, the number of outliers, and false alarms the results suggested that ANN-based hybrid exponentially weighted moving average provides better outcomes than alternative charts.ANN-based HEWMA control has a very good ability to detect out-of-control zones. This study discovered that the suggested HEWMA control chart is more effectively successful in detecting process mean points than the EWMA control chart. Aspects of ANN-based HEWMA can provide faster identification in comparison to other charts. **Novelty:** This work combines EWMA with ANN in an innovative method to develop the ANN-based HEWMA control chart. Applying this hybrid chart to standard charts improves the detection of process anomalies, decreases outliers and false alarms, and increases sensitivity and accuracy. It significantly increases the use of SPC charts because to its faster and more reliable monitoring capabilities, particularly in the healthcare sector.

INTRODUCTION

Quality control minimizes process uncertainty, directly affecting public health therefore, it is essential to expand in the healthcare sector. Although the healthcare industry has made progress in satisfying public needs and providing high-quality services, there are still large gaps in the instruments available for efficient process monitoring [1]. Many researchers emphasize the necessity of more inventive and trustworthy quality control techniques, especially in environmental health monitoring. Though still helpful, traditional SPC charts frequently lack the sensitivity and precision needed for contemporary healthcare applications. By combining ANN with EWMA control charts; this study seeks to overcome these drawbacks by producing a hybrid ANN-based HEWMA chart. By reducing outliers and false alarms, improving the detection of process anomalies, and offering a more reliable tool for monitoring air quality and other important health determinants, this innovative methodology closes the gaps in the available quality control techniques.

1.1 Control charts:

Statistical control charts, developed by Dr. Walter Shewhart in 1930, are a widely used tool for improving public healthcare and servicing processes. They aim to reduce variability and identify out-of-control signals, keeping processes stable. Control charts has three decision lines: central line (CL), lower control limit (LCL), and upper control limit (UCL). Xbar charts are particularly useful for single observations of material lots or batches. Zhang *et al.* [2] proposed EWMA, which improves the sensitivity of the chart. So that, EWMA control chart was compared to the CUSUM and basic EWMA charts. At last by modifying [3] two EWMA statistics known as HEWMA, the authors were able to evaluate the newly developed control chart's capabilities using both simulated and actual industry data. In order to observe the effectiveness of the EWMA control chart and HEWMA charts, [4] used the EWMA technique together with two additional pieces of data to produce the exponential type mean estimator. The HEWMA [5] charts are able to protect the run length characteristics and be able to identify when various process variability cause delays. Specifically, it has been monitor that for the number of shift sizes below zero indicated, the HEWMA chart outperforms the EWMA chart and remains dominant even in the event that there may be a shift delay in the process.

1.2 Artificial neural network (ANN):

The ANN model has been increasing in popularity recently as an effective substitute for traditional process control methods. They also examined how well the ANN performed with different numbers of nodes in hidden layers. Recent studies [6] on hybrid EWMA and ANN charts were developed. Even though the data sets from various fields showed almost constant variability that could be lifted using ANN-based chart statistics, the authors proposed different strategies for the construction of ANN and EWMA charts. Data were collected and analyzed throughout numerous laboratories to find out the Phase I control limits for every chart, and then, the Phase II procedure was observed by comparing these types of control charts. Since the EWMA control chart proved to be the most successful method under both normal and abnormal conditions, it was concluded that it was the ideal replacement for trend monitoring at all mid-check points. A new hybrid EWMA [7] [8] (HEWMA) control charts known as ANN- based HEWMA, for evaluating the air quality is described. It was created by merging two EWMA control charts for efficiently monitoring the process mean with the ANN scheme.

1.3 Limitations:

It has been noted that the assumptions underlying these traditional control charts are broken in contemporary healthcare processes; as a result, the traditional control charts are less responsive to variations in the process and the effectiveness of the control chart outputs is affected. ANN [9] theory does not assume data independence; it may be used to identify changes in process parameters. In order to examine the variability of the process mean they developed an ANN scheme. ANN may not have the same transparency and interpretability as conventional SPC charts because they are black-box models.

The aim of this study is to create a better ANN plan by expanding on the two-time smoothing weighted parameters. Conventional SPC charts have limits in terms of lowering outliers and false alarms, and they are unable to identify minute changes in sensitive processes. In addition, there appears to be a deficiency in the integration of advanced machine learning methods with SPC charts in order to improve their efficacy. According to this recent research, an important amount of data indicates inadequate use of ANN-based control charts; yet very few of them employ hybrid EWMA charts together with ANN. The field of understanding and developing new control chart forms that integrated with ANN is huge; even if real-world data rarely used inresearch,using this particular kind of chart.This field has a lot of opportunities. A few studies focus just on one type of chart, but this work provides a comprehensive understanding by comparing ANN-based charts with traditional charts based on real-world data. This study compares the effectiveness of an ANN-based EWMA and ANN-based HEWMA with the traditional Shewhart individual X chartfor air quality index data of Delhi (Jan-Dec 2023). Section 2 provides a methodology of the Shewhart X bar control charts, hybrid EWMA control charts, EWMA control charts and research methodology. Section 3 contains the outcomes and implementation of the research. Section4 discusses the conclusion of the research.

2. Methodology:

2.1 Shewhart Individual X Chart:

Individual measurements are frequently used to determine the sample size for process monitoring [10]. The Shewhart Individual X control chart is helpful in these circumstances. When samples are collected one at a time and there is no logical way to arrange the data, we utilize the Shewhart Individual X control chart. The following are the 3σ control limits for each individual control chart.

$$UCL=+3\sigma$$
$$LCL=-3\sigma$$

2.2 Exponentially Moving Average (EWMA) Control Chart:

Control charts of the memory kind, such as the EWMA created by Roberts[11] and the cumulative sum (CUSUM) introduced by Page, take into account both past and present data. These charts are meant to show changes in the process that range from small to reasonable. The in-control (IC) mean and the standard deviation of r_0 are assumed for the following observations. They are all independent and identically distributed. Next, the following is an example of the EWMA charting statistic:

$$z_i = \lambda X_i + (1-\lambda)z_{i-1}$$

where k is the smoothing parameter, with a range of 0 to 1 and X_i is the current observation.

2.3 Hybrid Exponential Weighted Moving Average:

Using a combination of two statistics, known as HEWMA [12], the efficiency of control can be increased. The HEWMA control chart outperformed the traditional memory-type control chart in terms of spotting changes in process parameters. Assume that each of the random variables X_1, X_2... X_3 has an identical and independent distribution. From this, we may use the formula provided to describe a pattern HE_1, HE_2...HE_t.

$$E_t = \lambda_2 X_i + (1-\lambda_2)E_{t-1}$$
$$HE_t = (1-\lambda_2)HE_{t-1} + \lambda_1 E_t$$

where the constants are k1 and k2. A further EWMA statistic, E_t, was suggested by the HE_t.

2.4 ANN Control Charts (ANNCC):

A neural network is a system of genetic neurons in the nervous system that communicates and processes information. The learning process of the human brain is simulated by an ANN. An arithmetical model that seeks to replicate the structural characteristics of a biological brain network is known as an artificial neural network (ANN) [13]. Three different sorts of layers make up ANNs in general: input, output, and hidden layers. While the output layers transmit signals out of the system under investigation, the input layers receive inputs from sources outside of it. The system's inputs and outputs, or hidden layer inputs and outputs, are essential for the network to comprehend the interdependencies in the model. In an ANN, the problem's information represented as weights of links. Training, also known as learning, it is the process of determining ANN weights. An input and identified output set of data used to train the ANNs. At the commencement of training, the initial weight value assigned randomly or based on experience. The learning processes change the weights so that, for a particular input, there is little variation between the neural network's output and the actual output. The activation function works as a summing function using the ANN model to turn its input components into output and also process the value of this input. Different activation functions are being used, including constant, exponential, Gauss Bell, Tanh sigmoid, logistic sigmoid, linear, and Morlet. Later, this study determined which ANN model was best based on the computations that ANN model needed to perform (training and validation). The available dataset contains both training and validation datasets.The MSE is used as a criterion to determine the ideal ANN model after the necessary computations for the model have been completed (the model is going to perform more effectively if the MSE is least). The study chose the best ANN model according to MSE (the model brings out more effectively when MSE is smaller). The least MSE indicates the optimal ANN model. After selecting the best function of activation for ANN model, this study create a HEWMA [14] control chart to examine the process mean. The process terminates when this difference goes below a predetermined threshold, and the network is regularly shown multiple examples of learning operations.

At this stage, the ANN considered as trained. The greater amount of input data an ANN [15] uses during training, the more successfully it may perform. How many input, output, and hidden layer nodes are required depends on the problem under study. The network will lack sufficient independence to fully analyse the process if the hidden layer contains fewer nodes than necessary. If there are too many, the instruction could take a while, and in some circumstances, the network will over fit the data. The artificial neural network's efficiency verified after training on our data. After that, the ANN model should trained and used for the intended purpose if the results are not sufficient or satisfactory. Following adequate training of the network, the proper quartile values for the in-control ANN output utilized to obtain a UCL value, which utilized as a cut-off point to determine whether the procedure remains under control or out of control. The provided quartile indicates an out-of-control state when its value is above it and an under-control state when it is below it. An educated ANN applied to the data with a change in the scope of the process to monitor the performance.Figure 1 shows the flowchart.For this study, the secondary data were collected from the public sector Central Pollution Control Board (CPCB), which is the official portal of the Government of India. This study involves 350 observations of the Delhi Air Quality Index data from Jan-Dec 2023.

2.5. Average run length:

Each number of k multiplied by the likelihood of finding the shift on the k^{th} observation to determine the average run length, which is then summed up. The following also provides it:

ARL (Average Run Length) = 1/a. ARL is mostly used in SPC for monitoring a control chart's abilities. According to Montgomery (2009), the average number of points required to establish that something is out of control is what matters.The ARL for the specified process computed using 10,000 simulated replications.

$$\text{ARL}=\frac{\textit{Total points}}{\textit{Total number of out of control points}}$$

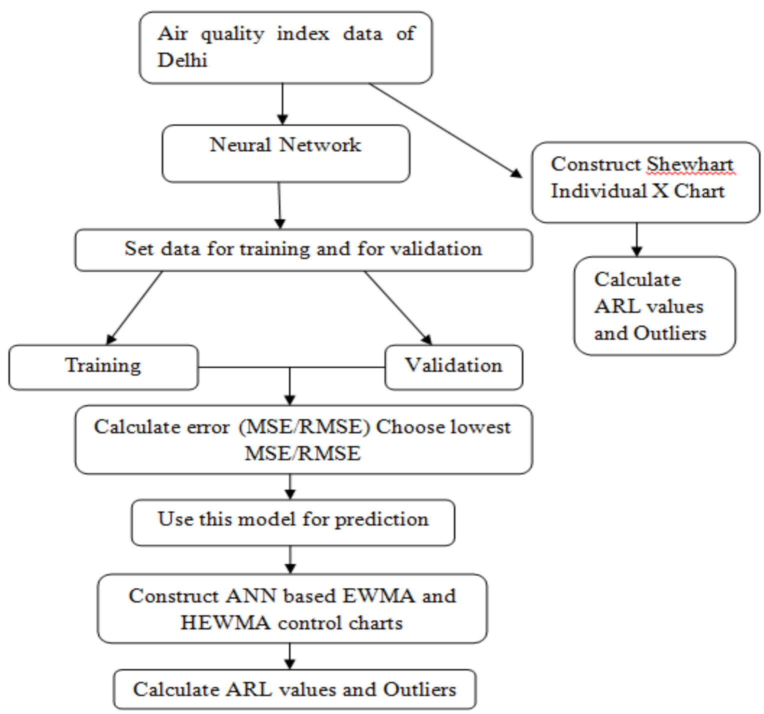

Figure1.Flow chart

3 Results and Discussion:

This study examines the efficiency of traditional control charts and ANN-based control charts by fitting air quality index data from Delhi. The secondary data were collected from Central Pollution Control Board (CPCB), which is the official portal of the Government of India. To efficiently monitor air quality data, this paper intends to create control charts based on artificial neural networks. Network topology and development parameters have been used to explain the Artificial Neural Network (ANN), a machine learning technology that replicates the structure of the human brain. ANN is a unique model for merging variables and data-based supervised learning classifiers, specifically because of the noisy and nonlinear character of air quality data. In order to monitor the process mean more effectively, a new HEWMA control chart is presented by combining two EWMA control charts. Prior research, S. Azmat *et al.*, [20] has focused mostly on ARL values and efficiency when evaluating control charts. This has led to shortcomings when managing noisy and nonlinear air quality data. This proposed ANN-based HEWMA control chart, on the other hand, outperforms the results of earlier studies, particularly when it comes to controlling measurement errors and fitting air quality parameters better. Table 1 describes the summary of the dataset's summary statistics. A network's infrastructure generated by the amount of nodes, hidden layers, and epochs. Once the weight function that best fit the data, identified and each viable design evaluated and tested. The optimal ANN configuration selection criteria were determined to be the MSE and RMSE values. We used cross-validation and MSE to obtain the optimal number of epochs (iterations). The RMSE was also recalculated for each layer update and node count, and the various weight functions were confirmed. To evaluate the effectiveness of the ANN approach against the conventional individual X charts by using air quality index data in terms of ARL and number of outliers. Figure 2 demonstrates the construction of ANN model. The variables $PM_{2.5}$, PM10, NO_2, SO_2, and O_3 are input layers, next the summation function and activation are hidden layers and the output layers are AQI

Table 1.Summary Statistics:

	PM2.5	PM10	NO2	SO2	O3	AQI
count	351	351	351	351	351	351
mean	24.5	38.87	15.90	25.21	66.99	73.81
std	19.90	33.80	1.55	13.76	28.12	34.98
min	2.62	3.87	2.95	4.75	6.15	16.41
25%	10.81	19.31	7.39	14.22	44.60	43.5
50%	24.87	37.66	10.04	19.45	69.79	78.33
75%	32.93	49.08	17.27	35.16	90.83	96.72
max	249.34	478	110.78	66.25	121.83	267.95

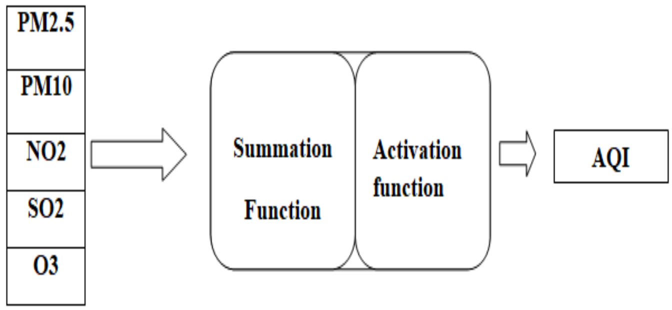

Figure 2. Inputs of the ANN model

Table 2.Training and Validation data for summary

Training Data Summary:

	PM2.5	PM10	NO2	SO2	O3	AQI
count	245	245	245	245	245	245
mean	23.04	36.81	15.45	25.74	67.13	71.95
std	14.44	23.80	15.5	13.45	27.92	32.66
min	2.62	3.87	2.95	4.75	7.35	16.41
max	108.62	157.76	107.94	64.95	121.83	178.94

Validation Data Summary:

	PM2.5	PM10	NO2	SO2	O3	AQI
count	106	106	106	106	106	106
mean	27.911	43.61	16.94	26.28	66.66	78.12
std	28.61	49.73	16.39	14.46	28.72	39.66
min	3.166	4.58	3.45	5.04	6.15	18.45
max	249	478.66	110.78	66.25	111.91	267.95

Table 3.Parameter settings

Parameter	Values
Trained data percentage	70%
Optimum Epoch	10,000
Test data percentage	30%
Number of hidden layers	2
Total number of nodes	64
Mathematical function	Tanh sigmoid

Table 2 describes summary statistics of comprised 70% training and 30% validation data. The construction of ANN model parameter setting is shown in Table 3. For prediction the ANN model structure is 2W (64/64) and 1W (64/1) obtained. The optimal configuration with the lowest mean squared error is 93.61 and the root mean squared error is 9.67. The mean squared difference (MSE) between the actual and predicted values in a regression problem is a metric used to measure it. The average of the squared differences between the expected and actual values is computed to assess the precision of the model. The root mean square error, or RMSE, is the mean squared difference between the real and expected values. It offers a consistent measurement of the model's prediction error in the same units as the target variable. It is a measurement of the residuals' dispersion. Figure.3 shows the RMSE with number of epochs.

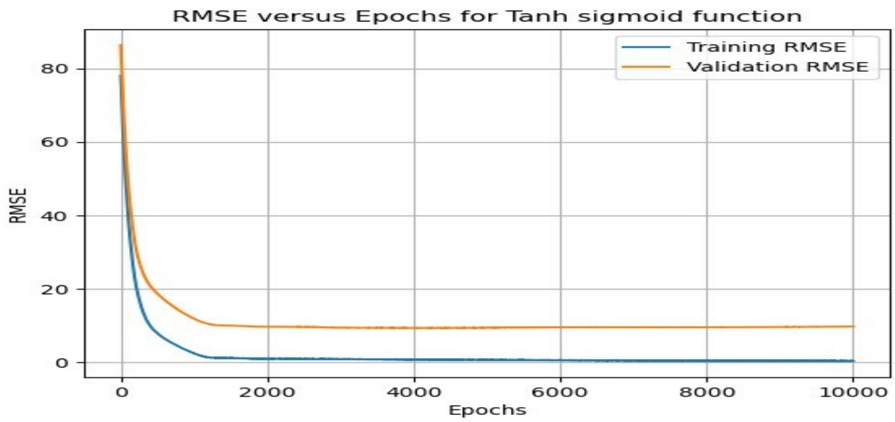

Figure 3. RMSE vs. epoch for Tanh Sigmoid function

After the network had received enough training, the proper measure was chosen as the threshold value. Then, the same trained ANN was applied to the data that was out of control with an increase in the desired mean size: 0.5, 1, 1.5, 2, 2.5, 3, 3.5, and 4. To illustrate the practical applications of the suggested control chart, this study offers an enhanced example. Use a typical normal distribution with mean 0 and variance 1 to standardize the secondary data in order to accomplish this. Assume that the process is under a control scenario. We now apply the suggested HEWMA and EWMA strategies to the produced observations. In ordered to compare the performance in terms of ARL with parameters k = 0.1, L = 2.824, k_1 = 0.1, k2= 0.1000001 and L = 2.3685 with shift 0.5 for the both proposed EWMA and HEWMA control charts. Another method Shewhart X bar control charts is constructed by traditional method. Table 4 shows the comparison of ARL values and outliers.

Table 4. Comparison of ARL and outliers of the Control charts

	ShewhartXbar control charts		ANN based EWMA control charts		ANN based HEWMA control charts	
Shifts	No of outliers	ARL	No of outliers	ARL	No of outliers	ARL
0.5	344	351	99	106	72	81
1	344	351	99	106	72	80
2	344	351	99	106	73	79
3	344	351	99	106	74	79
4	344	351	99	106	74	78

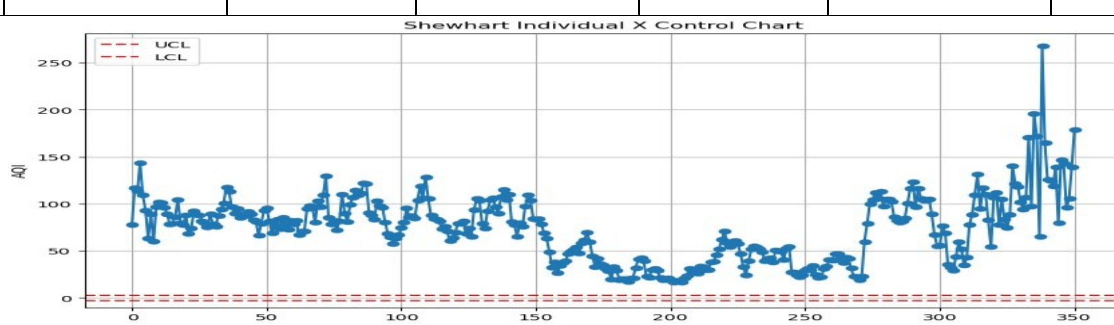

Figure 4.Shewhart X bar control charts

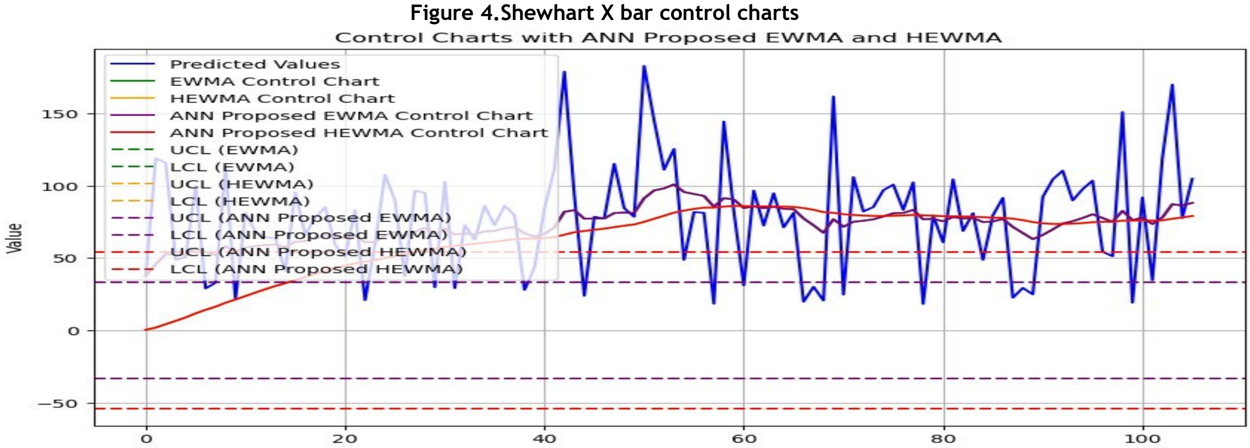

Figure 5. ANN based EWMA and HEWMA control charts

Table 5. False alarm Rate of control charts

False alarm rate	ANN based EWMA control charts	ANN based HEWMA control charts
	1	0.76

From Table 4, Shifts shows how much the process mean has shifted. EWMA stands for the ARL for each shift condition on the EWMA control chart. The ARL is the average number of samples required for the control chart to show an out-of-control condition. HEWMA stands for the ARL for every shift condition on the HEWMA control chart. Under each shift circumstance, the ARL values on the traditional control charts, EWMA control chart are often marginally higher than those on the HEWMA control chart. This shows that, in comparison to the HEWMA chart, Shewhart X bar control charts, EWMA chart might need an average of more samples to indicate an out-of-control condition. If it comes to detecting changes in the process mean, both control charts are helpful, but the HEWMA chart performs better in terms of ARL. From Table 4, Shewhart control charts have a higher ARL so need not to check False alarm Rate. Table 5 shows the False alarm rate of other two control charts, ANN-based EWMA control charts have 1% and ANN-based HEWMA control charts have 0.76 % rate. ANN -based HEWMA has lower false alarm rate compare to EWMA. Still, there is a need to study this, 0.76% false rate may be due to some festivals, functions cause peak in air quality data. Furthermore, it is crucial to recognize that the presence of null values or missing data in our dataset may have an impact on the reported false alarm rate of the proposed model. The model's performance may be impacted by null values, which could also be a factor in the high false alert rate. It could be necessary to do additional research and use preprocessing methods to resolve this problem and raise the precision of our forecasts. In contrast to previous study that just examined ARL values for only two types of charts, this study offers a comprehensive list of the efficiency of three different types of charts with different aspects. . As a result, this study consists on a thorough analysis of the ANN-based HEWMA control chart, including into consideration false alarm rates and RMSE values in along with ARL values. The ANN-based HEWMA control charts are better results than the Shewhart X bar control charts and ANN-based EWMA control charts by comparing RMSE values, ARL values, and false alarm rates. However, there are still issues that need to be investigated, including the false alarm rate which is especially high when null values are involved and the requirement for reliable data imputation techniques.

CONCLUSION

Air quality is difficult to predict because of the unpredictable nature of pollutants and particulates, which vary greatly in the environment, time, and volatility. An analysis of ANN for air quality measurement forecasting was reported in this paper. The basic ANN model consists of predicting $PM_{2.5}$, PM10, NO_2, SO_2, O_3 are input layers for AQI as output. This study's input optimization strategy that yielded predictions with the minimum mean square error was the feed-forward neural network. The outcome indicates the effectiveness and dependability of the suggested ANN-based HEWMA control chart method. Based on the initial results mentioned above, it appears that the HEWMA and ANN schemes were promising methods for measuring the air quality index. This study compares the effectiveness of the ANN-based HEWMA, ANN-based EWMA, and standard Shewhart individual X chart for air quality index data of Delhi (Jan -Dec 2023). The main objective of this study is to identify the most effective control charts to monitor air quality data. According to the preliminary results, ANN –based HEWMA control charts was promising procedure for the air quality data. It has a great ability to detect out-of-control points. There are very few researches that have looked into this approach in depth. Earlier research focused primarily on calculating average run length (ARL) values according to efficiency; this study combines RMSE, ARL, and false alarm rate metrics to evaluate control charts, providing a multi-faceted understanding of their performance. Although relatively new, the application of ANN-based HEWMA control charts offers potential for more precise data monitoring on air quality. The high false alarm rate in this study is one of the main limitations that can influence the accuracy of the control charts. Another major problem with the data is the presence of null values, which causes errors in the control chart results. In future studies, should concentrate on lowering the false alarm rate by utilizing sophisticated outlier identification techniques and carefully calibrated threshold levels. It is essential to handle null values, which calls for strong imputation techniques or other ways for efficient data handling. Further improvements in accuracy might come from fine-tuning the ANN-based HEWMA model and investigating hybrid models that combine new data sources or machine learning methods. As result by comparing, ARL values, number of outliers and false alarm of all three control charts, the proposed ANN-based HEWMA gives better results than other two charts. Also found that, the suggested HEWMA control chart is more selectively successful in detecting process mean points. When applied to standard charts, this hybrid chart increases sensitivity and accuracy, decreases outliers and false alarms, and improves process anomaly detection. It also makes SPC charts much more useful because it provides faster and more reliable monitoring.

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