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CSPRO: NOVEL COMPETITIVE SWARM POLITICAL RIDER OPTIMIZER BASED NARX FOR AIR POLLUTION PREDICTION

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Abstract:

Air pollution is caused due to surplus growth of dangerous substances in atmosphere such as gases emitted from vehicles and biochemical molecules. Continuous exposure to such gases and intake of such a substance by human causes a serious hazardous health issue like respiratory disorders, heart failure and so on. The air is heavily polluted in urban cities mainly in metropolitan cities, Particulate Matter (PM2.5) and PM10 which are minute particles which in size of micrometre can cause serious threat to human health. Therefore, it is mandatory to monitor the air quality on hour/daily basics for the living environment. In this Paper we have designed and developed a novel effective model for air quality prediction named as Competitive Swarm Political Rider Optimizer **(**CSPRO) based on Nonlinear Auto-Regressive Exogenous (NARX) model. Firstly, pre-processing of data is carried out by missing value imputation and then the technical indicators are extracted for prediction process. Air quality prediction is carried out using NARX model is trained by CSPRO. The proposed CSPRO based NARX has attained low Mean Absolute Prediction Error (MAPE) and minimum Mean Squared Error (MSE) of 9.22 and 0.275 respectively.

Keywords: Air quality prediction, Non-linear Auto-Regressive exogenous (NARX), Rider Optimization, Political Optimizer, Relative Strength Index.

1. Introduction

Air is one of the most essential and powerful natural agents for the survival of life on the planet [2]. All living organisms mainly plant, animal etc requires this natural resource for the basic survival. Hence, good quality of air for the survival of healthy life has become a necessary condition. In previous days, the fast growth industrialization and urbanization has increased the air pollutant concentration in the world [3]. According to world health organization 90 percent of world population is exposed to polluted air. Commonly seen air pollutants are CO2, SO2, PM2.5 and PM10 etc. Therefore, there is a need to monitor air quality on regular basis [8].

In concern with this government has been taken initiation by working with research institute to develop efficient controlling policies. Number of monitoring machine has been introduced covering most of metropolitan cities to collect and monitor air pollution data for further research. Based on the previous data the air pollution for next one hour can be predicted and accordingly preventive measures cane be taken to avoid exposure to pollutant air [3].

In today's life, the particulate matter PM have made a huge impact on human life. Whereas PM is a mixture of small particles including liquid droplets, which gets contracted in air. While breathing this substance get through respiratory system in human body and affect lungs and heart and create a serious health issue, if exposure to this substance to long time it may lead to severe lung diseases and early death [6]. The PM exits in two forms PM2.5 and PM10. The PM2.5 is of diameter minimum than 2.5μm, which is minute index to measure which has become a considerable interest for research in modern days [7]. As per research PM10 concentration is due to atmospheric pressure, surface radiation, wind speed and it is associated to sulphur dioxide, oxides of nitrogen [18] [1]. All meteorological factors react differently into different seasonal situation. Hence Air quality prediction can assist to take precaution in day-to-day life.

As air quality has become a major concern for whole world. Moreover, time series prediction model [22] and traditional machine learning models [23] are frequently used for air prediction. Frequently neuro-fuzzy network employed by genetic, particle swarm optimization and steepest descent back propagation [1] is used for forecasting air pollution which has led to better accuracy. Additionally forecasting approaches like artificial intelligence, decision tree and dep learning approaches [2] are used for predicting air quality. A deep learning approached namely transferred bi-directional LSTM Model [3] has smaller errors, especially for larger temporal resolution.

The main goal of the paper is to design and develop an efficient prediction model to predict the sulphur dioxide which is mainly named as Adaptive Political Rider Competitive Swarm Optimizer (A-PRCSO) based Non-linear autoregressive exogenous (NARX) model. The time series data is collected based on the location, which is fed for pre-processing stage, wherein missing value imputation is carried out by taking mean of the values. After pre-processing, the eminent technical indicators are identified by using different feature extraction techniques namely, triple exponential moving average (TEMA), Kelter channel (KC), Adaptive moving average (AMA), Rate of change (ROC), Simple Moving Average (SMA), Triangular moving average (TRIMA), Commodity Channel Index (CCI), Willam % R (WillR). Once the technical indicators are identified, SO2 prediction is carried out using NARX by using the extracted features and location information as input. The network classifier is trained using A-PRCSO, the new methodology will be designed by considering Political Optimization [10], Rider Optimization algorithm [11] and Competitive swarm Optimization [12].

The major contribution of this research is explicated as below:

- **Developed A-PRCSO-based NARX technique for SO2 prediction:** The NARX model is utilized for predicting SO2. In addition, NARX is trained by developed A-

PRCSO algorithm based on location. The developed PRCSO technique is devised by integrating PO, ROA and CSO algorithm. Here, the technical indicators and location information are extracted from pre-processed data for air quality detection.

The organization of this paper is arranged as follows, section 2 explicates the literature survey of existing air quality calculation techniques with its advantages and limitations. Section 3 specifies the air quality prediction model using developed A-PRCSO-based NARX approach. Section 4 displays the results and discussion of developed air quality prediction method and section 5 exhibits conclusion of paper.

2. Motivation

Prediction of air quality is one of the most significant processes for managing the air pollution in smart cities. Therefore, prediction model of air quality has various challenges due to different source emitting pollutant air, variation of pollutant concentration and high improbability. Hence the limitations and challenges faced by existing model is a stimulation to develop a novel model, termed as A-PRSCO-based NARX approach

2.1 Literature Survey

The literature survey of existing air quality prediction approaches with its advantages and disadvantages are briefed in this section. Xiangyu.Z *et.al.* [19] Devised long short-term air prediction model based on spatial-temporal mechanism. A spatial attention mechanism is used to take the influence of neighbouring sites on the prediction area. A temporal attention mechanism is used to identify time dependency of air quality. This paper uses Line graph embedding method to obtain a low dimensional vector representation for spatial features. This method evaluates on Beijing dataset. The experimental results show that this model shows the better accuracy. Jun Ma *et.al.* [3] introduced a deep learning-based method mainly transferred bi-directional LSTM model for forecasting air quality. The methodology includes the bi-directional LSTM model to check the long short-term dependences of PM2.5. It applies transferred learning technique to transfer the information learned from smaller to larger temporal solutions. This model as compared to other model has smaller errors for larger temporal resolutions. Zhang Luo *et.al* [7] implements Empirical mode decomposition along with Bi-LSTM neural network. PM2.5 time series data has been given as an input. This method improvised short term prediction mainly for sudden changes. The dataset was collected from Beijing hourly and daily for PM2.5. This model is more accurate as compared to another standard LSTM model. Sethi J *et.al* [8] has built a prediction model using supervised learning techniques for air quality prediction using AQI. Supervised learning has broadly classified into regression, classification and ensemble techniques. The observations are support vector machine from regression method, stacking ensemble from ensemble method and decision tree from classification method work efficiently and effectively than other technique. Pavani M *et.al*[9] develops a cost-effective model using wireless sensor network for monitoring air pollution. The data related to pollutants is collected on real time basis which includes the data of sulphur dioxide (SO2) and Ammonia/(NH3) which is acquired through Arduino based Core with pre-calibrated sensors off the self. The model is made of Arduino along with gas sensors and global system for mobile communication (GSM) and zig-be model. Air pollution is monitored using a system composed of wireless communication via ZigBee protocol. The above model proposed fine grained pollution data under different physical condition. Jin Z *et al.*[4] proposed hybrid deep learning predictor, where PM2.5 information decomposed into small components by empirical mode decomposition (EMD) at the first, a convolution neural network CNN is built based on frequency characteristic CNN classifies all components in fixed no of groups. A gated recurrent unit network is used to train each group and the result of GRU is fused to get the prediction. The accuracy of the present paper increased greatly.

3. Proposed Political Rider Competitive Swarm Optimizer approach for air quality and carbon monoxide prediction

Air pollution has become a serious issue especially for urbanization and industrialization; hence effective measures need to be taken to control air pollution for sustainable environment. This paper develops a systematic approach for SO2 prediction using proposed A-PRCSO based NARX and this model is mainly divided into three steps pre-processing, technical indicators extractions and prediction stage. Here pre-processing is done through missing value imputation and technical indicators are extracted by techniques like TEMA, KC, AMA, ROC, SMA, TRIMA, CCI, WillR. Once the technical indicators are extracted, the extracted features are given as input to proposed NARX and its network is trained using Adaptive Political Rider Competitive Swarm Optimizer. However, the devised model is composed of adaptive PO,CSO and ROA respectively. Figure 1 represents block diagram of developed A-PRCSO based NARX for SO2 prediction.

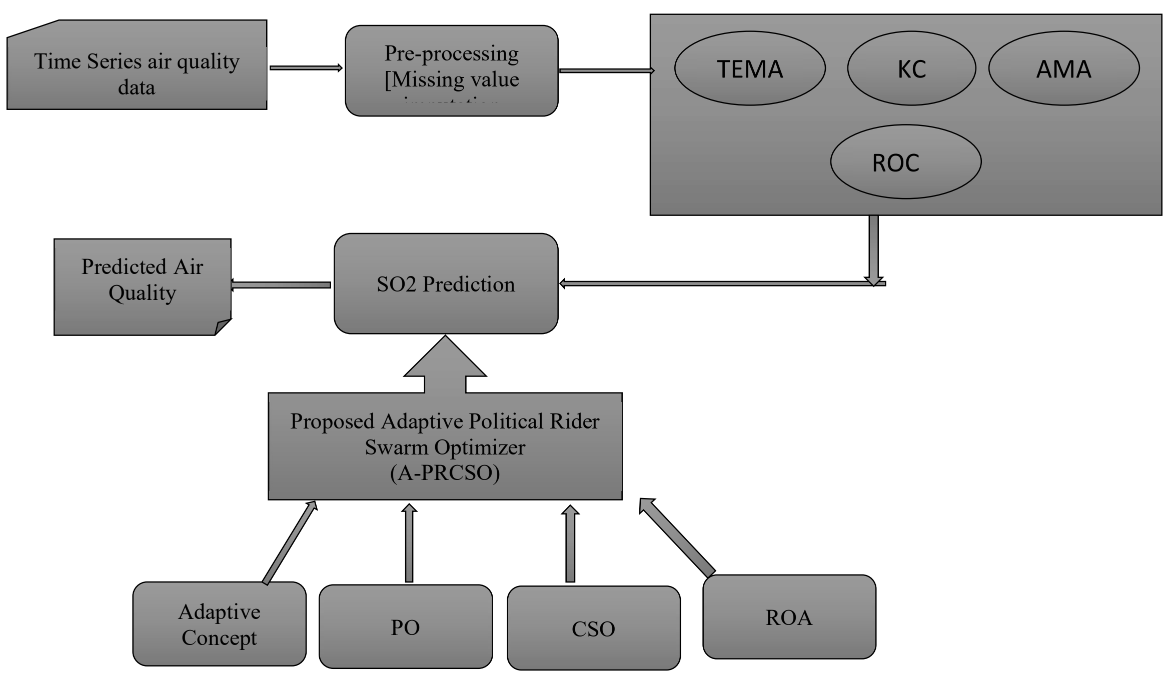

Figure1. Block diagram of developed A-PRCSO algorithm for predicting the air quality

3.1 Input data

The input given for the model is time series data collected from three cities from specific data set [21] with n no of samples which is illustrates as

I= {I1, I2…...In}

Here Ii represent i^{th} quality data in the dataset and It represents the total samples present in dataset

3.2 Pre-processing using Missing value imputation

The time series data taken will contain the redundant data, the redundant data needs to be removed and missing value imputation needs to be carried out for cleaning the data. The air quality data Ii is given as an input for pre-processing where redundant data is removed off by using missing value imputation by using mean or median mechanism. The output the pre-processing stage is represented as Oi.

3.3 Technical feature indicators extraction

The output Oi from pre-processing stage is taken and applied for technical feature indicator extraction which helps in increasing the accuracy of algorithm to predict air quality data. The Technical indicator extraction techniques used for technical indicators are explained in detailed below.

3.3.1 TEMA-Triple Exponential Moving Average

TEMA is a technical indicator which used multiple EMA and minimizes the lags. Which is calculated as follows

$$fa1 = (3 * \mathrm{ema1}) - (3 * \mathrm{ema2}) + \mathrm{ema3} \qquad (1)$$

The indicator is represented as $fa1$.

3.3.2 KC-Keltner Channel

Keltner channel is a volatile based technical indicator which includes three bands, upper band, middle band and lower band. The middle band is exponential moving average (EMA) and upper and lower band and above and below the EMA. The KC equation is as below

$$\mathrm{K} = \mathrm{EMA1} \qquad (2)$$

$$\mathrm{EUP} = \mathrm{EMA1} + 2 * \mathrm{ATR} \qquad (3)$$

$$\mathrm{ELW} = \mathrm{EMA1} - 2 * \mathrm{ATR} \qquad (4)$$

Where, ATR is average true range, K represents middle level, EUPrepresents upper band, ELWrepresents lower band and E1indicates EMA. The indicator is represented as$fa2$.

3.3.3 AMA-Adaptive moving average

AMA [13] is a technical indicator were in the scalable constant is replaced by fixed constant the smooth of EME out the air quality data.

$$fa3 = fa3(1) + \mathrm{b} * \left(\mathrm{C} - fa3(1)\right) \qquad (5)$$

where bis constant and C. The indicator is represented as $fa3$

3.3.4 ROC-Rate of Change

ROC is the technical indicator which measures the change in present air quality and previous air quality.

$$fa4 = \frac{Q(n)}{Q(n-1)} * 100 \tag{6}$$

The indicator is represented as $fa4$.

3.4 Air quality prediction using developed Competitive SwarmPolitical Rider Optimizer-based Non-linear auto-regressive exogenous model.

Once the effective technical indicators are extracted, then air quality prediction and sulphur dioxide prediction are done. The extracted technical indicatorsare usedfor predicting air quality prediction using NARX. In addition, the NARX[15] is trained by introduced optimization technique, namedCSPRO approach. The devisedCSPROmodel is newly devised by integrating Adaptive technique ROA, CSO, and PO.

3.4.1 Structure of Non -linear Auto-regressive exogenous model.

The NARX network is dynamic model mainly designed for input-output non-linear dynamic models. In this model the output is feedback to the input from the output neurons. NARX is used for time series prediction and it is belonging to class of non-linear models and it is formulated as

$$\mathrm{Q}(\mathrm{k}+1) = \mathrm{f}\,[\,\mathrm{Q}(\mathrm{k}) \ldots \ldots \mathrm{Q}(\mathrm{k}-\partial\mathrm{y}+1);\ \mathrm{Ii}\ (\mathrm{k}), \mathrm{Ii}\ (\mathrm{k}-\Theta-\partial\mathrm{Ii}+1)] \tag{12}$$

The above expression can be represented vector form.

$$\mathrm{Q}(\mathrm{k}+1) = \mathrm{f}\,[\mathrm{Q}(\mathrm{k});\ \mathrm{Ii}(\mathrm{k})] \tag{13}$$

Here, the vector Ii (k), Q(k) indicates input and output regressors. The non-linear function f(.) is unknown and this is an appropriate value. The output will be resulted into NARX network. The NARX model is trained into two modes. The first mode is where the result is fed back to input of fed-forward structure of NARX model. The second is known as series-parallel model where true output is used instead of estimated output, here the final structure is feed forward structure and back propagation technique is used to train it. At stage 1, series-parallel mode is generated for training and then it is converted to parallel mode for prediction purpose. The output from NARX is represented as X_i Figure 2 demonstrates the architecture of NARX.

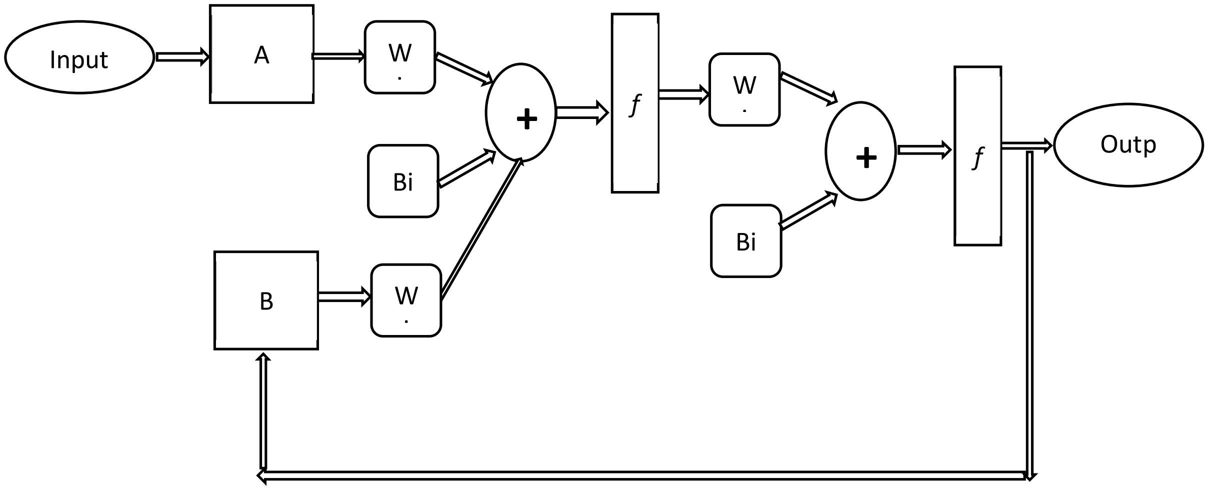

Figure 2. Architecture of NARX

Rider position status

Rider position status updates with the vector solution for a given problem and it is given as E=$[1 \times l]$, here l indicates the learning factor of NARX.

Fitness Parameter

The fitness factor is calculated to obtain the optimal solution it is defined as the change in difference between expected outputs(Ai)to estimated output (Ei)from NARX and is represented as

$$€ = \frac{1}{n}\sum_{i=1}^{m}[A_i - E_i]^2 \tag{14}$$

Where, n represents the total no of samples, the targeted result is notated as $A_i$and resultobtained from NARX is denoted asEi.

3.4.2 Adaptive PRCSO for training NARX

CSPRO is a model which is composed of concept of ROA, RO, and CSO which is mainly used to add the weights of NARX. Rider Optimization Algorithm employs group of competitive riders to achieve given target to become a winner. There are four different riders bypass, attacker, follower and over taker. The bypass rider tries to follow the bypass path to reach the target. The Follower rider follows the leading rider to reach the winning position. The over taker takes his own route to overtake the leading winner. At last, the attacker riders with the maximum speed to attack the leading rider. CSO is nature inspired algorithm, which is inspired through particle swarm optimization (PSO). The upgrade of particles is done without the inclusion of best location of each particle and global best location.CSO has proven better for exploitation and exploration stage. PO is inspired by multi-staged process of politics, wherein each party tries to maximize its seats parliament to form a government. By including the adaptive concept of ROA, PO and CSO we can increase the prediction accuracy of air quality. The steps of A-PRCSO algorithm are elaborated as follow:

Step 1: Initialization

Assume the rider is initialized into N-dimensional area into four groups mainly bypass, follower, over taker and attacker. The representation for same is:

$$X = \{X1, X2, X3 \ldots . Xm\} 1 \leq j \leq m (15)$$

Here, m denotes the total no of riders and Xjrepresents jthposition at time$t$. The number of riders in a group determines the number of riders.

$$m = br + fr + or + ar \qquad (16)$$

Here, br,fr,$or$and arrepresents number of bypasses, follower, over taker and attacker riders respectively. Hence the correlation between them is represented as:

$$br = fr = or = ar = \frac{m}{4} \qquad (17)$$

Once the rider's group is initialized then the factors like accelerator, steering, gear and brake are also initialized.

Step 2: Evaluation of fitness parameter

The objective is to determine the solution by computing the change in difference between expected outputs to actual output from NARX. Equation is stated in equation no (14).

Step 3: Evaluating the success rate

Once the riders and rider parameters are initialized the success rate of riders can be calculated based on the distance, and is given as

$$w_j = \frac{1}{\|Y_j - Tt\|} \qquad (18)$$

Here, $Y_j$is the location of the j^{th} rider and $Tt$is the location of target. To develop the success rate, the distance should be minimized and hence, the reciprocal of distance factor delivers the success rate of rider.

Step 4: Identifying leading rider

Calculating success rate will identify the leading rider who is very nearby to target location. The rider who is at minimum distance from target location and has high success rate is considered to be leading rider. The rider's position keeps on change based on time hence any rider can be at the leading position.

Step 5: Updating of rider's location

Each rider's location is updated to identify the winning rider of the race. The updating of rider's location is described as below:

(i) Updating position of bypass rider

Bypass rider follows the shortest path to reach the destination, without following the leading rider. The equation for bypass rider to update his location is as follows

$$Y_{t+1}^{Br}(i,h) = \partial \left[Y_t(\alpha, h) * \gamma(j) + Y_t(€, j) * \left[\left(1 - \gamma(j) \right) \right] \right] \qquad (19)$$

Here, $\partial$is random value and it value ranges between 0 and 1, αis the random value ranges between 1 and cand € is random values lies between [0,1].

(ii) Updating position of follower rider

Follower rider follows the leading rider to update his position with the target of winning. The equation of follower rider to update his position is as follows.

$$Y_{t+1}^{Fr}(i,h) = Y^{wr}(wr,h) + \left[Cos\left(G_{i,h}^{t}\right) * Y^{wr}(wr,h) * Dd_i^t \right] \qquad (20)$$

Here, h is the coordinate selector, leading rider position is Y^{wr} and wr is the representation of leading leader. However, $G_{i,h}^{t}$ is the steering angle of the i^{th} rider in the h^{th} coordinate and the distance to be covered by the i^{th} rider is specified as Dd_i^t

(iii) ***Updating position of over taker rider***

Over taker rider updates his position based on three main parameters mainly coordinate selector, relative success rate and direction indicator. Additionally, the change in leading riders' position and over taker riders' position is expressed suing coordinates. Later, the directional indicator of each rider in the race is calculated based on the success rate. The equation of over taker rider to updated his position is as follows

$$Y_{t+1}^{Or}(i,h) = Y_t(i,h) + [D_t(i) * Y^{wr}(wr,h)] \tag{21}$$

Here, $Y_t(i,h)$ indicates the position of the i^{th} rider in the h^{th} coordinate and $D_t(i)$ is the direction indicator of i^{th}.rider at time instant t. The formula for relative success rate is defined as:

The direction indicator is formulated depending upon the relative success rate as

$$D_t(i) = \left[\frac{2}{1-log(RSR_t(i))}\right] - 1 \tag{22}$$

Here, $RSR_t(i)$ implies the relative success rate of i^{th} rider at time period t.

By, combining ROA, PO and CSO the updated equation of overtaken is given as

$$Y_{t+1}^{Or}(i,h) = \left[1 - \left(\frac{N_2+\eta N_3-1}{N_2+\eta N_3}\right) * \frac{J_t^x(i)}{2v}\right]^{-1} * \left(\frac{N_2+\eta N_3-1}{N_2+\eta N_3}\right) * J_t^x(i) * \frac{(2v-1)}{2v} Y_t(i,h) - \left(\frac{N_2+\eta N_3-1}{N_2+\eta N_3}\right) * \frac{N_1 Y_t(i,h) + Y_t(z,h) + \eta N_3 \bar{N}_t}{1 - N_2 - \eta N_3}$$

$$\eta = 5 - \left(\frac{\frac{(Tt_{max} - Tt_{off})}{5}}{C}\right) * RSR_t(i) \tag{24}$$

Here, η is made as adaptive ROA, PO and CSO and $RSR_t(i)$ indicates relative success rate. The off time and maximum number of iterations is denoted as Tt_{off} and $Tt_{\max}$, respectively. The number of coordinates is indicated as C.

(iv) ***Updating position of attacker***

Attacker rider updates his position same as that of follower to reach the winner position. Rather than taking the selected values he updates values in all coordinates. The equation of over taker rider to update his position is as follows:

$$Y_{t+1}^{Ar}(i,h) = Y^{wr}(wr,h) + \left[Cos\left(G_{i,h}^{t}\right) * Y_t^{wr}(wr,i)\right] + D_j^t \quad (25)$$

Here, $Y^{wr}(wr,h)$ represent the location of leading position. The steering angle of i^{th}rider at h^{th}coordinator is represented $Cos\left(G_{i,h}^{t}\right)$ and distance travelled by i^{th} rider is represented as D_j^t.

Step 6: Confirming the solution feasibility

After updating the rider's position, the one having the optimal value is considered as optimal solution.

Step 7: Update riders' parameter

The rider parameter is updated to get the optimal solution**.** A counter as extra parameter is added to update. The steering angle and gear updated based on counter

Step 8: Termination

The steps are repeated tillTt_{off} is reached and the winner is identified.

The Pseudo code for CSPRO is

1. **Input:** Location of RidersX_t
2. **Output:** Winning Rider X^{wr}
3. **Begin**
4. Initialize the riders
5. Initialize rider parameters like steering angle G, gear Gr, brake Ba, accelerator Ac.
6. Calculate the fitness function Eq (14)
7. Calculate Relative Success rate RSR_t
8. while $Tt < Tt_{off}$
9. for i= 1to c
10. Update Bypass rider position Eq (19)
11. Update Follower rider position Eq (20)
12. Update Overtaker rider position Eq (21)
13. Update Attacker rider position Eq (25)
14. Check the feasibility
15. Updation of rider's parameter
16. **return**: winning rider
17. $t = t + 1$
18. end for
19. end while
20. Terminate

3.5 Result and Discussion

The Simulation discussion of proposed work of CSPRO based NARX model is carries on Delhi-city

3.5.1 Experimental setup

The proposed methodology is implemented in PYTHON tool using windows 10 OS, 4 GB RAM, and intel core-i5 processor

3.5.2 Dataset Description

The proposed model CSPRO is using air quality time- series data from Indian air quality data [5], which effectively predicts the air quality prediction. Moreover, dataset is comprised of air quality data and Air Quality Index (AQI) from different location of India on hourly basis and daily basis. The data contains in five different files such as city hour, station hour, station day, city day, and stations. Three cities are taken for predicting air quality data prediction.

3.5.3 Performance Measure

The Proposed CSPRO using NARX is measured using performance metrics like Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE).

(i) MSE
Mean Squared Eror is defined as the average squared difference between the actual values and the estimated values by NARX classifier and it is defined in Eq. (14).
(ii) MAPE
Mean Absolute Prediction Error is the mean of difference between real value and estimated value.

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}|P_i - A_i| \qquad (26)$$

Here, m signifies the total samples, P_i denotes the absolute value and the estimated result from NARX is expressed as A_i.

3.5.4 Comparative Analysis

The performance of proposed CSPRO is compared and analysed with different methods like, deep learning [20], Bidirectional LSTM [16], weighted fuzzy method [17],RCSO-based Rider Deep LSTM, and PRCSO-based DRNN.

(i) Analysis on city-1

Figure 3 illustrates the performance of CSPRO based NARX with respect to MSE on city-1. Considering training set of 90% the MSE of deep learning obtained value 0.375, Bidirectional LSTM obtained value 0.353, weighted fuzzy method vale of MSE is 0.272, RCSO-based Rider Deep LSTM is 0.173, PRCSO-based DRNN is 0.128. However, the proposed A-PRCSO gained MSE of value 0.119.

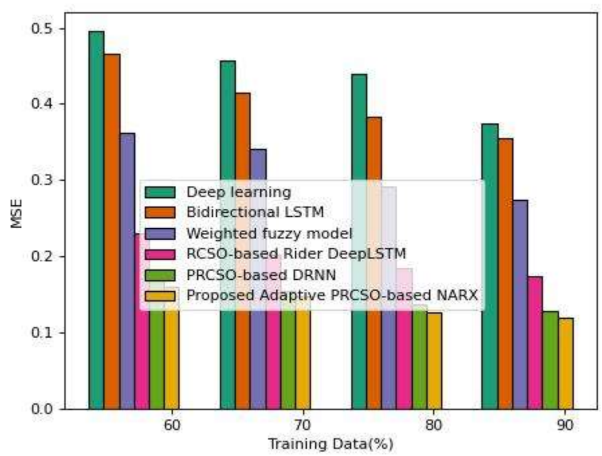

Figure 3: Analysis of MSE of city-1

Figure 4 illustrates the performance of CSPRO based NARX with respect to *city12*. By considering the training set as 90% the MAPE for proposed CSPRO is 3.806% as compared to following algorithm like deep learning, Bi-directional LSTM. Weighted fuzzy model, RCSO-based Rider Deep LSTM, PRCSO based DRNN is 44.759%,39.976%,36.742%, 8.279% and 3.995% respectively.

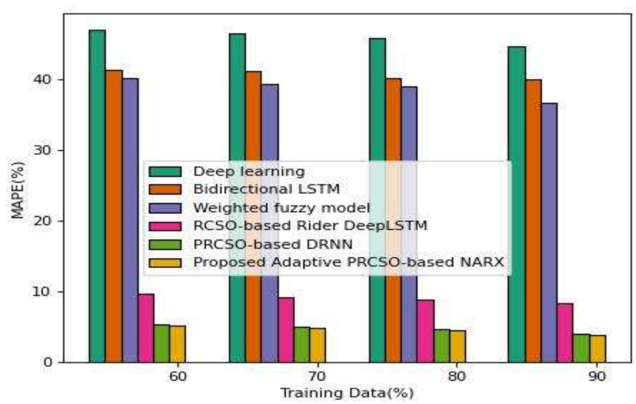

Figure 4: Analysis of MAPE of city-1

(ii) Analysis on city-2

Figure 5 illustrates the performance of CSPRO based NARX with respect to MSE on city-2. Considering training set of 90% the MSE of deep learning obtained value 0.439, Bidirectional LSTM obtained value 0.369, weighted fuzzy method vale of MSE is 0.308, RCSO-based Rider Deep LSTM is 0.218, PRCSO-based DRNN is 0.117. However, the proposed CSPRO gained MSE of value 0.068

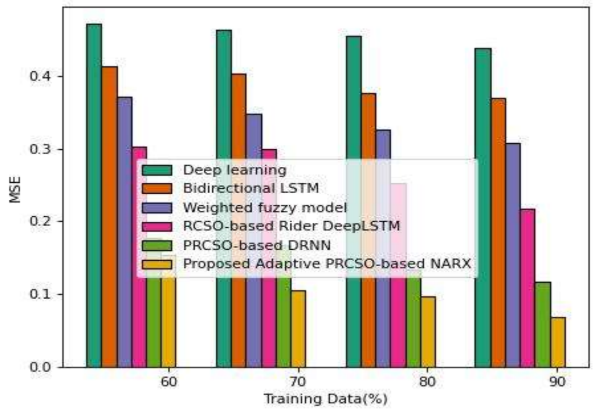

Figure 5: Analysis of MSE based on city-2

The following figure 6 depicts the performance of proposed work with respect to MAPE on city-2, considering training set of 90%, the MAPE of deep learning method, Bidirectional LSTM, weighted fuzzy method, RCSO-based Rider Deep LSTM, PRCSO-based DRNN obtained are 42.325%, 35.401%, 32.430%, 8.277%, and 3.449%, respectively and the MAPE obtained for proposed work is 3.108%.

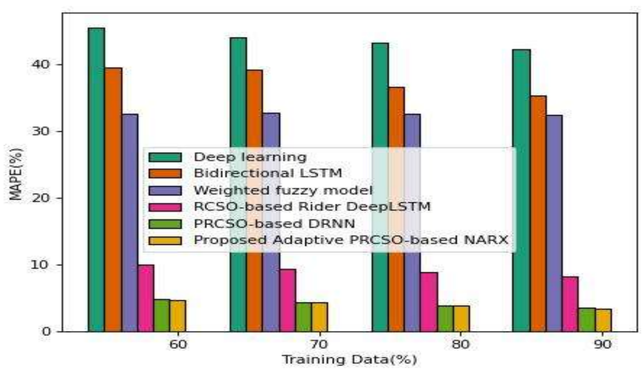

Figure 6: Analysis of MAPE based on city-2

(iii) ***Analysis on city-3***

Figure 7depicts the evaluation of modelled technique in terms of MSE. For training data=90%, MSE attained by Adaptive PRCSO-based NARX is 0.109 while the conventional models yielded the MSE as 0.440 for deep learning, 0.375 for Bidirectional LSTM, 0.304 for weighted fuzzy method, 0.269 for RCSO-based Rider Deep LSTM, and 0.123 for PRCSO-based DRNN.

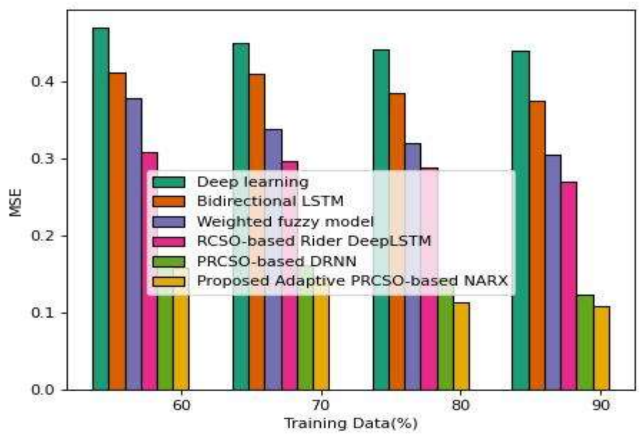

Figure 7 Analysis of MSE based on city-3

The analysis done by proposed Adaptive PRCSO-based NARX in accordance with MAPE is illustrated in figure 8. When the training data as 90%, MAPE obtained by designed technique is 4.097%, whereas the MAPE yielded by existing techniques, such as deep learning, bidirectional LSTM, weighted fuzzy model, RCSO-based Rider Deep LSTM, and PRCSO-based DRNN is 42.708%, 38.472%, 31.386%, 7.119%, and 4.119%, respectively

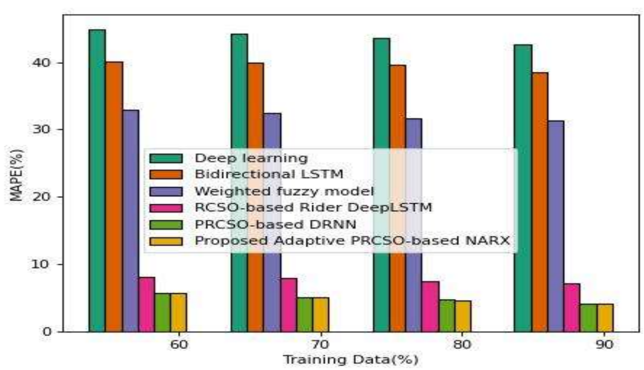

Figure 8: Analysis of MAPE based on city-3

3.5.5 Comparative Analysis

This section depicts the comparative discussion of developed CSPRO-based NARX with existing techniques. Table 1 represents the comparison based on MSE and MAPE of three cities for air quality prediction for 90% training data. The given table shows that the proposed model CSPRO performs better for air quality prediction with MSE of 0.09% and MAPE of 2.76%.

Table 1: Comparative Discussion

Based on	For	Metrics	Deep learning	Bidirectional LSTM	Weighted Fuzzy model	RCSO-based Rider Deep LSTM	Proposed PRCSO-based DRNN
Air Quality	City-1	MSE	**6.21%**	**2.34%**	**1.55%**	**.54%**	**0.09%**
		MAPE (%)	40.95%	36.169%	32.935%	7.11%	2.76%
	City-2	MSE	3.71%	3.01%	2.4%	1.5%	0.34%
		MAPE (%)	38.99%	32%	29.02%	4.887%	0.08%
	City3	MSE	3.31%	2.65%	1.95%	1.6%	0.14%
		MAPE (%)	38.613%	34.38%	27.289%	3.022%	0.022%

4. Conclusion

This paper presents the developed air quality prediction approach based on CSPRO based NARX model. Here, the time series data is taken from a dataset and then the pre-processing is taken to remove the redundant data. The missing value imputation is carried out to remove redundant data and pre-processed data is given to technical indicator extraction process. A time series model named NARX is used for predicting data for air quality. The NARX is trained by developed CSPRO. In addition, CSPROis newly designed by combiningPO, CSO and ROA method. The performance measures used to evaluate proposed model is MSE and MAPE. The developed model CSPRO based NARX obtained better performance with regards to MAPE of 2.76% and MSE of .09%. In addition, the devised CSPRO-based DRNN technique can be further improved by including other effective optimization algorithm with deep learning technique.

5. References

[1] Lin, Y.C., Lee, S.J., Ouyang, C.S. and Wu, C.H., “Air quality prediction by neuro-fuzzy modeling approach”, Applied soft computing, vol.86, pp.105898, January 2020.

[2] Gaganjot Kaur Kang, Jerry Zeyu Gao, Sen Chiao, Shengqiang Lu and Gang Xie, "Air quality prediction: Big data and machine learning approaches", International Journal of Environmental Science and Development, vol.9, no.1, pp.8-16, 2018.

[3] Ma, J., Cheng, J.C., Lin, C., Tan, Y. and Zhang, J., “Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques”, Atmospheric Environment, vol.214, pp.116885., October 2019.

[4] Jin, X.B., Yang, N.X., Wang, X.Y., Bai, Y.T.,Su, T.L. and Kong, J.L., "Deep hybrid model based on EMD with classification by frequency characteristics for long-term air quality prediction", Mathematics, vol.8, no.2, pp.214, February 2020.

[5] Venkat Rao Pasupuleti, Uhasri, Pavan Kalyan, Srikanth and Hari Kiran Reddy, "Air quality prediction of data log by machine learning", In proceedings of 6th International Conference on Advanced Computing and Communication Systems (ICACCS), pp. 1395-1399, 2020.

[6] Turner, M.C., Krewski, D., Pope III, C.A., Chen, Y., Gapstur, S.M. and Thun, M.J., "Long-term ambient fine particulate matter air pollution and lung cancer in a large cohort of never-smokers", American journal of respiratory and critical care medicine, vol.184, no.12, pp.1374-1381, December 2011

[7] Zhang, L., Liu, P., Zhao, L., Wang, G., Zhang, W. and Liu, J., "Air quality predictions with a semi-supervised bidirectional LSTM neural network", Atmospheric Pollution Research, vol.12, no.1, pp.328-339, January 2021.

[8] Sethi, J. and Mittal, M., "Ambient air quality estimation using supervised learning techniques", EAI Endorsed Transactions on Scalable Information Systems, vol.6, no.22, 2019

[9] Pavani, M. and Kumar, K.K., "Monitoring real-time urban Sulphur Dioxide and Ammonia emissions using the Wireless Sensor Networks", ARPN Journal of Engineering and Applied Sciences, vol.14, no.20, pp.3504-3508, 2019.

[10] QamarAskari, IrfanYounas, MehreenSaeed, "Political Optimizer: A novel socio-inspired meta-heuristic for global optimization", Knowledge-Based Systems, pp.105709, 2020.

[11] Binu, D. and Kariyappa, B.S., "RideNN: A new rider optimization algorithm-based neural network for fault diagnosis in analog circuits", IEEE Transactions on Instrumentation and Measurement, vol. 68, no.1, pp.2-26, 2018.

[12] Cheng, R. and Jin, Y., "A competitive swarm optimizer for large scale optimization", IEEE transactions on cybernetics, vol.45, no.2, pp.191-204, 2014.

[13] Di, X., "Stock trend prediction with technical indicators using SVM", Standford: Leland Stanford Junior University, 2014.

[14] Vargas, M.R., Dos Anjos, C.E., Bichara, G.L. and Evsukoff, A.G., "Deep leaming for stock market prediction using technical indicators and financial news articles", In 2018 international joint conference on neural networks (IJCNN), pp. 1-8, July 2018.

[15] Xie, H., Tang, H. and Liao, Y.H., "Time series prediction based on NARX neural networks: An advanced approach", In 2009 International conference on machine learning and cybernetics, vol. 3, pp. 1275-1279, July 2009

[16] Zhang, L., Liu, P., Zhao, L., Wang, G., Zhang, W. and Liu, J., "Air quality predictions with a semi-supervised bidirectional LSTM neural network", Atmospheric Pollution Research, 2020.

[17] Olvera-García, M.Á., Carbajal-Hernández, J.J., Sánchez-Fernández, L.P. and Hernández-Bautista, I., “Air quality assessment using a weighted Fuzzy Inference System”, Ecological informatics, vol.33, pp.57-74, 2016.

[18] Monn, C.H., Braendli, O., Schaeppi, G., Schindler, C., Ackermann-Liebrich, U., Leuenberger, P. and Sapaldia Team, “Particulate matter< 10 µm (PM10) and total suspended particulates (TSP) in urban, rural and alpine air in Switzerland”, Atmospheric Environment, vol.29, no.19, pp.2565-2573, 1995

[19] Xiangyu Zou, Xiangyu Zou, Duan Zhao, Bin Sun, Yongxin He and Stelios Fuentes, "Air quality prediction based on a spatiotemporal attention mechanism", Mobile Information Systems, vol.2021, pp.12, 2021.

[20] Ma, J., Cheng, J.C., Lin, C., Tan, Y. and Zhang, J., "Improving air quality prediction accuracy at larger temporal resolutions using deep learning and transfer learning techniques", Atmospheric Environment, vol.214, pp.116885, 2019.

[21] India Air Quality dataset taken from, “https://www.kaggle.com/shrutibhargava94/india-air-quality-data#__sid=js0”, assessed on June 2022.

[22] Benhaddi, M. and Ouarzazi, J., “Multivariate Time Series Forecasting with Dilated Residual Convolution Neural Networks for Urban Air Quality Prediction”, Arabian Journal for Science and Engineering, vol.46, no.4, pp.3423-3442, April 2021.

[23] Kumar, Ram and Aher, Pushpalata and Zope, Sharmila and Patil, Nisha and Taskar, Avinash and Kale, Sunil M and Gadekar, Amit R, Intelligent Chat-Bot Using AI for Medical Care (August 11, 2022). Available at SSRN: https://ssrn.com/abstract=4187948 or http://dx.doi.org/10.2139/ssrn.4187948

[24] Kumar, Ram and Patil, Manoj, Improved the Image Enhancement Using Filtering and Wavelet Transformation Methodologies (July 22, 2022). Available at SSRN: https://ssrn.com/abstract=4182372

[25] Ram Kumar, Manoj Eknath Patil ,” Improved the Image Enhancement Using Filtering and Wavelet Transformation Methodologies”, Turkish Journal of Computer and Mathematics Education ,Vol.13 No.3(2022), 987-993.

[26] Ram Kumar, Jasvinder Pal Singh, Gaurav Srivastava, “A Survey Paper on Altered Fingerprint Identification & Classification” International Journal of Electronics Communication and Computer Engineering ,Volume 3, Issue 5, ISSN (Online): 2249–071X, ISSN (Print): 2278–4209.

[27] Li, R., Dong, Y., Zhu, Z., Li, C. and Yang, H., "A dynamic evaluation framework for ambient air pollution monitoring", Applied Mathematical Modeling, vol.65, pp.52-71, January 2019.