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Rainfall prediction using Back Propagation Neural Network Model with Improved Flower Pollination Optimization Algorithm

Nisha Malik
Faculty of Engineering and IT, University of Technology Sydney, Australia
nishamalik641@gmail.com

Abstract: Rainfall prediction is the recent research as it set up the farmers to move with the effectual decision-making regarding agriculture both in irrigation and cultivation. The conventional prediction techniques are daunting, the rainfall prediction depends upon three main factors such as rainfall, humidity, and rainfall recorded in the preceding years that ensued in enormous time-consumption and leverages enormous computational efforts related with the evaluation. Hence, this work adopts the rainfall prediction model based on the deep learning network: Back Propagation Neural Network system. The weights of deep learning are tuned optimally by exploiting the Improved Flower Pollination Algorithm to ease the global optimal tuning of the weights and promise improved prediction accuracy. Conversely, the developed deep learning model is modeled in the MapReduce model which set up the effectual handling of the big data.

Keywords: Rainfall; Prediction; Neural Network; Mapreduce; IFPOA

Nomenclature

Abbreviations	Descriptions
ML	Machine Learning
ANNs	Artificial Neural Networks
AI	Artificial Intelligent
IFPA	Improved Flower Pollination algorithm
KNN	k-Nearest Neighbours
DSMIA	Dynamic Self-Organizing Multilayer Network enthused using the Immune Algorithm
FSV	Fixed-Step Screening Verification
MLP	Multi-Layer Perceptron
EEMD	Ensemble Empirical Mode Decomposition
MSE	Mean Square Error
SVM	Support Vector Machines
MLP	Multi-Layer Perception Classification
ConvLSTM	Convolutional Long Short Term Memory
FPA	Flower Pollination Method
NN	Neural Network
GP	Genetic Programming
CLR	Clusters Linear Regression
RBNN	Radial Basis Neural Networks
PSO	Particle Swarm Optimization
SVR	Support Vector Regression
BP	Back-Propagation
ANFIS	Adaptive Network-based Fuzzy Inference System optimized
IS	Intelligent Systems
BPNN	Back Propagation Neural Network
LSM	Least Squares Method
LR	Logistic Regression
MCM	Markov Chain Model
RBFN	Radial Basis Function Network
MSE	Mean Squared Error
RMSE	Root MSE
DGP	Decomposition Genetic Programming
RO	Random Optimization

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1. Introduction

Rainfall prediction remnants a severe apprehension and have paid attention to the interest of the scientific community, industries, risk management entities, and the governments [1]. Rainfall is a climatic aspect, which affects a lot of human activities namely agricultural production, construction, forestry power generation, and tourism, between others. Thus, the prediction of rainfall is necessary as this variable is the one using the utmost correlation using the difficult natural measures namely flooding, mass movements, and landslides [4]. These occurrences encompass exaggerated society for years. Consequently, for rainfall prediction encompassing a suitable technique creates it probable to take precautionary and alleviation metrics for this usual phenomenon [12].

In the prospect of an exacting place, rainfall prediction is the employ of science and technology to envisage the state of the earth's atmosphere [6]. At present, using computer-aided modeling rainfall prediction is performed. Even though it has been helped by technology however the accurateness cannot achieve 100% and there is still the error possibility. Even though, the present rainfall prediction information is required in several fields, like aviation and agriculture fields [13].

Several stochastic models were endeavored to predict the incidence of rainfall, to examine its cyclic unpredictability, and to predict monthly/ yearly rainfall over a few known geographical areas [14]. Each day rainfall occurrence was examined using the Markov chain used a chain dependent stochastic method, named MCM to examine inter-annual unpredictability of area average complete precipitation. Moreover, to imitate precipitation amount mixed exponential distribution showing a realistic spatial correlation in multiple sites [2].

One of the main elements in data-driven approaches like ML, soft computing, data mining, etc, which is attributed by diverse researchers. Recently, deep learning is considered as the flourishing mechanism in ANN to resolve the complex difficulty and dealing with the enormous quantity of data. Deep learning is fundamentally a sequence of multilayer architecture that is trained. The most important changes that affect the technique are weight and the learning rate of the layers. A deep learning model was extensively used in fields such as image recognition, bioinformatics, and natural language processing. An ANN is a detailed processing model that approximately copies the human brain-behavior which imitates the connectivity and operations of biological neurons [15].

The most important objective of the work is to present the IFPA model. Here, this method is used for the prediction of rainfall is performed by exploiting the BPNN which can handle the time-series data efficiently. For the effectual prediction, optimal weights are formulated by exploiting the developed IFPA technique.

2. Literature Review

In 2017, Tomoaki Kashiwao et al [1], developed and analyzed a local rainfall (precipitation) prediction model based on the ANNs. This model can robotically attain meteorological data exploited to prediction of the rainfall from the Internet. In this system, meteorological data from the apparatus deployed in a local point was collective between users. The ultimate objective of the paper was the sensible employ of “big data” for accurate rainfall prediction. Since NN approaches for the model, they have exploited an MLP with a hybrid technique collected of BP and RO techniques, and RBFN with an LSM.

In 2020, Binh Thai Pham et al [2], developed and compared various advanced AI techniques called ANFISPSO, SVM, and ANN to predict the everyday rainfall. Hence, meteorological variable parameters like utmost temperature, least temperature, relative humidity, wind speed, and solar radiation were composed along with exploited as input parameters and everyday rainfall as a parameter of the output in the techniques.

In 2018, Sam Cramer et al [3], evaluated a new approach named DGP that was a technique that putrefies the issue of rainfall to sub-issues. Putrefaction permits the GP to spotlight on every sub-issue, ahead of integrating back into the complete issue. For each sub-issues, the GP does this via having a divide regression formulation, based on the rainfall level. As they had turned their interest to sub-issues, this minimizes the complexity while dealing with the data sets using the maximum volatility and values of excessive rainfall.

In 2018, Keh-Jian Shou and Jia-Fei Lin [4], worked on the landslide susceptibility study techniques, such as LR and SVMs, were trained ahead of being useful. The rainfall predictions were intense and their effect of landslide receptiveness was compared, discussed, and evaluated.

In 2017, Sam Cramer et al [5] worked on the most important impact of the ML techniques and further generally IS have over the present conventional methods for prediction of rainfall in rainfall derivatives. The predictive performance of the present conventional methods was applied and compared with the Markov chain comprehensive for the prediction of the rainfall and 6 additional popular ML approaches, such as GP, SVR, RBNN, M5 Model trees, M5 Rules, and KNN.

In 2018, Yu Xiang et al [6], worked on the information concerning the short-to-long time variation within innovative time series for rainfall was discovered exploiting EEMD based on the evaluation on rainfall datasets gathered by meteorological stations. This technique uses several supervised learning techniques for diverse modules of input data that use SVR in favor of a short-period prediction module when ANN in favor of long-period prediction modules.

3. BPNN for Training the IFPA

3.1 BPNN Model

Hybrid modeling of the BPNN technique integrating utilizing the prior BPNN information, which is a multi-layer feedforward ANN that is trained using the error backpropagation model developed in [7]. The training procedure is used for the optimization of the weights and thresholds for a BPNN model. If the thresholds, and weights, are appropriate, the model appropriate training samples degree may convene needs; in the interim approach has an improved prediction performance. Eq. (1) indicates the model function for the BPNN.

$$\begin{cases} h_i(a) = f_1(w_{i-h}a + m_{i-h}) \\ b = f_2(w_{h-o}h_i(a) + m_{h-o}) \end{cases} \tag{1}$$

In eq. (1), m_{i-h} and m_{h-o} indicates the thresholds, w_{i-h} and w_{h-o} represents the weights. $h_i(a)$ indicates the i^{th} hidden layer neuron of the output function and b indicates the model output. f_1 states the transport function from the input layer to the hidden layer and f_2 indicates the transport function from the hidden layer to the output layer, correspondingly.

The BPNN approach is distorted addicted to resolving the fitness model of optimization issues based on system information. Initially, technicians verify the model object to acquire the method information and the approach is transformed into a nonlinear constraint optimizing issue in eq. (2).

$$\min\ b = E_D + \eta E_w \tag{2}$$

$$\text{s.t. } L_0 = \sum_{i=1}^{N_i} \sum_{j=1}^{J_i} \left[\frac{1 - h(i, j)}{2} \right] = 0 \quad i = 1,2,\ldots\ldots, N;\ j = 1,2,\ldots\ldots, J \tag{3}$$

In eq. (3), J_i indicates the amount of identified monotone intervals of the i^{th} variable, N indicates the input dimension A and L_0 is described as constraint violated degree that is computed with the FSV technique [8].

To obtain L_0, each recognized monotonic variable is separated into a plurality of intervals using the fixed-step, and in the interim other variables obtain a fixed value. Subsequently, the model output values are computed while the monotonic variable obtains diverse endpoint values. These values of the output are exploited to ensure the information of the monotonicity.

For eq. (2) to optimize the issue using the penalty model technique, the optimizing object is modifying as eq. (4).

$$\min\ b_{new} = E_D + \eta E_w + \gamma L_0 \tag{4}$$

In eq. (4), γ indicates the penalty factor of monotone constraint [8].

3.2 Conventional FPA

The FPA is developed in [9] that were enthused using the pollination procedure of flowers. In FPA, there are 2 solution steps, such as local and global pollination. FPA is formulated like 4 principles [9].

(i) The global pollination procedures are cross-pollination and biotic via that the pollen conveys pollinators execute the levy flight.

(ii) Local pollination is analyzed as self-pollination and abiotic.

(iii) The probability of reproduction is contemplated as flower constancy that is proportional to the similarity of 2 flowers is stated.

(iv) The switching probability $\rho \in [0, 1]$ manages the global and local pollination.

The flower pollens are performed using the pollinators in the global pollination procedure, eg: insects. Pollens can move over an extensive distance as insects can frequently fly and go in an extensive range. This makes sure the reproduction and the pollination of the fittest g_*.

The initial principle also flower constancy is indicated in eq. (5).

$$y_i^{t+1} = y_i^t + S\left(y_i^t - g_*\right) \tag{5}$$

In eq. (5), y_i^t indicates the t iteration in pollen i, and g_* indicates present optimal solution establish between every solution in the present generation.

The S parameter indicates the strength of the pollination that fundamentally in step size. As insects can travel over an extensive distance using diverse distance steps, a Levy flight is exploited to imitate this feature powerfully [10] [11]. Eq. (6) indicates the Levy distribution, $\Gamma(\lambda)$ indicates the standard gamma function with $\lambda = 1.5$, and this distribution is suitable for great steps $l > 0$.

$$S \sim \frac{\lambda\Gamma(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, \ \left(l >> l_0 > 0\right) \tag{6}$$

In eq. (6), local pollination and flower constancy is stated y_j^t and y_k^t indicates the pollens from the diverse flowers of the similar plant species. This fundamentally imitates the flower constancy in an inadequate neighborhood

$$y_i^{t+1} = y_i^t + \varepsilon\left(y_j^t - y_k^t\right) \tag{7}$$

On the whole flower pollination performance able to happen at both global and local scales. Neighboring flower scraps in the not-thus far-distant neighborhood are additional probable to be pollinated using the local flower pollens which those distant. Here a switch probability p is exploited to switch among global pollination into exhaustive local pollination.

3.3 Proposed Improved FPA

The p is exploited to switch among local and global pollination. For fine-tuning it is a significant parameter for optimized vectors solution, and it can help in regulating the convergence rate of the method to the best solution. For switch probability, the conventional exploits fixed value and cannot be altered throughout novel generations. The most important disadvantage of this algorithm emerges in the iterations number the method requires to discover the best solution.

In untimely generations, huge switch probabilities resolve mainly probable make the flowers to the global pollination process that increase the solution vectors variety. Generally, in ultimate generations, a small switch probability drives the flowers to the local pollination process that increases the fine-tuning for the vectors solution to the best vector solution.

The explanation diversity among the proposed and conventional techniques is in the approach of altering switch probability. To enhance the performance of the FPA and eradicate disadvantages slander by fixed values of altering switch probability p alters enthusiastically using generation number.

$$p(g_n) = p_{max}\exp(c.g_n) \tag{8}$$

$$c = \frac{Ln\left(\frac{p_{min}}{p_{max}}\right)}{NS} \tag{9}$$

In eq. (9), p_{min} indicates minimum altering switch probability, $p(g_n)$ indicates altering switch probability for every generation, p_{max} indicates the utmost altering p, and NS indicates the number of vector solution generations. The fundamental steps of the proposed algorithm are stated in algorithm 1.

4. Deep Learning-Based Mapreduce Framework for the Developed Rainfall Prediction Model

In planning the agriculture, the prediction of rainfall plays a significant role and the associated activities which remain as the cornerstone of the Indian Economy. Some huge models predict the rainfall by exploiting the weather data, although many techniques declined in negotiating with the big data. The weather data is the time series data and uses the big data form, asserting the require for the efficient technique to tackle with the prediction. MapReduce model resolves the problems related to the big data as it can parallel computing, acquit from computational complexity. At first, for the prediction, the input weather data is subjected to the MapReduce model which functions based on the map and reduces models, IFPA based BPNN. The developed technique trains the weights of the BPNN model. From the individual mappers, the outputs which are trained with several delays are integrated to form the input to the reducer, by exploiting that the prediction is obtained. The architecture diagram to predict the rainfall is demonstrated in fig. 1.

Algorithm 1: Pseudocode of the developed IFPA

Objective function $f(y), y = (y_1, \ldots, y_d)^T$
Initialize n flowers population $y_i (i = 1,2,\ldots,n)$
In the initial population, find the optimal solution g_*
Describe a switch probability $p \in [0,1]$
While $(t < max\_iter)$
Using eq. (9) p change dynamically
For $i = 1,2,\ldots,n$
If $rn < p$
Illustrate the step vector S that follows a levy distribution
Using eq. (5) global pollination is performed
else
From uniform distribution Illustrate $\in$ in [0,1]
Arbitrarily select k and j between all the solutions
Using eq. (7) local pollination is performed
End if
Estimate the new solutions
Update the new population if new solutions are enhanced
End for
Discover the present optimal solution g_*
End while

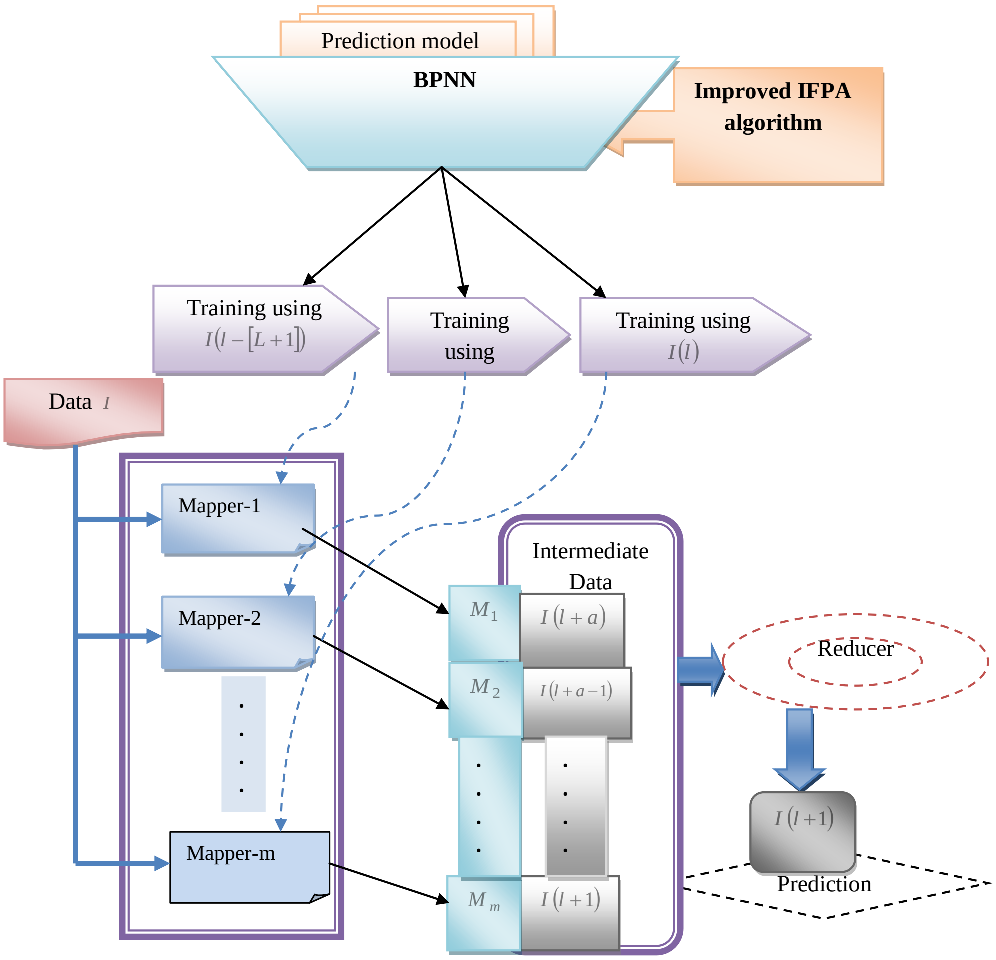

Fig. 1. *Architectural illustration of the rainfall prediction*

Consider I as the input weather data, which is exploited for the prediction of rainfall by exploiting the MapReduce framework. The MapReduce framework structure is stated as follow:

4.1 Rainfall Prediction using the MapReduce Framework

Mapreduce increases implication owing to the capability to pact with the enormous number of data-parallel, in an extremely consistent way. The MapReduce framework enhances the visualization and offers the effectual prediction environment with an extremely scalable environment. The MapReduce framework carries out the capability to accumulate and deal out enormous sets of data during the prosperity of the servers which restrains the high dispensation power of the framework. In addition, the MapReduce framework works on the multiple sources of the data irrespective of whether they are unstructured or structure. From the distributed resources the weather data enters is subjected to the individual mappers to train the BPNN in attendance in it. The MapReduce programming comprises of 2 functions, like mapper and reducer functions affianced in mapping the input data. The map and reduce functions of the MapReduce framework exploits the IFPA algorithm-based BPNN. The mapper module comprises of several mappers to procedure the input weather data, and the middle data formed during integrating the output of the mappers is exploited to train the reducer that presents the ultimate prediction.

i) Mapper Phase: In the mapper module, the mappers operate based on the map function based on the BPNN which is tuned optimally by exploiting the developed method. Consider there are a total of m mappers that is indicated as eq. (10).

$$M = \{M_1, M_2, ..., M_j, ..., M_m\} \tag{10}$$

In eq. (10), M_j indicates the j^{th} mapper. The individual mappers with the BPNN are trained by exploiting the input weather data employing several delays. For example, the BPNN in mapper-1 is trained to employ the data $I(l-[L+1])$ as a result that the predicted output from the mapper 1 is indicated as $I(l+a)$. Similarly, the mapper 2 is trained by exploiting the weather data $I(l-[L+2])$ to produce the predicted output $I(l+a-1)$. The m^{th} mapper is trained by exploiting the weather data $I(l)$ to produce the predicted output $I(l+1)$. Conversely, one can say that the individual mapper performs the prediction by exploiting the records with a delay $[L+1]$, $[L+2]$, etc. The predicted output from the mappers is stated in eq. (11).

$$\tilde{I}_{l+1}, ..., \tilde{I}_{l+a} = \underset{I_{\tau+1}, ..., I_{\tau+a}}{\arg\max}\ \rho\left(I_{l+1}, ..., I_{l+a} \middle| \tilde{I}_{l-L+1}, \tilde{I}_{l-L+2}, ..., \tilde{I}_l\right) \tag{11}$$

$$\tilde{I}_{l+1}, ..., \tilde{I}_{l+a} \approx \underset{I_{l+1}, ..., I_{l+a}}{\arg\max}\ \rho\left(I_{l+1}, ..., I_{l+a} \middle| Q_{encode}\left(\tilde{I}_{l-L+1}, \tilde{I}_{l-L+2}, ..., \tilde{I}_l\right)\right) \tag{12}$$

$$\tilde{I}_{l+1}, ..., \tilde{I}_{l+a} \approx \upsilon_{forecast}\ \rho\left(Q_{encode}\left(\tilde{I}_{l-L+1}, \tilde{I}_{l-L+2}, ..., \tilde{I}_l\right)\right) \tag{13}$$

The output from the mappers is integrated to train the reducers which are inherent with the BPNN.

ii) Reducer phase: The reducer exploits the reduced function, BPNN to carry out the ultimate rainfall prediction. Here, the BPNN is tuned optimally by exploiting the developed model. The data input to the reducer is stated in eq. (14).

$$I^{inter} = \{I(l+a), I(l+a-1), ..., I(l+1)\} \tag{14}$$

The reducer is trained by exploiting the intermediate data, I^{inter} to carry out the ultimate prediction. The predicted output is called as, $I(l+1)$.

Testing phase: Throughout the testing step, the test data is subjected to the mappers with several data delays to attain the integrated output to ensue the ultimate prediction in the reducer. From the reducer, the ultimate prediction of the MapReduce framework set up the precise generation of the prediction consequences.

5. Results and Discussions

5.1 Experimental Procedure

In this section, the efficiency of the prediction models via validating the data attained from the Rainfall Prediction dataset. For the analysis, the measures employed exhibits the efficient prediction model by the performance analysis.

The simulation analysis was done in the MATLAB and the performance was done by exploiting the database obtained from the Rainfall Prediction dataset [16] that comprises the weather data of the rainfall predicted in the whole India and from the year 1901 to 2015 in the state, Tamil Nadu. These 2 databases that present the detail regarding the rainfall year-wise, data month-wise, and on a periodical basis.

For the analysis, the measures exploited such as the PRD [17], and MSE. The MSE of the algorithm is calculated as the mean square difference among the target output and the estimated output.

The algorithms obtained for the comparison include the MLP algorithm [20], ConvLSTM, CLR technique [18], and DSMIA [19], S-SGD-based ConvLSTM which were evaluated with the developed model to show the efficiency of the developed model.

5.2 Performance Analysis

Fig. 2 exhibits that the investigation of the developed and traditional techniques regarding MSE by varying the training percentage. Fig. 3 exhibits that the investigation of the developed and traditional techniques regarding PRD by altering the training percentage. Here, the prediction accuracy of the developed method is maximum that is shown by the least value of the error regarding MSE and PRD that is found to be least.

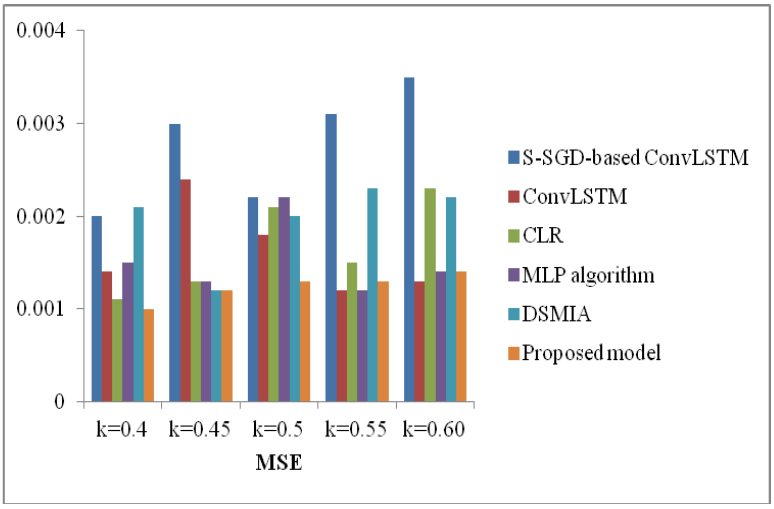

Fig. 2. *Bar chart of the developed and traditional techniques regarding MSE*

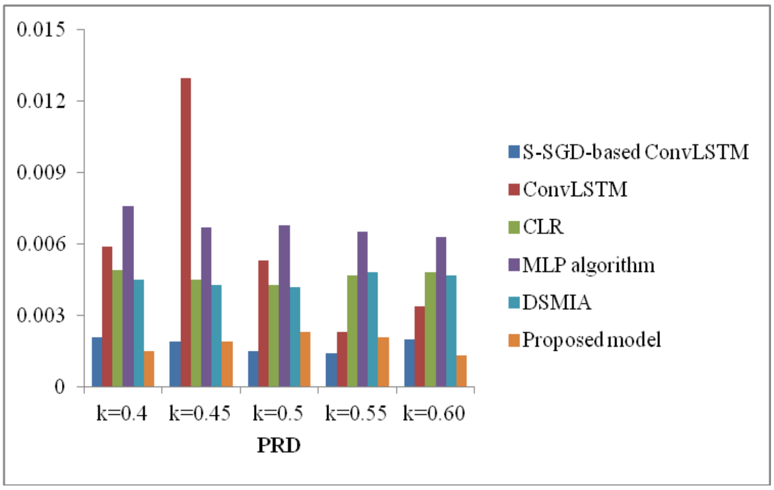

Fig. 3. *Bar chart of the developed and traditional techniques regarding PRD*

6. Conclusion

The prediction of the rainfall model was on the basis of the deep learning model that was interpreted to render an enhanced prediction performance. The rainfall data was a time-series data and it does not tolerates the dynamic data update and therefore, the developed prediction technique based on the MapReduce model tackles using the dynamically updating rainfall data efficiently. The MapReduce framework uses the deep learning framework based on the BPNN that was tuned optimally adopting the developed IFPA. The developed approach set up the optimal tuning of the weights and the developed approach was the enhancement of Flower pollination approach. The efficiency of the developed algorithm for the prediction of the rainfall model was shown by the evaluation by exploiting datasets obtained from the Prediction of Rainfall database. The prediction precise of the developed technique was maximum that was shown by the least value of the error regarding the MSE and Percentage RMSE that was obtained be minimum.

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