Prior Recognition of Flash Floods: Concrete Optimal Neural Network Configuration Analysis for Multi-Resolution Sensing

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ABSTRACT Flash floods can demolish infrastructure and property within seconds as they are very sudden. Flash floods are the main cause of the casualties and loss of properties. Existing natural disaster prediction algorithms contains false alarms. Indefinite techniques have been applied to overcome this leading issue in many countries. A competent flood management system must have the potential and tendency to identify the flash floods and atmospheric and climatic changes on early basis with less false alarm rate. Techniques which have been designed for the flash flood investigation may be categorized into following types a. Sensors based direct measurement b. Radar images c. Satellite based X-band images. The proposed research consisted of Artificial intelligence-based decision making for multi-modal sensing (direct measurement from multi-resolution sensors). A combination of sensors like Passive infrared (PIR), water level sensor, ultrasonic sensor, temperature sensor, pressure and altimeter sensors have been integrated on a single device to investigate the flash floods. The use of most suitable pair of measurement sensors can substantially enhance the advantage of more accuracy and reliability compared to a single sensor. In recent trends Particle swarm optimization is very popular for solving stochastic global optimization problems. The data was trained and processed by modified multi-layer feed forward neural network optimized by particle swarm optimization algorithm. Hybrid Modified Particle swarm optimization has been combined with feed forward neural network for the vigorous investigation of flash floods with less false alarm rate. Simulated results showed that the proposed research algorithm Modified multi-layer feed forward neural network optimized by Particle swarm optimization for multi-modal sensing performed very well in terms of evaluation parameters compared to other existing strategies with minimum false alarm ratio. Moreover, modified multi-layer feed forward neural network optimized by article swarm optimization algorithm results have been compared with the cuckoo search, modified cuckoo search, particle swarm optimization and Multi-layer perceptron neural network configurations for the validation purpose.

INDEX TERMS Flash floods, sensors, multi-resolution sensing, early forecasting system, artificial intelligence, modified multi-layer feed forward neural network, particle swarm optimization algorithm, multi-layer perceptron.

I. INTRODUCTION

Many countries like Pakistan, Malaysia, Indonesia, Japan, Bangladesh, France etc. are badly affected annually due to the flash floods. In 2010 the whole world observed that how extensively Pakistan was devastated by deadly flood.

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International strategy for disaster reduction (ISDR) by United Nations highlighted S seven points based plan to provide the funding for the disaster management efficiently [1]. Early warning predictive analysis systems have been implemented in many countries and running successfully but forecasting the exact actual timings with much detailed information is very complex as false alarms may be detected due to the inadequate processing algorithms. Sensors and Instrumentation

always introduce some kind of errors and false alarm which may lead towards incorrect measurement and observations. All types of transducers in which transduction method can be resistive transducer, inductive and capacitive may generate some type of errors and omissions during the observation and measurement. For example, high ratio of false alarm rate in forecasting disaster events leads towards the high number of casualties and infrastructural loss. Disaster management authorities cannot predict natural hazards accurately and precisely like flash floods, tsunami and earthquake. Floods and seismic events are not identified due to the low accuracy of sensors and propagation of lost information. It has also been noticed that during the transmission of wireless data values to the control unit, few data bits are lost which causes wrong observations. A competent early warning system was strongly needed for forecasting any type of natural hazards like tsunami, flash floods and seismic events. Intense floods can be regarded as the basic cause of infrastructural losses and casualties in various countries like Malaysia, Pakistan, Southern France, India, Philippines, Bangladesh, Nepal, China, Canada, United States of America and others. Large buildings, cattle and personal belonging are devastated in fraction of seconds due to floods. Usually flash floods are caused due to many reasons like heavy precipitation, wave currents, melting of ice debris in ocean, Cloud to ground flashes, broken reservoir (dam)and thunderstorm and flood induced inside the ocean. Forestation may reduce the intensity of the floods as forest minimizes the flow of the run offs. Floods intensity are not deteriorated due to the deforestation [2]. Early forecasting is very tough and complex due to the uncertainty in data, incompetent algorithms, and dependence on uncertain precipitation velocity [3]. More than one hundred and twenty thousand casualties were recorded because of the flash floods during 1992 and 2005 [4]. Around $597 billion economic losses have been projected between 2016 to 2035 [5]. Flash floods are known as very destructive hazards all around the world. Climatic variations increase the frequency of the hazards which includes the floods [6]–[9]. Especially those floods which are produced by the heaviest rainfall in minimum time [10]. Many approaches have been carried out to detect the floods as they are abrupt. Approaches can be defined as AI based methods, sensors-based methods, image processing methods using satellite and radar images and nowcasting techniques. Flash flood investigation techniques have been discussed in the next section covering almost all the existing state of the art techniques which have been applied for the detection of flash floods. In the proposed research appropriate sensors have been selected and the proposed hybrid novel algorithm named as MFN-PSO was applied to the data set for the vigorous detection of flash floods.

II. FLASH FLOODS INVESTIGATION TECHNIQUES

Various approaches were designed to detect the flash floods vigorously and robustly. Mainly, the techniques can be divided into two categories:

- Engineering Based Techniques
- Non-Engineering Based Techniques

Engineering based approaches can be described as building of dams and reservoirs to store the overmuch water which leads towards deadliest floods. Whereas the non-engineering methods are based on artificial intelligence and machine learning algorithms [11]. The early identification of flash floods can be classified as the direct measurement of sensors and transducers, radar imaging and X-band images from satellite. A generic comparison has been performed and published based on detailed literature review [12]. Various research reports have been completed to detect the actual event of flash floods. Several authors used direct measurement approach based on sensors and some researchers proposed hybrid approach based on radar and satellite imaging. Morphological and other image processing methods were developed to improve the clearness and reduce ambiguities in satellite and radar based images for the investigation of flash floods [13]. Radar and satellite-based images also contain ambiguities. Multi-feature fusion classifier algorithm based on extraction and segmentation was designed to reduce errors and ambiguities in radar and satellite based images [14]. Partial Differential Equation (PDE) was applied to the system to measure wave pattern and speed of tsunami torrent. A capable false alarm free predictive system was required for the detection of flash floods so that evacuation routes and emergency exits may be announced [15]. Generally designing of forecasting model for the identification flash floods can be regarded as the most difficult task as sewages discharge are the most complex combination of various factors, the factors can also be the intricate land structure, precipitation magnitude and rainfall event time. Prediction systems may also differ with each other due to the false alarm in the many systems [16]. Direct sensors measurement can be acknowledged as more trustworthy in contrast with other methods. Sensors like seismic, passive infra-red, acoustic, pyroelectric and magnetic transducers are recognized as unattended ground sensors (UGS) for the unending vigilance of illegal intrusion. Normally Unattended ground sensors (UGS) have large amount of false alarms due to the incompetency of forecasting algorithms. Less battery backup can also be known as an acute problem during the surveillance data transmission [17]. In langrangian sensing approaches, many individual sensors were spread on specific sea surface which has to be monitored. These micro sensors record the various parameters to identify the floods. Micro sensors track the change, observe it and transmit it to the receiver. To receive the data smoothly with higher accuracy, receiver must be in range with these micro sensors. False alarms were found in langrangian sensing therefore some artificial intelligence based algorithm were applied on the system [18]. Acute flash floods have been recorded in many countries like Pakistan, India and Malaysia etc. Several countries' economy depends on the crops and crops depend on water which is used for irrigation. Irrigation system of any country relies on many big rivers, mini rivers and canals. In Pakistan, agriculture can be acknowledged as a back bone

of country therefore it has been given a lot of importance. Generally, the river water depends on glaciers. Glaciers and severe rainfall in monsoon season boost the upstream level of dams, lakes and rivers to the dangerous levels that causes floods. Many design strategies were invented and applied to separate the genuine signal from false signal for instance Extended Kalman Filtering (EKF) was developed to improve the precision in distinguishing false alarms. Wavelet Transform Technique has been adapted to recognize the fake alarms [19]. False alarms were limited by using morphological and timing data. Data mining approach was additionally applied to diminish the false alarm and close calls. Decision Tree a machine learning tool is also used for classification. It performed like SVM (support vector machine). Bagged decision is similar as decision tree. The main distinction is that it doesn't accept the entire information as input for the prediction model [20]. Abrupt substantial precipitation is regular in Mediterranean space which causes numerous infrastructural loss and human lives loss. It had become real issue, for instance, twenty casualties and 1.2 billion Euros loss were documented in the GARD department. This loss can be increased up to 15000 Euros in provincial territories. Radar pictures were not clear and exact while rain estimating instrument didn't perform appropriately and reliably as they required maintenance routinely. A research was applied on Garden de Mialet a mini basin of the Gardon d'Anduze. This watershed was 220 square kilometers and its height ranges from 147 meters to 1170 meters with 36 % slopes. The event time span was from 26 hours to 143 hours and are equally sacattered at interims of under 48 hours. Normal total precipitation was seen between 44 mm to 462 mm. It has been seen that in potential floods received signal contain high pace of errors and distortion. Precipitation can be considered as the most exact instrument however productivity is around 20%. TOPMODEL covered all the parts of hydrological and severe steamy precipitation like moisture and inclines. Multi-layer perceptron model was decided for comprehensive estimation of prediction related to variable nonlinear models. Multi-layer perceptron was applied with feed forward neural network having of one layer of variable nonlinear neurons and one output linear neuron. Non-Linear and Linear properties were analyzed that performed precisely [21]. A non-linear function was reduced by using Multi-layer perceptron that was trained by Levenberg-Marquardt algorithm [22]. Multi-layer perceptron has been frequently used to solve the prediction problems. The MLP architecture may contain one or more than one hidden layers [23]. Normally, UGS (Unattended Ground sensors) have high false alarm rate because of the poor efficiency and incompetent algorithms. They do have low battery backup issues for wireless communications as well. It is extremely difficult to classify such examples like (walking and digging activity) from just seismic sign with low SNR (Signal to Noise ratio). Geophones were deployed into 3-axis with the motive that walking and digging must be identified and classified. MSTSA (Multi-scale Time Series) approach recognizes rapidly. Seismic time series is

changed to zero mean signal and down sampled to 1 KHz from 4KHz.That was known as de-noised and high peak was recorded by auto correlation [24]. To deal with the water assets unambiguous and error free precipitation information is obligatory. Without a doubt it is the most troublesome exercise to develop model on account of the perplexity of the climatic nature [2], [3]. ANN has the capacities to easily comprehend from the past examples to contribute a helpful solution if the data contains outliers or missed data. Practically All ANN can discriminate the precipitation in rainy season, besides model can't perceive the parameters that aren't fed to the system. Because of this reality it can just evaluate the time span of a precipitation. Neural system can be viewed as a part of AI that was developed in 1960 based on the biological behavior and structure of brain. Data and information have been accumulated from the Malaysian Meteorological Department located in Petaling Jaya. Past data from the time of (2007 o 2010) that was measured by rain gauges was used. After the data analysis, it was planned that to train the system data of this period (1 Jan 2010 to 31st Jan 2010) would be utilized. Data that was to be used from the departments contained errors, distortion and missed values having N/A and - 33.3 values. Data filtering can be used to retain the missed data or deviations. N/A and - 33.3 were put back by 0 and 0.1. It's important to improve the insufficiencies of data for the smooth and legitimate authentication and testing. The model having the least error was chosen to compare the changes with the actual outcomes. Mean Square Error was utilized to evaluate the error, MSE value was 0.2. A framework was designed utilizing SCADA (supervisory control and data acquisition) technology to stop floods, in first and second model (A and B) forward back propagation (FBP) was adapted. [25]. Artificial Neural Network (ANN) is the most widely used approach for the determination and locating the affected are for floods. After the getting the results of Artificial Neural Network training by Rosenlatt in 1958 ANN was known as a detection model. Rising water level was predicted by utilizing neural system autoregressive model with exogenous information (NNARX) method. This model was created in MATLAB neural network tool box. Precipitation intensity depends on different components (factors) like pressure, wind, temperature, velocity and direction, subsequently the flood estimation system must be exceptionally accurate and intelligent to issue prior warning [26]. The strategy was an extension of ARX model; five data inputs were fed to the NNARX model to classify the hazard (rising water level). The prediction time span can be set at any ordinary water level so that, the increase in level must be detected. ST1, ST2, ST3 and ST4 that demonstrated four higher stream and dy/dk showed the variation of water level at the flood occurrence area. The data which has been taken for testing and authentication was from first November 2014 to first December 2014 from department of Irrigation and Drainage Malaysia [27]. Several methods were adopted but proposed research which has been mentioned using Modified multi-layer feed forward neural network optimized by Particle Swarm Optimization achieved

excellent results in terms of accuracy and precision. Lowest Root mean square value was achieved 0.0037 using proposed method along with the 97.34 best fit.

III. PROBLEM STATEMENT

Sensors and gauges create errors and omissions during the measurement due to the poor sensitivity and calibration issues. Sensors and transducers also get affected due to the harsh environment and surroundings. Disaster authorities are unable to forecast the hurricane, flash floods, thunderstorm, tsunami and other natural disaster accurately and precisely due to the incompetent algorithm and higher rate of false alarm. Basically, false alarm rate is the estimation of fraction of predicted events that could not happen and key yardstick metrics for the validation and verification of National weather service (NWS) alerts [28]. Commonly, Sensors do have high false alarm rate due to the incapable and incompetent algorithms and communication. For example it is very crucial to identify and discriminate such activities like (digging, walking) from only seismic sign in real time with low SNR (Signal to noise ratio) [136]. Moreover, the wrong predictions of intense floods would create a negative impact for the disaster management authorities and due to the frequent wrong forecasting, no one would believe about the true positive event. It has been observed that sometimes artificial neural network weights are not updated with best optimal weights values to reduce the errors in predictive analysis. During the training phase the stochastic gradient usually stuck in local minima [29].

IV. METHODOLOGY

In our suggested solution a multi modal sensing gadget has been designed for the collection of data. The research phase can be classified into two phases a) compilation of data b) categorization of faulty data. Following sensors have been proposed to evaluate the flash floods a) MQ2 sensor for estimated the heightened level of CO_2 b) a) ultrasonic sensor for measuring the distance of the water Pressure sensor c) Temperature sensor d) PIR sensor e) water level module. Legitimate selection of transducers for the vigorous investigation of floods causes better testing and simulation results.

Figure 1 demonstrated that a genuine and competent cost-effective solution has been designed for the forecasting of flash floods accurately by utilizing direct observations from the sensors. Researchers have followed direct sensors measurement approach by using bunch of sensors named as Passive infra-red (PIR), ultrasonic sensor, water or humidity sensor, temperature and pressure sensors. Gas sensor has also been deployed to identify the heightened levels of carbon dioxide in the environment as the soil is saturated more and the probability of flash flood occurrence becomes sure in this situation. A suitable combination of measurement sensors can improve the detection probability of event compared to a single transducer. The data has been collected from the Kund Malir sea shore located in Pakistan. Appropriate sensors were
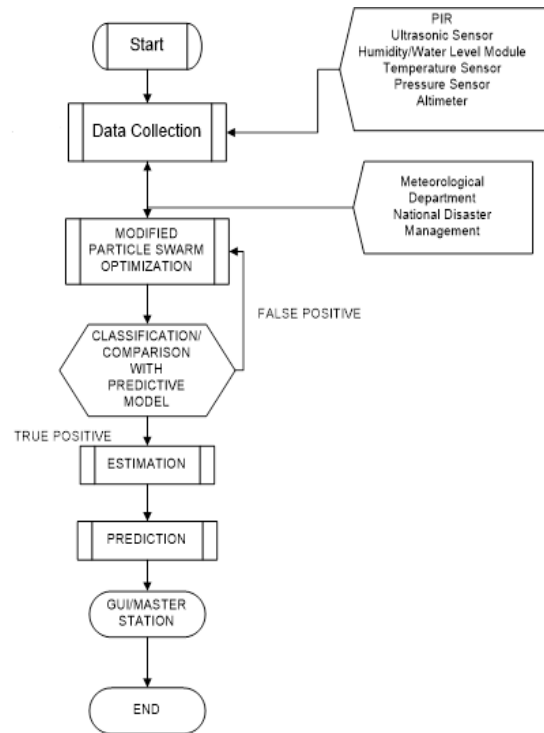

FIGURE 1. Methodology flow diagram.

selected to collect the data for the prediction of flash floods. Data set was filtered out and classified using the hybrid algorithm. Proposed algorithm also performed optimization to achieve the better optimal results. Usually collected huge data set is disorganized, redundant and contained missed and repetitive values. To resolve the issue of redundancy the data was organized into the tables for the smooth processing. Redundancy can be defined as the repetitive values that usually increase the size of the data set. The useless and undesired data is generally minimized and eliminated with the normalization. The normalized data was then processed for the forecasting floods. The research has been branched into three phases robust data classification, estimation and prediction.

A. SELECTION OF TRANSDUCERS

Selection of suitable and reliable sensors was very difficult as almost every process variable has been used to measure the flash flood. According to the literature review all the given parameters have been given significance for the robust investigation of flash floods.

- Water Level
- Rainfall intensity
- Critical upstream levels
- Precipitation velocity
- Pressure
- Temperature
- Color of the water
- Wind speed

- Wave current pattern, direction
- Global Positioning System Precipitable Water Vapor (GPS PWV)
- Soil humidity
- Clouds to ground (CG) lightning flashes
- Oceanic Bottom Pressure
- Precipitation Velocity
- Lightening Potential Index (Lightning activity as a forecasting tool)
- Carbon dioxide level
- Atmospheric humidity

All these parameters have been used as a yardstick to measure the flash floods vigorously in past researches [4]. Prediction using single sensor cannot be acknowledged as a genuine and reliable therefore pair of sensors were suggested. Two or more than two sensors could give you then benefit of more accuracy and reliability of the event prediction with less false alarm rate. Therefore, bunch of appropriate sensors were selected on the basis of accuracy, precision, sensitivity and ambient temperature.

B. HC-SR04 SENSING MODULE

The ultrasonic ranging module HC-SR04 is a 4-pin sensor module. It propagates a signal of around 40000 Hz which returns back to the module. It computes the distance without having any contact with the body. Ultrasonic sensors have been utilized for the measurement of water distance to the coastal bed.

C. HC-SR501 SENSING MODULE

PIR (Passive infrared sensor) sensor that indicated the motion of the flash flood or the position of displacement of the flash flood. It detects the change in the propagated radiations. Pair of PIR sensor may also be used to identify the object motion accurately.

D. MQ2 SENSOR

MQ2 gas sensor is used for the measurement of gas leakage identification. Here it has been used to identify the increased levels of carbon dioxide. Measurement of soil containing atmospheric carbon dioxide levels as the plants receive less quantity of water from the soil due to the raised levels of carbon dioxide. Because of this unique biological latest research, the soil gets saturated rapidly which causes more floods and run-offs.

E. WATER LEVEL MODULE

Water level modules are used to evaluate the height and amplitude of the water. There are so many water level sensors are available like pressure level sensors, ultrasonic water level sensors, capacitance level sensors and radar level sensors but for sure they are not acknowledged as cost-effective solution. Water level module, rainfall drops module has been used with the combination of other sensors for more accurate and reliable identification of flash floods.
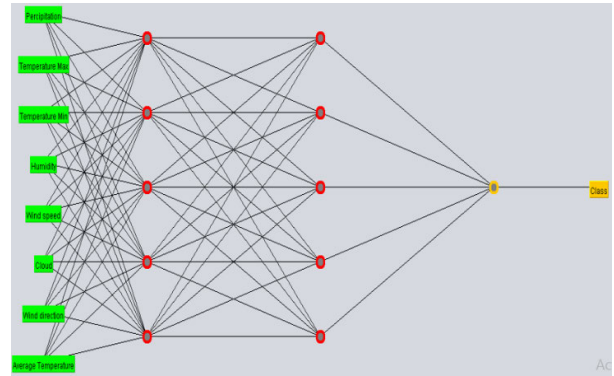

FIGURE 2. Predictive analysis model for PMD data.

F. BAROMETRIC PRESSURE AND TEMPERATURE SENSOR BMP-280

The barometric pressure and temperature sensor (BMP-280). BMP-280 is based on piezo-resistive technology. It has been interfaced with controller (Arduino) to estimate the temperature and surroundings pressure. BMP-280 measured the barometric pressure and altitude.

G. DATA COLLECTION VIA MULTI-MODAL DEVICE

Fig.1 Data collection through multi-modal sensing.

Fig. 3 displays the data collection process from multi-modal sensing device comprising of sensors at the sea shore at Karachi. Pakistan. Large Data was collected on hourly basis. Data was received from multi-modal sensing gadget per second cycle rate. The parameters x1, x2, x3, x4, x5, and x6 are the process variables which have been measured by using sensors. x1 denotes ultrasonic sensor, x2 = Passive infra-red sensor, x3 = carbon dioxide level indicator, x4 = water level sensor, x5 = environmental pressure and x6 is for temperature. All the parameters have been interfaced with the Arduino for the data collection. The data can be received on personal computers or at cellular phones wirelessly or wired. Each of the sensing parameter was different from each other having different ranges and resolution. Therefore, data collection device was named as multi-modal sensing device or multi-resolution sensing gadget [30]–[32].

V. MODIFIED MLTI-LAYER NEURAL NETWORKS CONFIGURATIONS WITH SPECIFICATIONS

Various configuration model for the suitable multi-layer neural network model have been discussed below.

A. NEURAL NETWORK CONFIGURATION DESIGN FOR THE PAKISTAN METEOROLOGICAL DEPARTMENT

Figure 2 represents Multi-layer perceptron based neural network was structured with two hidden layers and five neurons in each layer for PMD data. PMD data comprised of precipitation, maximum temperature, minimum temperature, humidity, wind speed, cloud, wind direction and average temperature. This NN configurations possessed two hidden layers with fine neurons in each layer.
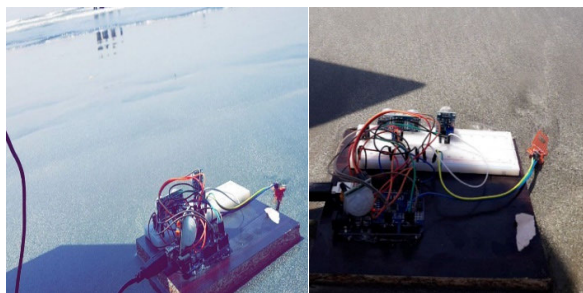
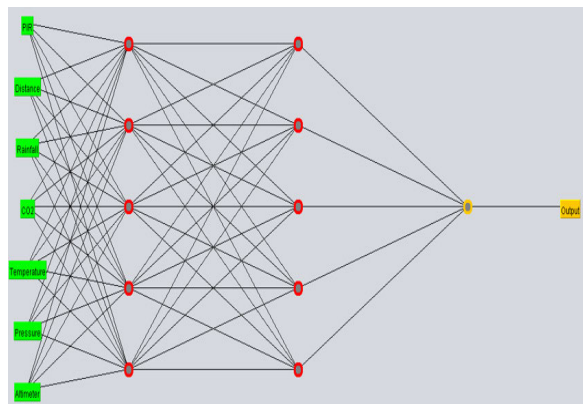**FIGURE 3.** Data collection from Kund Malir, Pakistan.

FIGURE 4. MLP based predictive analysis model for collected multi-resolution data set.

B. ESTIMATION OF NEURAL WEIGHTS FOR PAKISTAN METEOROLOGICAL DEPARTMENT DATA

Table no. 1 shows that values for each node have been calculated in neural network configuration comprising of two layers with five neurons in each layer.

C. ESTIMATION OF NEURAL WEIGHTS FOR PAKISTAN METEOROLOGICAL DEPARTMENT DATA

The elapsed time was found to be 11.59 seconds to process the 500 epochs for the three thousand instances. Suitable learning rate was selected between 0.1 to 0.3 with the momentum of 0.2. Error rate at each epoch was found to be 0.035132.

D. MULTI-LAYER PERCEPTRON NEURAL NETWORK CONFIGURATION FOR COLLECTED MULTI-RESOLUTION DATA

Figure 4 elaborates that MLP based neural network design was developed for data which was collected from multi-modal sensing device. Seven attributes data was fed to the NN design comprised of two layers and five neurons in each layer.

E. MULTI-LAYER PERCEPTRON WEIGHTS CALCULATIONS FOR MULTI-RESOLUTION DATA SET

Table no. 6 represented the calculated weights values on each neuron using multi-layer perceptron neural network sigmoid function.

TABLE 1. Weights estimation.

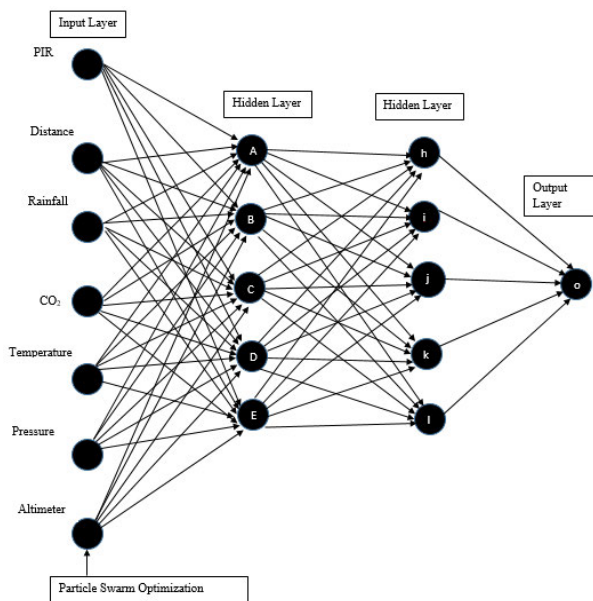| Attributes	Sigmoid Node 1 Weights	Sigmoid Node 2 Weights	Sigmoid Node 3 Weights	Sigmoid Node 4 Weights	Sigmoid Node 5 Weights
Precipitation	5.7427410	5.8453450	-9.950754008	2.01140643170	0.718554615811
Temperature Max	-7.6468520	-7.3595497	-16.72745389	-6.60161272849	-7.64835722012
Temperature Min	-5.5938058	-5.1157551	-12.38186561	-3.77772711818	-4.84267669602
Humidity	0.8769528	0.61597055	-2.0108125434	3.53437288119	1.70637704337
Wind speed	-0.1691230	0.032097017	-0.361914822	2.15814247591	0.425486906765
Cloudiness	-2.3971060	-2.27223967	1.18168892018	0.46517257550	-1.80128123409
Wind direction	0.31228046	-0.29405937	1.6625286981	0.419967916480	-0.94351521207
Average Temperature	-7.2459580	-6.8748720	16.114789942	6.0161683804	7.17578350967
Threshold	-4.264254	-3.573024	12.63155	5.9144008	6.7263938
Nodes	Sigmoid Node 6 Weights	Sigmoid Node 7 Weights	Sigmoid Node 8 Weights	Sigmoid Node 9 Weights	Sigmoid Node 10 Weights
1	-1.11137887	-10.94341	-1.0876040367	-1.1313344983	-1.156770434
2	-1.51357754	10.263944	-1.3408491171	-1.5168776328	-1.407685510
3	-12.2511413	6.7033502	-1.18796446447	-3.00472281368	-1.9344465327
4	6.4572423	3.0211645	-1.3137413126	1.80486166347	1.375344547
5	-5.934194398	3.8084794	-1.4569238359	1.5552636407	1.457695236
Threshold	7.149178	-3.8197885	-2.5890679	-2.20255472	-2.6579178

F. PROPOSED PREDICTIVE MODEL

In Fig. no. 5, input layer "j" and hidden layer "k" was suggested with output layer. The nodes PIR, distance, rainfall, CO_2, temperature pressure and altimeter were fed to the neurons as an input. After taking the inputs from the node,

TABLE 2. Neural network configuration specifications.

Activation Function	Sigmoid
Number of Epochs	500
Error per Epoch	0.035132
Learning rate	0.3
Momentum	0.2
Number of Layers	2
Number of neurons	5 for each layer
Number of attributes	Eight
Number of instances	3000
Elapsed time	11.59 seconds

FIGURE 5. Proposed MFN-PSO predictive model.

TABLE 3. Weights estimation for MLP design.

Attributes	Sigmoid Node 1 Weights	Sigmoid Node 2 Weights	Sigmoid Node 3 Weights	Sigmoid Node 4 Weights	Sigmoid Node 5 Weights
PIR	-0.01268	-0.044187	-0.0323008	-0.008752	0.015039
Distance	0.021163	0.0442227	0.04493603	0.0119092	0.0221521
Rainfall	-0.047200	-0.0346520	-0.0407528	0.043975	0.025245
CO$_2$	-0.03120	0.0455677	-0.0460503	-0.028992	0.0132217
Temperature	0.028324	-0.0138634	-0.035112	0.008446	0.0333318
Pressure	0.017129	-0.0098199	-0.00971921	0.007630	-0.0278526
Altimeter	0.042100	-0.020703	0.03307619	-0.041523	0.0269617
Threshold	-0.0484316	-0.0335128	0.0243148	0.042831	-0.011043
Nodes	Sigmoid Node 6 Weights	Sigmoid Node 7 Weights	Sigmoid Node 8 Weights	Sigmoid Node 9 Weights	Sigmoid Node 10 Weights
1	-0.042760	0.008261	-0.011316	-0.020882	-2.940E-4
2	-0.0375171	-0.01394	0.016896	-0.036369	0.0031175
3	0.0030043	-0.04590	0.011216	-0.006248	0.0202018
4	0.04313	0.027268	-0.02587	0.009208	0.009279
5	-0.04829	-0.04701	-0.01058	-0.0408869	0.043709
Threshold	-0.012599	-0.01717	0.0022849	0.0494899	0.0379545

first and second layer contained neurons. The neurons have been connected to each other with the links. Each link of the layer has its own identity and error that should be minimized. Non-linear function has been calculated by log sigmoid.

G. MULTI-LAYER FEED FORWARD NEURAL NETWORK OPTIMIZED BY PARTICLE SWARM OPTIMIZATION MFN-PSO WEIGHTS ESTIMATION (TRAINING)

Table no. 8 demonstrates values of each node that have been calculated using the following equations. The elapsed time was found to be 2.39 seconds to process the 500 epochs for the three thousand instances. Suitable learning rate was selected between 0.1 to 0.3 with the momentum of 0.2. Error rate at each epoch was found to be 0.001335278.

H. MULTI-LAYER FEED FORWARD NEURAL NETWORK OPTIMIZED BY PARTICLE SWARM OPTIMIZATION MFN-PSO NEURAL NETWORK CONFIGURATION SPECIFICATIONS (TRAINING)

Table no. 9 highlighted the MFN-PSO configuration specifications. Error per epoch has been calculated as 0.001335278 which is very less compared to the other existing computation techniques.

I. I.MULTI-LAYER FEED FORWARD NEURAL NETWORK OPTIMIZED BY PARTICLE SWARM OPTIMIZATION WEIGHTS ESTIMATION (TESTING)

Multi-layer feed forward neural network was optimized by particle swarm optimization and their weights were calculated which have been mentioned in the table 6.

TABLE 4. MFN-PSO weights estimation for training.

Layer 1 Attributes	Sigmoid Node 1 Weights	Sigmoid Node 2 Weights	Sigmoid Node 3 Weights	Sigmoid Node 4 Weights	Sigmoid Node 5 Weights
PIR	-1.32595	-0.13894	-0.4443	-0.06682	-3.53807
Distance	4.95062	0.16707	-0.10351	0.69831	0.00255
Rainfall	0.08670	-2.45273	-0.58322	-2.9117	-4.15027
Carbon Dioxide	0.5575	-2.31064	-0.00186	-5.69170	0.46825
Temperature	-0.6050	1.325048	-0.18891	2.15163	-0.12392
Pressure	1.686	1.656462	0.10794	0.5512	0.54390
Altimeter	1.633	1.150860	2.6570	1.92896	3.338388
Threshold	0.501123	-1.7094	-0.090362	-2.3492	-0.676650
Layer 2 Nodes	Sigmoid Node 6 Weights	Sigmoid Node 7 Weights	Sigmoid Node 8 Weights	Sigmoid Node 9 Weights	Sigmoid Node 10 Weights
1	-0.78325	-0.79759	-0.8352	-0.8423	-0.7977
2	-0.7327	-0.766640	-0.8079	-0.71331	-0.7567
3	-0.46050	-0.431350	-0.4664	-0.43412	-0.43587
4	-2.06636	-2.03361	-1.9807	-2.05234	-2.0456
5	-0.83869	-0.82450	-0.77788	-0.8090	-0.8425096
Threshold	-1.28077	-1.2889	-1.28523	-1.27093	-1.2773

TABLE 5. MFN-PSO specifications (training).

Activation Function	Sigmoid
Number of Epochs	500
Error per Epoch	0.001335278
Learning rate	0.3
Momentum	0.1
Number of Layers	2
Number of neurons	10
Number of attributes	8
Number of instances	9876

Table 6 showed that data was split, 70% was used for training and 30% data was utilized for the testing of proposed algorithm. Weights for the proposed MFN-PSO were calculated for testing data in Table 10.

J. MULTI-LAYER FEED FORWARD NEURAL NETWORK CONFIGURATION SPECIFICATIONS (TESTING)

Multi-layer feed forward neural network was optimized by particle swarm optimization and their weights were

TABLE 6. MFN-PSO weights estimation for training.

Layer 1 Attributes	Sigmoid Node 1 Weights	Sigmoid Node 2 Weights	Sigmoid Node 3 Weights	Sigmoid Node 4 Weights	Sigmoid Node 5 Weights
PIR	3.7909	2.005799	5.9347	3.8133	2.60054
Distance	0.9218	1.37850	3.3606	0.6968	0.98219
Rainfall	0.0635	-0.3343	-6.6763	-1.5431	-1.06804
Carbon Dioxide	-0.4225	-0.16663	0.19377	0.0565	-0.42121
Temperature	0.81298	1.21864	3.48959	0.6975	1.21776
Pressure	1.4770	1.52393	2.77273	1.4825	0.82883
Altimeter	-2.2983	-0.59007	-1.20033	-2.2954	-1.34785
Threshold	-3.6357	-1.6506	-3.7410	-3.7474	-3.2537
Layer 2 Nodes	Sigmoid Node 6 Weights	Sigmoid Node 7 Weights	Sigmoid Node 8 Weights	Sigmoid Node 9 Weights	Sigmoid Node 10 Weights
1	-0.70667	-0.5214	-0.52164	-0.5205	-0.49924
2	0.51337	0.0314	-0.0190	0.22450	0.144661
3	3.60602	1.8420	0.91530	2.30459	2.401401
4	-1.9297	-1.5865	-1.4695	-1.51809	-1.583203
5	-0.52259	-0.54998	-0.45463	-0.46985	-0.522237
Threshold	0.04403	-0.3104	-0.49025	-0.36382	-0.2151559

calculated. Mentioned neural network model was designed according to the given specification for testing.

Table 7 showed the specification for the proposed MFN-PSO comprising of two hidden layer and five neurons in each. Momentum was selected to be 0.1. Error per epoch was minimized to 0.00258394.

K. MFN-PSO NEURAL NETWORK TRAINING AND TESTING CURVES

Figure 6 and 7 portrayed the graphical analysis for the training and testing curves of proposed algorithm. The graph was plotted between mean squared error (MSE) and 1000 Epochs. Best performance value was found to be 0.96296 at the particular epoch 730.

VI. HISTORICAL AND COLLECTED DATA STATISCAL ANALYSIS

Historical data set which was collected from multi-resolution device and Pakistan meteorological department have been highlighted and explained

TABLE 7. MFN-PSO specifications (testing).

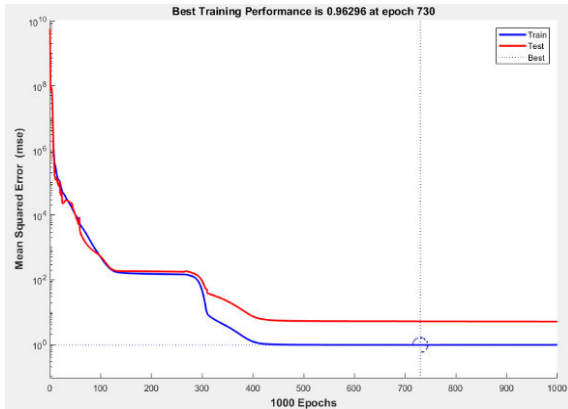| Activation Function	Sigmoid
Number of Epochs	500
Error per Epoch	0.00258394
Learning rate	0.1
Momentum	0.2
Number of Layers	2
Number of neurons	10
Number of attributes	7
Number of instances	9876

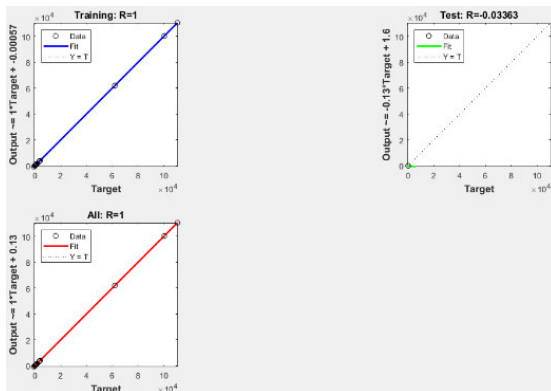**FIGURE 6.** Training and testing curves for MFN-PSO.

FIGURE 7. Regression plots for MFN-PSO.

A. COLLECTED DATA SET

Table 8 displayed the collected data set. More than ten thousand numbers of instances were recorded. The data set has seven types of attributes. Column no. 1 represented the

TABLE 8. Collected multi-resolution data set [30].

S.No	PIR	Distance mm	Rainfall	CO₂ ppm	Temperature °Celsius	Pressure hectopascal	Altimeter
1	0	300	0	0	30.13	100270.57	44.47
2	0	37.42	458	539	29.95	100268.39	44.26
3	0	37.18	459	533	29.71	100277.53	43.76
4	0	3661.34	453	418	29.6	100279.78	43.61
5	0	3654.66	453	397	29.46	100277.46	43.86
6	0	3691.18	450	356	37	100280.05	43.76
7	0	3691.18	450	356	29.4	100280.05	43.76
8	1	4.51	504	355	28	110424.17	-776
9	1	4.39	494	412	23	110424.17	-776
10	1	4.96	485	399	23	110424.17	-776
11	1	4.84	479	382	23	100283.5	-776
12	1	5.06	476	349	23	110424.17	-776
13	1	4.66	483	400	23	110424.17	-776
14	1	4.66	478	387	23	110424.17	-776
15	1	32.45	551	392	23	110424.17	-776
16	0	22.45	512	387	23	110424.17	-776
17	0	29.64	518	388	23	110424.17	-776
18	1	3619.3	529	389	23	110424.17	-776
19	1	78.39	498	386	23	110424.17	-776
20	0	0	491	385	23	110424.17	-776
21	0	30.13	517	397	23	110424.17	-776
22	0	36.96	501	395	23	110424.17	-776
23	0	31.92	496	392	23	110424.17	-776
24	0	32.95	497	390	23	110424.17	-776
25	0	41.18	503	387	23	110424.17	-776
26	0	135.14	494	385	23	110424.17	-776
27	0	3846.76	496	385	23	110424.17	-776
28	0	6.47	519	393	56	110424.17	-776
29	0	104.96	506	389	23	110424.17	-776
30	0	103.76	498	387	23	110424.17	-776

number of instances. Column no. 2 is the output of the passive infra-red sensor depicting the presence of water in the vicinity of PIR sensor. Column no. 3 has been acknowledged as water distance in millimeter. Rainfall data values have been mentioned in column no. 4. Column no. 5 demonstrated the carbon dioxide level in the environment. Temperature was presented in the column no. 6. Wind pressure was measured in the column no. 6. Column no. 7 shows the multi-modal sensing device altimeter [30].

B. STATISTICAL INFORMATION FOR THE DATA

In Table no. 9 the statistical analysis has been performed to evaluate the data set. Mean, Median and standard deviation along with the minimum and maximum values of each attribute have been calculated and mentioned in the given table by using following formulas.

Mean:

$$\mu = \text{sum of the data values/number of terms} \qquad (1)$$

Median:

$$\text{Median} = n + 1/2 \qquad (2)$$

Standard Deviation:

$$\sigma = \sqrt{1/N \sum_{i=1}^{N} (xi - \mu)^2} \qquad (3)$$

N = Number of terms
Xi = Data value
μ = sum of the data values/number of terms

TABLE 9. Statistical analysis.

Evaluation Parameters	Min.	Max.	Standard Deviation σ	Mean (μ)	Median
Flood Motion	0	1	0.49839	0.54	1
Distance	0	3846.76	1000.605	337.95	4.45
Rainfall	50	737	111.250	567.06	551
CO_2	70	1014	293.667	775.825	1007
Temperature	23	56	3.1664	26.2562	26.64
Pressure	61905.55	110424.17	23404.863	81149.6	61905.55
Altimeter	5.7	3927.77	1915.121	2350.09	3927.77

C. DATA NORMALIZATION

Data Normalization was performed to scale the non-structured data. The collected data and historical data were already filtered and to achieve smooth results the given data normalization technique was adopted.

```
input =
xlsread(filename,sheetname1,
'A1:Z10000');
% Inputs of Training Data
    PIR = input(:, 1);
    Distance = input(:, 2);
    Rainfall = input(:, 3);
    CO2 = input(:, 4);
    Temperature = input(:, 5);
    Pressure = input(:, 6);
    Altimeter = input(:, 7);

    LE = length(input(:, 1));
    target = zeros(LE, 1);
    DistanceUB=50; %Maximum limit
    of distance
    RainFallUB=300;%Maximum limit of
    Rain
    CO2UB=600; %Corbon oxide values
    TempUB=50; %Temperature upper
    limitation
    PressureUB=5000;%Uper Limit of
    Pressure
    AltimeterUB=1000; %Uper Limit of
    Altimeter
    for u = 1:LE
        end
```

Following equation was used for the data normalization (min-max) of each attribute.

A* = (A-mean(A))* std(B)/std(A) + mean(B)

TABLE 10. Historical PMD multi-resolution data set [31].

Precipitation Past 24 hrs.(mm)	Temperature Max °C	Temperature Min °C	Humidity 1200 UTC (%)	Wind speed 1200 UTC (knots)	Cloudiness 1200 UTC (okta)	Wind direction 1200 UTC (degree)	Average Temperature °C	Class
0	29.4	16.5	29	6	0	225	23	1
0	31.5	14	50	6	5	225	22.8	1
0	29.8	14	50	6	0	225	21.9	1
0	30.5	14.5	63	8	5	225	22.5	1
0	28.7	15.3	37	4	0	180	22	1
0	29.5	16	58	6	5	225	22.8	1
0	27.5	16.6	52	6	4	225	22.1	1
0	28	14.5	55	10	3	225	21.3	1
0	28.2	13.5	55	10	2	225	20.9	1
0	28.5	14	56	8	3	225	21.3	1
0	28	15.5	62	8	4	225	21.8	1
0	28	17	19	4	0	315	22.5	1
0	28.5	15	19	8	0	45	21.8	1
0	26.5	14	32	4	0	225	20.3	1
0	27	14	24	0	0	0	20.5	1
0	27.5	13.5	47	12	1	225	20.5	1
0	27	14.5	46	6	4	225	20.8	1
0	28	15	45	4	2	180	21.5	1
3.1	28	14	39	12	2	225	21	1
0	27.3	10.5	32	8	0	225	18.9	0
0	27.5	11.5	45	10	0	225	19.5	0
0	27	13	54	10	4	225	20	1
0	27.5	13.5	39	6	0	135	20.5	1
0	26	13.5	47	8	0	225	19.8	0
0	26.5	13	57	6	3	225	19.8	0
0	25.5	13.5	59	14	4	225	19.5	0
0	27.3	17	49	6	6	135	22.2	1
0	24	16.5	62	8	3	225	20.3	1
0	27.5	16.5	56	16	4	225	22	1
0	37	25	46	10	0	248	31	2
0	37.5	25	61	12	4	225	31.3	2
0	35	26	59	16	6	225	30.5	2

D. HISTORICAL DATA SET

Table 10 represented the collected data set form Pakistan Meteorological Department (PMD). Data set comprised of attributes for example precipitation, maximum temperature, minimum temperature, humidity, wind speed, cloudiness, wind direction and average temperature. Attributes were measured by PMD for the detection of flash floods.

In Table no. 11 the statistical analysis has been performed to evaluate the data set. Mean, median and standard deviation along with the minimum and maximum values of each attribute have been calculated and mentioned in the given table by using 1, 2 and 3 equations.

VII. MATHEMATICAL EXPRESSIONS FOR MULTI-LAYER FEED FORWARD NEURAL NETWORK OPTIMIZED BY PARTICLE SWARM OPTIMIZATION

Mathematical analysis for the designed algorithm named as multi-layer feed forward neural network optimized by particle swarm optimization has been discussed.

A. MATHEMATICAL EXPRESSIONS FOR THE INPUT LAYER "j"

$$y_j^1 = \text{logsig}(x_1 w_{11} + x_2 w_{21} + x_3 w_{31} + x_4 w_{41} + x_5 w_{51}$$
$$+ \ x_6 w_{61} - \theta_j) \tag{4}$$

TABLE 11. Pakistan meteorological department data set [31].

Evaluation Parameters	Min.	Max.	Standard Deviation σ	Mean (μ)	Median
Precipitation	0	43.4	3.67846	0.54705	0
Temperature Maximum	15.8	42	3.463644	32.910	33
Temperature Minimum	8.6	30.8	5.82204	22.261	24.5
Humidity	1	98	19.55237	48.837	55
Wind speed	0	20	4.09127	9.668	10
Cloudiness	0	36	2.88706	2.5718	225
Wind direction	0	360	64.45667	207.8467	225
Average Temperature	13.9	35.5	4.2858	27.61258	29.3

$$y_j^2 = \text{logsig}(x_1 w_{12} + x_2 w_{22} + x_3 w_{32} + x_4 w_{42} + x_5 w_{52} + x_6 w_{62} - \theta_j) \tag{5}$$

$$y_j^3 = \text{logsig}(x_1 w_{13} + x_2 w_{23} + x_3 w_{33} + x_4 w_{43} + x_5 w_{53} + x_6 w_{63} - \theta_j) \tag{6}$$

$$y_j^4 = \text{logsig}(x_1 w_{14} + x_2 w_{24} + x_3 w_{34} + x_4 w_{44} + x_5 w_{54} + x_6 w_{64} - \theta_j) \tag{7}$$

$$y_j^5 = \text{logsig}(x_1 w_{15} + x_2 w_{25} + x_3 w_{35} + x_4 w_{45} + x_5 w_{55} + x_6 w_{65} - \theta_j) \tag{8}$$

B. MATHEMATICAL ANALYSIS FOR HIDDEN LAYER "k"

$$A_j^1 = \text{logsig}(x_1 w_{11} + x_2 w_{21} + x_3 w_{31} + x_4 w_{41} + x_5 w_{51} + x_6 w_{61} - \theta_j) \tag{9}$$

$$A_j^2 = \text{logsig}(x_1 w_{12} + x_2 w_{22} + x_3 w_{32} + x_4 w_{42} + x_5 w_{52} + x_6 w_{62} - \theta_j) \tag{10}$$

$$A_j^3 = \text{logsig}(x_1 w_{13} + x_2 w_{23} + x_3 w_{33} + x_4 w_{43} + x_5 w_{53} + x_6 w_{63} - \theta_j) \tag{11}$$

$$A_j^4 = \text{logsig}(x_1 w_{14} + x_2 w_{24} + x_3 w_{34} + x_4 w_{44} + x_5 w_{54} + x_6 w_{64} - \theta_j) \tag{12}$$

$$A_j^5 = \text{logsig}(x_1 w_{15} + x_2 w_{25} + x_3 w_{35} + x_4 w_{45} + x_5 w_{55} + x_6 w_{65} - \theta_j) \tag{13}$$

C. MATHEMATICAL EQUATIONS FOR OUTPUT LAYER "o"

$$O_j^1 = \text{logsig}(x_1 w_{11} + x_2 w_{21} + x_3 w_{31} + x_4 w_{41} + x_5 w_{51} - \theta_j) \tag{14}$$

Desired or target data may be represented by "y_d"

$$y_d = \text{Targeted data set} \tag{15}$$

A test vector has been designed to calculate the probability of the flash floods which has been given below:

x = [PIR, Distance, Rainfall, CO_2, Temperature, Pressure, Altimeter];

Furthermore, to test the data values, seventy-five percent of input data values has been trained, evaluated and the probability result was represented in percentage by using the given function:

```
result = result_net(x');
probability = result *100;
if probability < 0
    probability = 0;
end
if probability > 100
    probability = 100;
```

The collected data set can be imported in the MATLAB simulation tool. The data file then converted into the variable form so that it may be treated as a variable data file in the MATLAB. Training of the proposed algorithm has been performed by this collected data. Actually in swarm intelligence algorithms every particle has its own velocity that determines the direction of traveling.

$$x^i k + 1 = x^i k + v^i k + 1 \tag{16}$$

Eq.16 determines the computation of the position of the particle that was calculated in the algorithm.

$$\% \text{ Position update} \tag{17}$$

```
for i = 1:pop
    for j = 1:kk
        x(i, j) = x(i, j) + v(i, j);
    end
end
```

"x" represents the updated particle position and "v" represents its corresponding updated particle velocity. "k + 1" determines the corresponding time.

The velocity was updated in particle swarm optimization using the cost function:

$$v^i k + 1 = w.v_k^i + c1.r1(\text{pbest}_k^i - x_k^i) + c2r2(\text{gbest}_k^g - x_k^i)); \tag{18}$$

Velocity update in MATLAB;

$$v(i, j) = w * v(i, j) + c1 * \text{rand} * (\text{pbest}(i, j) - x(i, j)) + c2 * \text{rand} * (\text{gbest}(1, j) - x(i, j)); \tag{19}$$

"k" denotes the recent updated step number, components r1 and r2 are two random series between the range of (0, 1), c1 and c2 are the acceleration PSO constants.

"w" variable represents the inertia weights which are useful in modifying the particle velocity for the local and global search for the convergence.

$$w = wmax + \frac{wmax - wmin}{kmax}.k \tag{20}$$

TABLE 12. Statistical analysis for different values of "c1" and c2".

Value "c1"	Value "c2"	Training "R"	Training "E²"	Testing "R"	Testing "E²"
1.3	1.5	0.713	0.699	0.711	0.724
1.7	2.0	0.767	0.713	0.833	0.772
2.1	2.3	0.881	0.788	0.883	0.736
2.3	2.5	0.667	0.651	0.831	0.792
1.3	2.3	0.876	0.879	0.901	0.897
1.5	2.5	0.937	0.946	0.963	0.971

The inertia weight can be computed by using the eq. 20 whereas the wmax and wmin was set as 1 and 0 respectively. Lower values of inertia are used for local and search and maximum values are for the global search. Maximum inertia weight values that are set to reduce during the Particle swarm optimization execution will search global first and search locally in the end of the algorithm processing.

D. SELECTION OF "c1" AND "c2" COGNITIVE CONSTANT VALUES FOR MFN-PSO

Table no. 12 presented the various values for coefficients of correlation (R) and Nash-Sutcliffe coefficient (E²) which have been calculated by using different constants values c1 and c2. The accelerating constants "c1" and "c2" are normally used to determine the particle's "pbest" and "gbest" values.

E. EVALUATION PARAMETERS FOR THE SELECTION OF "c1" AND "c2"

Evaluation parameters for the statistical analysis of accelerating constants "c1" and "c2" have been calculated by using the following formulas:

1. Coefficient of correlation (R), as shown at the bottom of the next page.

2. Nash-Sutcliffe coefficient (E²):

$$E^2 = 1 - \frac{\sum_k^j (Measured\ value - Forecasted\ value)\ 2}{\sum_k^j (Measred\ value - Mean\ measured\ value)\ 2} \tag{22}$$

Initialization of MFN-PSO values

$$c1 = 1.5; \quad c2 = 2.5; \tag{23}$$

Usually the components of velocity can be hold between the range of v_{max} and v_{min} to regulate the too much moving outside the search space range. Furthermore, the number of hidden layers can be calculated by the following equation 8.

$$HL_j^h = TF_j^h \times \sum_i^n w_{ij}^h ip_i + bn_j^h \tag{24}$$

where "Ip_i" represents the input neurons for the training of neurons, w_{ij} is the weight values between input neuron

and hidden layer while the element bn_j represents the biased neuron at its activation.

$$Ip_i = (Ip_i - Ip_i^{mn}) \times \frac{2}{Ip_i^{mx} - Ip_i^{mn}} - 1 \tag{25}$$

where,

Ip_i = variable for inputs
Ipi_i^{mx} = minimum data value
Ipi_i^{mn} = minimum data value

Data normalization was performed using the equation no. 9. Output parameters have been computed by the input parameters. The hidden neurons obtained from the input neurons the number of net inputs for a hidden neuron can be estimated using the equation no. 10.

$$HN_j^h = \sum_i^n w_{ij}^h ip_i + bn_j^h \tag{26}$$

The multi-layer feed forward neural network has been configured and achieved optimal results by applying improved particle swarm optimization on the data. The following pseudo code has been coded in the MATLAB for the development of MFN-PSO. Every neuron comprises of current position and current velocity and they are corresponding to each other. The position can be determined by using the updated velocity. The weights are usually adjusted in particle swarm optimization when neuron was found to be far away from the global best position. Therefore, a pseudo code which has been coded in the MATLAB has been presented here for the updated global best position and computation of fitness.

```
% updating pbest and fitness
for i = 1:pop
    if f(i, 1) < f0(i, 1)
        pbest(i, :) = x(i, :);
        f0(i, 1) = f(i, 1);
end
```

Basically the weight is updated according to the current velocity of the particle and the updated position is determined by the updated velocity also. The algorithm initialized all the weight values to any random values and begins the training. Weight is passed through each data set and the weight fitness is compared. The maximum fitness determines the global best search position.

Mean squared error of multi-layer feed forward neural network optimized with PSO was computed using the following equation.

MFNPSO MSE

$$= \frac{\sum_{i=1}^N \times (net - PSO_{calculated} - net - PSO_{predicted})2}{N} \tag{27}$$

Modified MFN-PSO training was performed successfully and mean square error (MSE) was calculated in MATLAB as:

PSO_err = sum((net_PSO(inputs) − targets).^2)/length
$$\times (net\_PSO(inputs)) \tag{28}$$

F. MULTI-LAYER FEED FORWARD NEURAL NETWORK OPTIMIZED BY MODIFIED CUCKOO SEARCH

Modified cuckoo search is the hybrid algorithm comprises of feed forward propagation and cuckoo search. Cuckoo search can be acknowledged as famous metaheuristic algorithm for the optimization and data fusion in various engineering problems. Solution vector was presented by eggs as Cuckoo search is a nature stimulated algorithm and cuckoo lays one egg in the nest at a time. A host can recognize a unique egg with the probability of $p_a \in (0, 1)$. In multiresolution optimization, each modal has its own optimization direction or target which may contradict each other

Local random walk function can be presented as:

$$u^{t+1} = u^t + \alpha s \otimes H(p_a - \varepsilon) \otimes (u^t - u^t), \quad (29)$$

where u_i^{t+1} and u_k^t are two different solutions and $H(u)$ is a Heaviside Function.

While Global random walk is described as

$$v^{t+1} = v^t + \alpha L(s, \lambda), \quad (30)$$

Cuckoo search random walk objective was given as:

$$\text{function nest} = \text{get\_cuckoos(nest, best, Lb, Ub)} \quad (31)$$

Levy flights exponent and coefficient are given as:

$$\beta = 3/2; \quad (32)$$

$$\text{sigma} = (\text{gamma}(1 + \beta)^* \sin(\text{pi}^*\beta/2)/(\text{gamma}((1 + \beta)/2) {}^*\beta * 2^{\wedge}((\beta - 1)/2)))^{\wedge}(1/\beta); \quad (33)$$

Levy flights by Mantegna's algorithm are described as:

$$u = \text{randn(size(s))}^*\text{sigma}; \quad (34)$$

$$v = \text{randn(size(s))}; \quad (35)$$

$$\text{step} = u./\text{abs}(v).^{\wedge}(1/\beta); \quad (36)$$

If the solution is found as the best solution, it remains unchanged.

$$\text{stepsize} = 0.01^*\text{step}.^*(\text{s-best}); \quad (37)$$

MFN-CS Function value can be represented as:

$$\text{Function Value} = \text{cuckoo\_search(Cuckoo\_Iterations}, \\ \text{inputs, targets)} \quad (38)$$

Number of nests (or different solutions) can be given as:

$$\text{Nests} = 20; \quad (39)$$

The discovery rate of alien eggs/solutions is

$$\text{pa} = 0.25; \quad (40)$$

Lower bounds and upper bounds are represented as:

$$\text{Lb} = -1.5^*\text{ones}(1, \text{kk}); \quad (41)$$
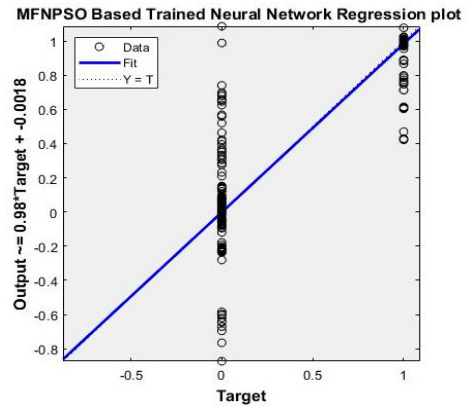

FIGURE 8. Regression plots for MFN-PSO.

$$\text{Ub}s = 1.5^*\text{ones}(1, \text{kk}); \quad (42)$$

Randomly initials solutions are described as:

$$\text{nest} = \text{zeros(Nests, kk)}; \quad (43)$$

$$\text{for i} = 1 : \text{Nests} \quad (44)$$

$$\text{nest(i, :)} = \text{Lb} + (\text{Ub} - \text{Lb}). * \text{rand(size(Lb))}; \quad (45)$$

end

To achieve the best current fitness was described as:

$$\text{fitness} = 10^{\wedge}10^*\text{ones(Nests, 1)}; \quad (46)$$

To properly execute and validate the MFN-Cuckoo search, Mean squared error was calculated by using the following equation:

$$\text{MFN-Cuckoo\_err} = \text{sum}((\text{net\_cuckoo(inputs)} - \text{targets}).^{\wedge}2) \\ /\text{length(net\_cuckoo(inputs))}; \quad (47)$$

Activation function of the modified cuckoo search can be given as:

$$f = \text{sum}((\text{net(inputs)} - \text{targets}).^{\wedge}2)/\text{length(inputs)}; \quad (48)$$

VIII. SIMULATED RESULTS

A. REGRESSION PLOTS FOR MFN-PSO AND MFN-CS

Fig. 8 displays the regression plot for the Modified feed forward neural network with PSO. Regression plots are the visual analysis for the predictions model therefore it can be used as a yardstick to evaluate the predictive model. The graph has been plotted with actual and predicted. The blue line is intersecting with the dotted desired results.

Fig. 9 displays the regression plot for the Modified feed forward neural network with Cuckoo search. Regression plots are the correlation between actual and predicted. Regression plots are the visual analysis for the predictions model therefore it can be used as a yardstick to evaluate the predictive

$$R = \frac{\sum (Measured - Mean\ measured)(Forecasted - Mean\ forecasted)}{\sqrt{\sum (Measured - Mean\ measured)2 \sum (Forecasted - Mean\ forecasted)\ 2}} \quad (21)$$
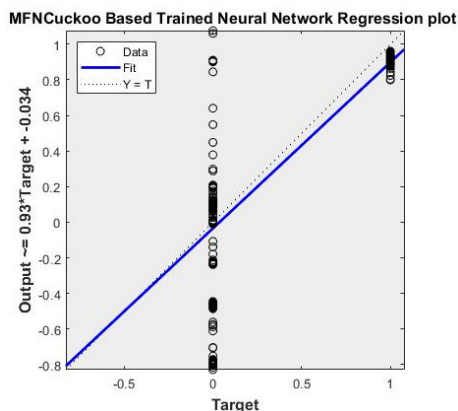
FIGURE 9. Regression plots for MFN-CS.

model. The graph has been plotted with actual and predicted. The blue line is intersecting with the dotted desired results.

Fig. 10 demonstrated the graphical comparison of traditional simple particle swarm optimization (PSO) and MFN-PSO. Flash identification probabilities have been plotted on x-axis and numbers of instances have been plotted on y-axis. The green line shows the PSO based measurements while blue dashed line shows the proposed MFN-PSO results. Results proved that traditional PSO worked better for the prediction of flash floods but the proposed hybrid MFN-PSO performed better than the PSO and other state of the art flash floods investigation algorithm.

Fig. 11 reveals the MATLAB pictorial results for the comparative analysis of PSO and Cuckoo Search. PSO and Cuckoo search have been applied to identify the floods truly

and exactly. Red line indicates the PSO results while blue one represents the Cuckoo search results.

Fig. 12 represented the visual analysis for the comparison MFN-PSO and MFN-CS. Modified feed forward neural network with particle swarm optimization and Modified feed forward neural network with Cuckoo search both algorithms have been applied to the same data and same time. The results of proposed MFN-PSO have been compared with MFN-CS. They have performed better than the existing approaches but MFN-PSO achieved the best results concretely. The appropriate rate of learning rate was selected and stochastic gradient of particle swarm optimization was also taken into the account foe the development of a competent algorithm.

Table 13 elaborated the detailed parametric comparative analysis of state of the art predictive algorithms for the identification of flash floods. The data sets were collected from own developed multi-modal sensing device and Pakistan Meteorological Department. Missed data values and repetitive values have been filtered out by data normalization. Proposed Modified multi-layer feed forward neural network with Particle Swarm Optimization was applied to both of the data and results have been compared in terms of mean square error, training time, elapsed time, mean, standard deviation, variance, best value and worst values. Mean squared error of 0.0013707 was achieved with the elapsed time of 39.17731 for MFN-PSO. MFN-PSO results have been compared to the PSO, Cuckoo Search, MFN-CS and Multi-layer perceptron algorithms results. Comparative analysis proved that proposed algorithm MFN-PSO performed better than the existing approaches. Various existing issued in algorithms like selection of learning rate and momentum,

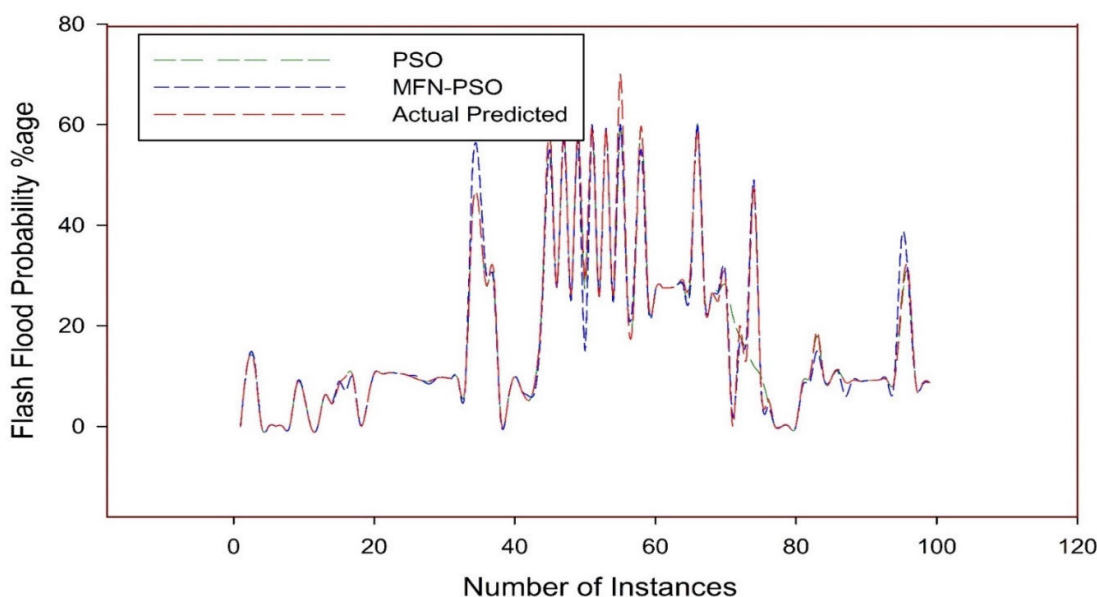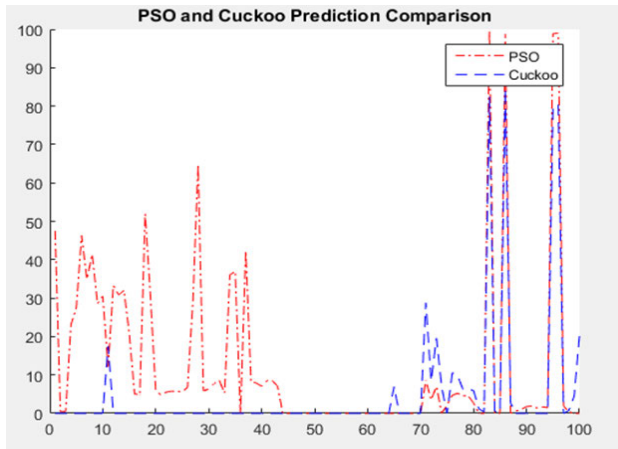**FIGURE 10.** Graphical comparison for PSO and MFN-PSO.

FIGURE 11. PSO and CS comparison.

TABLE 13. Parametric comparison of state-of-the-art algorithms.

Performance Indices for proposed algorithms	PSO	MFN-PSO	CUCKOO SEARCH	MFN-CUCKOO SEARCH	MLP
Number of Iterations	30	30	30	30	30
Number Of Instances	9876	9876	9876	9876	9876
Mean	0.03167	0.029377	0.03012	0.039678	0.02991
Standard Deviation	0.016907	0.016907	0.01709	0.01719	0.01711
Variance	0.0002858	0.0002713	0.0001154 3	0.0001164	0.0001 1642
Best Value	0.01335	0.015707	0.030151	0.030151	0.04331
Error	0.00047	0.0013707	0.033462	0.030151	0.02113
Training Time (sec)	38.832	39.93773	40.934	40.912	42.7313
Accuracy (%)	96.23	98.889	97.762	97.891	94.325
Elapsed Time (sec)	39.8732	39.17731	41.242	41.313	42.393

stochastic gradient issue, selection of appropriate layers and neurons have been resolved to develop a robust algorithm.

IX. DISCUSSION

Numerous methods and procedures have been developed for the robust identification of the flash floods as flash floods are acknowledged as superior disaster in natural disasters.

TABLE 14. Comparative analysis of AI based approaches [4].

Performance Indices	ANN	SVM	ANFIS	NNARX	Modified MFN-PSO
RMSE	0.194	0.390	0.116	0.090	0.0037
Best Fit	73	64	78	80.10	97.3
Results	Satisfactory	Unsatisfactory	Satisfactory	Satisfactory	Satisfactory
Hourly Data	6 hrs	6 hrs	3 hrs	3 hrs	3 hrs
Accuracy	73	64	78	80.16	98.89
Precision	Medium	Low	High	High	High
Reliability	Medium	Low	High	High	High
Power Utilization	Limited	Limited	Limited	Limited	Limited

The electronics sensors and circuitry were used to collect the data more accurately and precisely. Classification filter process and optimization was made very convenient by using proposed algorithm. The proposed algorithm MFN-PSO does not require any advance computational resources. Simulated results proved that proposed algorithm MFN-PSO performed better compared to other existing approaches.

This research was carried out to identify the flash floods accurately and precisely. To smoothly execute the research, the Modified Multi-layer feed forward neural network with PSO and modified multi-layer feed forward neural network with Cuckoo search was developed for the identification of floods.

Modified cuckoo search has been applied on the actual data. MFN Cuckoo search has been used to discriminate and detect the flash floods reliably. The MFN Cuckoo search simulated results have shown that proposed strategy has performed better than the existing trends for the determination of flash floods. The simulated results on real time data were compared with the existing MFN-PSO (Combined hybrid algorithm) method. Processed time and accuracy with less error are the most significant parameter to judge the performance level of the algorithm.

MATLAB results have been compared with MFN-PSO and it has been proved that proposed algorithm has performed more accurately and rapidly with 0.0013707 mean squared errors than the available techniques. The innovation of the proposed research is the bunch of transducers that has been correlated to identify the flash flood robustly. Measurement of CO_2 levels and soil magnetic flux were processed using MLP algorithm can be acknowledged as a novel approach that was proposed in earlier research paper. MFN-Cuckoo search performed 100 iterations normalized the data more rapidly with the 0.030151 error. The proposed algorithm increased the credibility of early warning systems for flash floods.

In Table 14. Various performances indices of different AI based algorithms have been represented to show the comparative analysis. Comparative analysis has been performed in terms of RMSE, Best Fit, Accuracy, hourly data, accuracy and power utilization. The analysis proved that root mean square (RMSE), best fit and accuracy of modified MFN-PSO was found to be 0.0037, 97.3 and 98.89% respectively.
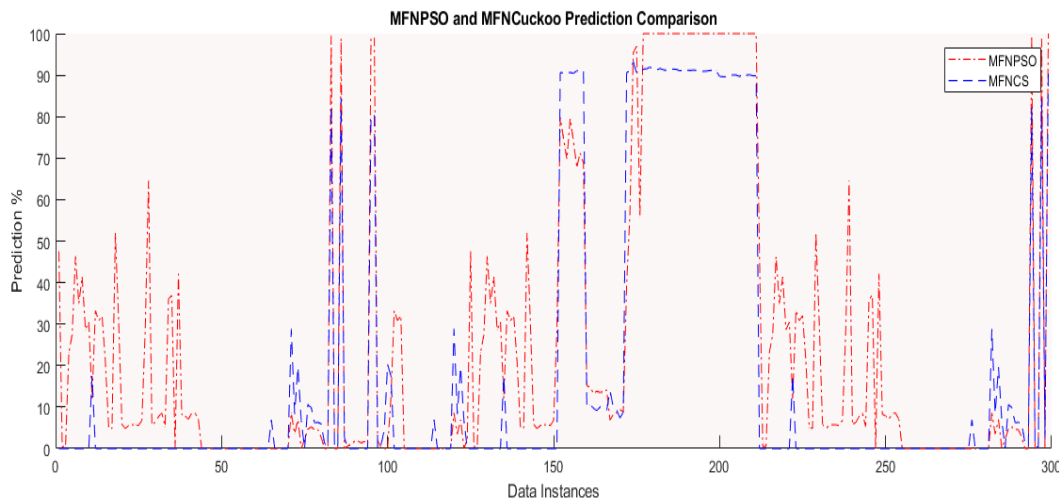
FIGURE 12. Graphical comparison for MFN-PSO and MFN-CS.

The comparative analysis proved that proposed algorithm MFN-PSO worked better than the other existing approaches.

X. CONCLUSION

Simulated results proved that proposed algorithm worked as a better classifier and forecasting tool for the flash floods. Our proposed research can be considered as a cost-effective novel solution. False alarm rate has been reduced by using feed forward propagation with the combination of particle swarm optimization (PSO). It can be concluded on the basis of the results that our proposed research can predict the flash floods in very less time as elapsed time has been mentioned in the output. Moreover, it the proposed algorithms can be adopted to identify the actual event in many real-life applications by collecting their respective data. The real time data can be processed by the proposed algorithms with the slight modification in MATLAB code. The proposed algorithms can be used for the breast cancer classification, prediction of seizures, prediction of syndromes in unborn, heart disease classification and other prediction and classification applications with less false alarm rate.

XI. LIMITATIONS

1. Real time data collection is possible but more computational resources required for the collection of real time data and real time process of proposed algorithm.
2. MATLAB data acquisition was not designed to compute the real time data.
   An effort was made to achieve the real time data acquisition using interface between Arduino support package and Simulink but it was not successfully executed as sampling frequency varied.
3. The direct real time data from Arduino can be received through serial communication by manually coding Arduino but data receiving rate was late.

4. Almost all the tuning parameters have been modified manually to get the best optimal results such as learning rate, momentum, number of iterations, number of layers, number of neurons and constant "c1" and "c2" values. These parameters should be adjusted automatically to resolve the stochastic gradient problem.

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