Early Identification of Flash Floods: Artificial Intelligence based Forecasting using Modified Cuckoo Search

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Summary
Flash floods are one of the most dangerous natural disaster which can devastate number of buildings, lands, cattle and human lives within seconds. The early and sure identification of flash flood can be regarded as the most complex task. Heavy precipitation and chocked streams may also cause flash floods. Cattles have to suffer due to the extreme floods. Generally intensified floods damage all the objects that comes around in the affected area of flood including vehicles, roads, building and bridges as well. Diversified approaches have been developed and designed to predict the flash floods accurately and precisely. Construction on the basis of modeling of dams and reservoirs to prevent the flash floods have been suggested by researchers. Many Artificial intelligence-based methods like NNARX, PSO, MLP, Cuckoo search, Bayesian classifier, dempster Shafer and ANFIS have been designed to forecast the flash floods with less false alarm. Direct measurement from instruments and gauges were also considered important for the data collection. Several parameters have been used in the past to detect the flash floods like precipitation velocity, wind velocity, wind direction, temperature, humidity, soil moisture, pressure, water color and cloud to ground (CG) flashes. In our proposed research the multi-sensor data has been collected and artificial intelligence based a unique algorithm modified cuckoo search has been designed to reduce the false alarm. Results were successfully achieved in the MATLAB. Results have also been bench marked by comparing the MLP-PSO. Graphical analysis proved that our proposed algorithm worked better than the other existing approaches.
Keywords:
Modified cuckoo search, flash floods, PSO, Artificial Intelligence, Predictive analysis

1. Introduction

Flash floods are acknowledged as the most alarming natural threat therefore faster analysis was required. Usually an agricultural country's economy depends upon the irrigation system. Irrigation can be acknowledged as the back-bone of agricultural country. Irrigation water has been given significance as they consist of several large and small rivers and canals. The river height increases to the dangerous level due to the northern glaciers which also intensify the water level of dams and canals to the critical condition. This cautionary condition cause flash floods as they are very sudden [1]. Many consolidated variables have been examined vigorously to identify the flash floods like wind speed, precipitation speed, water color, wind direction, upstream level, soil moisture, oceanic wave current, wave pattern, cloud to ground (CG) flashes and temperature. All these parameters have been observed, discriminated and filtered by artificial intelligence (AI) based algorithms to identify the intense run offs more accurately [2]. Modified Particle swarm optimization (MPSO), Adaptive neuro fuzzy interference system (ANFIS), Neural network autoregressive model with exogenous input (NNARX), Extended Kalman Filtering (EKF), Fuzzy Inference systems (FIS) and more artificial intelligence (AI) based algorithms have been developed in past to attain more efficiency in predicting floods [2]. AI based classifiers based on fuzzy logic have been designed to diminish the false alarms [2].

To eradicate the false alarm during hard and rigid environmental surroundings a sensor fusion algorithm was developed using directed Acyclic Graph (DAG) and probability tables [3]. Artificial Neural Network (ANN) methods have been utilized to develop the predictive analysis model of linear and non-linear meteorological and hydrological processes like high precipitation and run offs relationship, precipitation analysis using radar and forecasting of precipitation and flash floods [4]. Various characteristics of water module sensors have been evaluated like water peak observation in run time and run offs identification vigorously that is generally due to the heavy rain [5]. Combined Neural Network Autoregressive with Exogenous Input (NNARX) with Extended Kalman Filter (EKF) was recommended for designing the predictive analysis model for the prediction of complicated run offs. The real time supervisory control and data acquisition (SCADA) based system was constructed at Klang river in Malaysia [6]. Developed predictive model confirmed that

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hybrid combo worked better than the NNARX [6]. Geomagnetic field that is emitted from the earth center was also determined for the prediction of the flash floods confirming the fact that magnetic field recorded by Tesla meters minimized briskly during the flash flood event [7]. Hourly predictive model was designed at Petaling bridge, Klang river, Malaysia for the robust detection of floods. Hourly based investigation of water height was predicted using NNARX [8]. Genuine data value reading of soil moisture can be acknowledged as a fundamental for the identification of intense run off. These soil moisture readings can be utilized with the prediction model (hydrological) to enhance the reliability and accuracy. Results confirmed that assimilation of soil moisture from various regions can enhance the predictive model capabilities. [9]. Floods routing areas can also be copied accordingly by using computational fluid dynamics method. Excrement discharge, flash flood flow and flow disorder were measured using OPENFOAM simulations [10]. Ultrasonic and temperature sensors have been deployed to observe the flash floods and artificial neural network was designed on the remotely collected data set. Results verified that this approach could compute the water height accurately with error less than 2cm [11].

Sensitivity measurement was done to know the rainfall indication and errors of satellite for the flood forecasting (medium size). The earth complex surroundings were regarded as an in important factor in the prediction of flash floods [12]. Another methodology has been studied out using depth distance of water and flood mapping. Spectral-temporal principal component analysis (STPCA) was advanced to spectral-temporal minimum noise fraction (STMNF). Spectral-temporal minimum noise fraction (STMNF) technique attained accuracy of 97.09% with a kappa coefficient of 0.889 in flood mapping [13]. Flash floods are very frequent at western Himalayan. Most of the western Himalayan has been covered by low heightened clouds with severe intense rain cycles. A nowcasting model for intense rain events has been developed by using cloud top cooling rate (CTCR) to predict the locations of heavy rainfall. The proposed model performed better with 82.8% accuracy in determining genuine intense rain episodes with false alarm rate of 29.7% [14]. Signal attenuation and distortion in Television satellites due to the rainfall was calculated and flood mapping was done. It has been noticed that Ku band frequencies deteriorated due to rain fall and climate change. Simulated maps of run offs were compared with the existing mapping methods to verify the approach [15]. Genuine analysis of severe rainfall and wind speed is necessary for the rigorous determination of flash flood flow. Generally, rainfall observations are done by instruments, gauges, radar and satellite-based images. Freshly a novel strategy commercial wireless communication networks (CWCNs) has been developed to identify the rain, snow and storm [16].

2. Problem Statement

Forecasting the correct time and accurate location of flash floods requires advance computational resources based high resolution modeling of water, climate, meteorological bathymetry and large data sets for calculation assessment and true positive detection. Generally incapable and incompetent algorithms would not be able to identify the flash floods more rigorously and briskly due to the false alarms. High false alarm rate is well known as the critical issue as it would be more difficult to classify the true positive event and false positive event. Early warning decision making is badly required to propagate the evacuation routes during the flash flood emergency [2][7][17]. False alarm ratio in identifying the flash floods are high as the input data may contains missed values, repetitive and inconsistency in the variable and prediction model [18]. Mostly sensors and transducers have high false alarm rate due to the incapable algorithms [19]. Harsh atmospheric conditions also affect the sensors and gauges [20].

3. Methodology

3.1 Main Flow Diagram

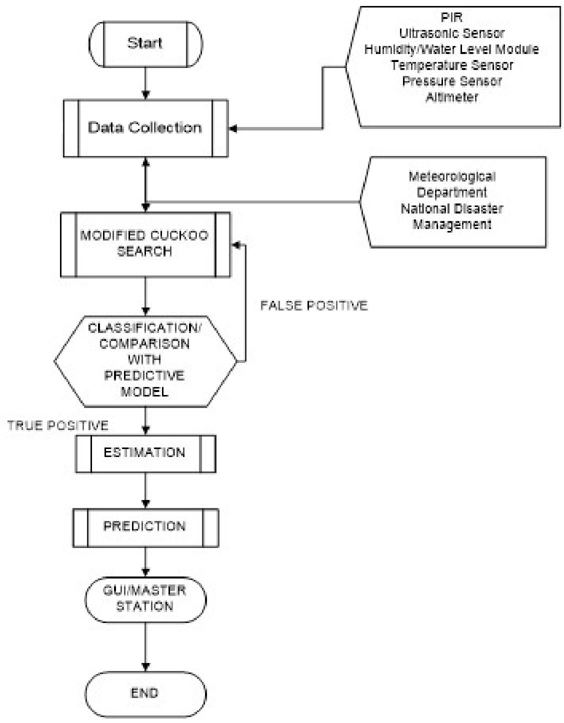


Fig. 1 Main Flow Diagram

Fig. 1 explains the fundamental flow diagram of the proposed solution for the identification of floods. Large number data set has been collected from the Kund, Malir Karachi, Pakistan. Water height has been computed by the water level module. Ultrasonic sensors have been utilized to record the distance of floods. Passive infrared sensor (PIR) was used to identify the presence of the flood as it buzzes upon the detection of water. Temperature and pressure transducers have been used to record the values of temperature and pressure. Altimeter gives off the latitude reading from the center of earth. The large data set has been calculated by the multi-modal sensing gadget. The multi-modal sensing gadget consisted of water level module, passive infrared (PIR), temperature, pressure and ultrasonic sensors that were interfaced with the Arduino micro controller. ESP8266 Wi-Fi module was also installed as the data may be attained wirelessly on remote locations and with wired to the personal computer application. Data was received serially on serial port. Modified Cuckoo search with hybrid ANN feed forward propagation was tested on the large collected data for the prior warning of the flash floods with the less false alarm rate. True positive event and false positive was classified and true value was optimized by the modified cuckoo search producing best optimal results.

3.2 Modified Cuckoo Search Algorithm Implementation

Cuckoo search has been designed with the combination of feed forward network. Cuckoo search can be regarded as well-known metaheuristics algorithm for solving the optimization and data fusion in several complex engineering problems. Solution vector was designed by egg as Cuckoo search is a nature inspired algorithm and cuckoo lays one egg in the nest at a time. A host can identify a unique egg with the probability of pa ∈ (0, 1). In multimodal optimization, each modal has its own optimization pattern or target which may vary with each other. Cuckoo search has the capability to manage the multimodal optimization issued rigorously. Several techniques of the cuckoo search with different variants have been developed to get the better multi objective problem resolution. Thresholds and ranges have been set. Six parameters threshold have been decided. Distance, rainfall, Carbon dioxide levels, temperature, pressure and altimeter. Moreover, the sensors were correlated to each other and probabilities were also estimated to predict the flash floods.

```
DistanceUB = 50;        %Maximumlinit of distance
RainFallUB = 300;       %Maximum limit of Rain
CO2UB = 600;            %Corbon oxide values
TempUB = 50;            %Temperature uper limitation
PressureUB = 5000;      %Uper Limit of Pressure
AltimeterUB = 1000;     %Uper Limit of Altimeter
```

```
for u = 1:LE
  if (PIR(u,1) == 1) && (Distance(u,1) < DistanceUB) && (Rainfall(u,1) > RainFallUB) && (CO2(u,1) > CO2UB) && (Temperature(u,1) < TempUB) && (Pressure(u,1) > PressureUB) && (Altimeter(u,1) > AltimeterUB)
     target(u,1) = 1;
  end
end
```

Artificial neural network feed forward propagation was applied to discriminate the date with the combination of the famous cuckoo search

```
m=length(inputs(:,1));
o=length(targets(:,1));
n=5;
net=feedforwardnet(n);
net=configure(net,inputs,targets);
kk=m*n+n+n+o;
% Lower bounds and Upper Bounds
Lb = -1.5*ones(1,kk);
Ub = 1.5*ones(1,kk);
% Random initial solutions
nest = zeros(Nests,kk);
for i=1:Nests
nest(i,:)=Lb+(Ub-Lb).*rand(size(Lb));
end
```

Local random walk can be represented as:

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

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

While Global random walk is described as

$$x^{t+1} = x^t + \alpha L(s, \lambda), \quad (2)$$

Cuckoo search random walk function was given as:

function nest=get_cuckoos(nest,best,Lb,Ub) (3)

Levy flights exponent and coefficient are given as:

beta=3/2; (4)

sigma=(gamma(1+beta)*sin(pi*beta/2)/(gamma((1+beta)/2)*beta*2^((beta- 1)/2)))^(1/beta);
(5)

Levy flights by Mantegna's algorithm can be defined as:

```
u=randn(size(s))*sigma;
v=randn(size(s));
step=u./abs(v).^(1/beta);
```

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

stepsize=0.01*step*(s-best); (6)

ANN-CS Function value can be defined as:

Function
Value=cuckoo_search(Cuckoo_Iterations,inputs,targets)
Number of nests (or different solutions) can be given as:
Nests=20;

The discovery rate of alien eggs/solutions is
pa=0.25;

Lower bounds and upper bounds are represented as:
Lb = -1.5*ones(1,kk);
Ub = 1.5*ones(1,kk);
Randomly initials solutions are described as:
nest = zeros(Nests,kk);
for i=1:Nests
nest(i,:)=Lb+(Ub-Lb).*rand(size(Lb));
end
To achieve the best current fitness function was described as:

fitness=10^10*ones(Nests,1); (7)

After the iterations new solution were generated. New solutions have been estimated and then counter was updated. To compute the mean error was very difficult due to the unpredictability in the model. Mean squared error (MSE) produced statistical analysis as it is the difference between the predicted and calculated values. To properly implement and verify the ANN-Cuckoo search, mean squared error was estimated by using the following equation:

ANN Cuckoo_err = sum((net_cuckoo(inputs)-targets) ^2)/length(net_cuckoo(inputs)); (8)
Activation trigge function of the modified cuckoo search can be described as:

f=sum((net(inputs)-targets) ^2)/length(inputs); (9)

4. Results and Simulations

4.1 Data Normalization

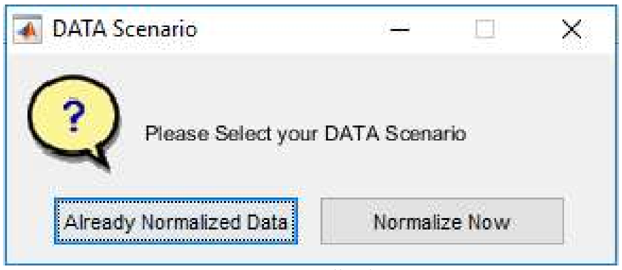


Fig. 2 Data Normalization

Fig. 2 shows that two scenarios were set for the normalization of the data. Usually data contains repetitive and missing values, for the smooth implementation of algorithm data set must be in an organized form. Data set was normalized to reduce the inconsistent values, repetitive values in data set and undesired parameters like units. Following two types of data switching were fixed in the code

```
case 'Already Normalized Data'
       filename = 'datafile.xlsx';  % Excel File containing Training Data
       sheetname1 = 'Sheet1';
sheetname2 = 'Sheet2';
```

In already normalized data selection mode the data is imported directly from the data file.

```
input = xlsread(filename,sheetname1,'A1:Z10000');  % Inputs of Training Data
target = xlsread(filename,sheetname2,'A1:Z10000');  % Targets of training Data
inputs=input';
targets=target';
   case 'Normalize Now'
       filename = 'datafile.xlsx';  % Excel File containing Training Data
       sheetname1 = 'Sheet1';
       input =
xlsread(filename,sheetname1,'A1:Z10000');  % Inputs of Training Data
```

If the user selects normalize now mode, then the collected data file is treated with the training data file so that the data valued would be smooth.

4.2 Regression Plot

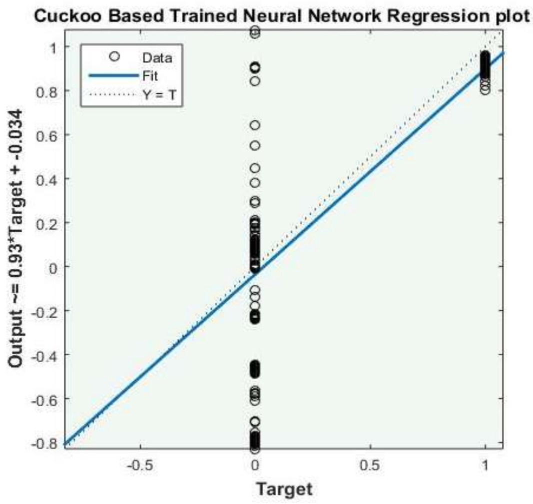
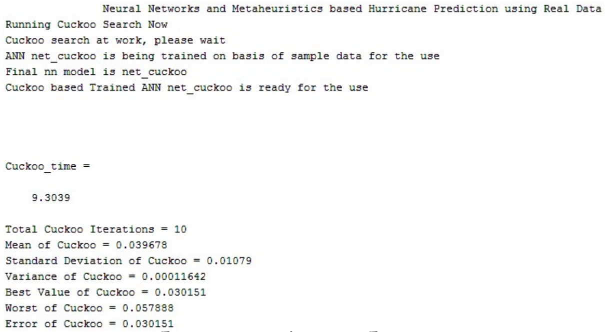


Fig. 3 Regression Plot

Regression plot is the graphical illustration of training predictive model. Regression plot showed the relation between the data set measured parameters and targets. Regression plot was produced in MATLAB using following instructions;
figure;

plotregression(targets,net_cuckoo(inputs))
title('Cuckoo Based Trained Neural Network Regression plot ')
disp('Cuckoo based Trained ANN net_cuckoo is ready for the use');

4.3 MATLAB Simulated Results



```
Neural Networks and Metaheuristics based Hurricane Prediction using Real Data
Running Cuckoo Search Now
Cuckoo search at work, please wait
ANN net_cuckoo is being trained on basis of sample data for the use
Final nn model is net_cuckoo
Cuckoo based Trained ANN net_cuckoo is ready for the use

Cuckoo_time =

    9.3039

Total Cuckoo Iterations = 10
Mean of Cuckoo = 0.039678
Standard Deviation of Cuckoo = 0.01079
Variance of Cuckoo = 0.00011642
Best Value of Cuckoo = 0.030151
Worst of Cuckoo = 0.057888
Error of Cuckoo = 0.030151
```

Fig. 4 represented that after the normalization of the data set the algorithm started to run. Initially the ANN cuckoo search based on the combination of the feed forward propagation and cuckoo search was trained according to the given training data file. Test vector of was designed to compute the flash floods probabilities. The data set was collected from own fabricated multi modal sensing gadget contained six sensors for the measurement of six parameters. All six sensors outputs were correlated to each other to determine the true positive event. The training time of modified cuckoo search algorithm was found to be 9.3039 seconds. Results confirmed that pair of sensors could detect floods better compared to only one single sensor-based analysis as single sensor output may produce false positive. When all sensors crossed threshold the activation function of algorithm was triggered. Data set was processed by using modified cuckoo search and following simulation output resulted,

Running ANN Cuckoo Search Now
Ann Cuckoo search at work, please wait
ANN net_cuckoo is being trained on basis of sample data for the use
Final nn model is net_cuckoo
Cuckoo based Trained ANN net_cuckoo is ready for the use
Cuckoo_time =9.3039 seconds

S.No 1 = [0 0 0 23.19 100270.57 44.47] Flood Probability = 0%
S.No 2 = [0 458 539 29.95 100268.39 44.26] Flood Probability = 0%
S.No 3 = [0 459 533 29.71 100277.53 43.76] Flood Probability = 0%
S.No 4 = [0 453 418 29.6 100279.78 43.61] Flood Probability = 0%
S.No 5 = [0 453 397 29.46 100277.46 43.86] Flood Probability = 0%
S.No 6 = [0 450 356 37 100280.05 43.76] Flood Probability = 0%
S.No 7 = [0 450 356 29.4 100280.05 43.76] Flood Probability = 0%
S.No 8 = [1 504 355 28 110424.17 -776] Flood Probability = 0%
S.No 9 = [1 494 412 23 110424.17 -776] Flood Probability = 0%
S.No 10 = [1 485 399 23 110424.17 -776] Flood Probability = 0%
S.No 11 = [1 479 382 23 100283.5 -776] Flood Probability = 17.5216%
S.No 12 = [1 476 349 23 110424.17 -776] Flood Probability = 0%
S.No 13 = [1 483 400 23 110424.17 -776] Flood Probability = 0%
S.No 14 = [1 478 387 23 110424.17 -776] Flood Probability = 0%
S.No 15 = [1 551 392 23 110424.17 -776] Flood Probability = 0%
S.No 16 = [0 512 387 23 110424.17 -776] Flood Probability = 0%
S.No 17 = [0 518 388 23 110424.17 -776] Flood Probability = 0%
S.No 18 = [1 529 389 23 110424.17 -776] Flood Probability = 0%
S.No 19 = [1 498 386 23 110424.17 -776] Flood Probability = 0%
S.No 20 = [0 491 385 23 110424.17 -776] Flood Probability = 0%
.S.No 280 = [0 503 1011 23 110424.17 -776] Flood Probability = 0%
S.No 281 = [0 500 1011 23 110424.17 -776] Flood Probability = 0%
S.No 282 = [0 497 314 26.64 61905.55 3927.77] Flood Probability = 28.8334%
S.No 283 = [0 497 661 26.64 61905.55 3927.77] Flood Probability = 8.3209%
S.No 284 = [0 493 437 26.64 61905.55 3927.77] Flood Probability = 19.643%
S.No 285 = [0 494 545 26.64 61905.55 3927.77] Flood Probability = 6.7261%
S.No 286 = [0 487 1008 26.64 61905.55 3927.77] Flood Probability = 0%
S.No 287 = [0 486 591 26.64 61905.55 3927.77] Flood Probability = 10.6098%
S.No 288 = [0 473 571 26.64 61905.55 3927.77] Flood Probability = 9.8485%
S.No 289 = [0 466 635 26.64 61905.55 3927.77] Flood Probability = 6.2554%
S.No 290 = [0 467 636 26.64 61905.55 3927.77] Flood Probability = 6.3102%
S.No 291 = [0 500 743 26.64 61905.55 3927.77] Flood Probability = 5.955%

S.No 292 = [0 514 1012 26.64 61905.55 3927.77]
Flood Probability = 1.2256%
S.No 293 = [0 501 1012 26.64 61905.55 3927.77]
Flood Probability = 0.33702%
S.No 294 = [1 506 1012 26.64 61905.55 3927.77]
Flood Probability = 82.4184%
S.No 295 = [0 504 1013 26.64 61905.55 3927.77]
Flood Probability = 0.49817%
S.No 296 = [0 501 1013 26.64 61905.55 3927.77]
Flood Probability = 0.29575%
S.No 297 = [1 530 1012 26.64 61905.55 3927.77]
Flood Probability = 84.4613%
S.No 298 = [0 532 1011 26.64 61905.55 3927.77]
Flood Probability = 2.6593%
S.No 299 = [1 621 1013 26.64 61905.55 3927.77]
Flood Probability = 90.5414%
Elapsed time is 9.225149 seconds.
>>
The elapsed time was calculated to be 9.225149 seconds.

4.4 Graphical Analysis of Modified Cuckoo search

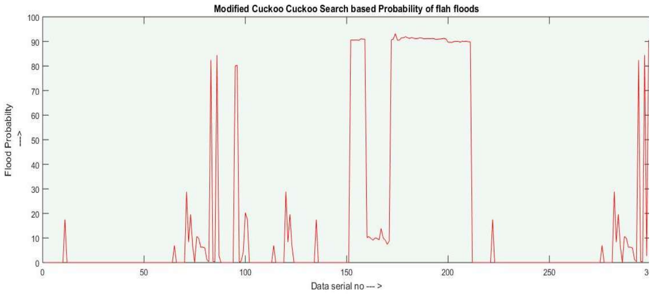


Figure 4. Graphical analysis of modified cuckoo search (Line Graph)

Fig. 4 exhibited the graphical analysis of the forecasting model based on modified cuckoo search for determination of flash floods. Modified cuckoo search has been used to discriminate true positive event and attain better optimized results. Data set has been presented serially on x-axis and calculated probabilities have been given on y axis.

4.5 Pictorial analysis of Modified Cuckoo search

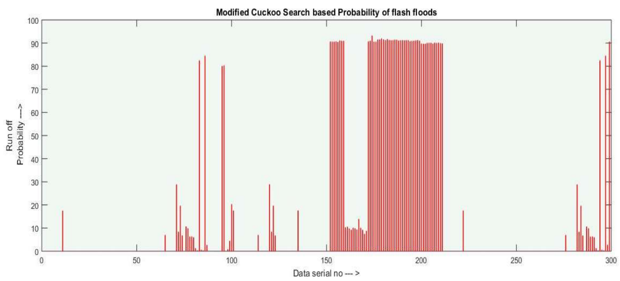


Figure 5. Pictorial analysis of modified cuckoo search (Line Graph)

The Fig. 5 represented the pictorial analysis of identification of sever run-offs. The bar graph shows the probability of run-offs on the y-axis and x-axis is representing the data set serial. The graph has been plotted in MATLAB.

5. Benchmarking

For the validation of the proposed algorithm the results of ANN cuckoo search have been compared with the MLP-PSO. The comparative analysis has been shown graphically. The MLP-PSO has been applied in our past researches [19]. Same data set was applied to the algorithm and ten compared.

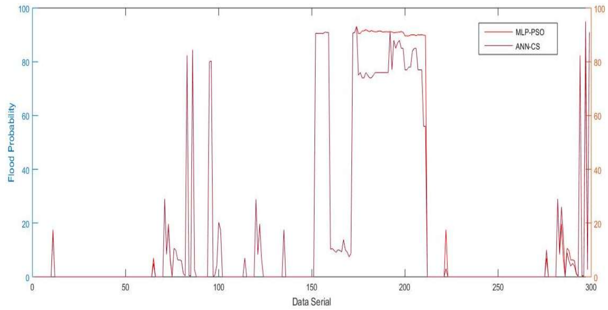


Figure 6. Comparison of proposed modified cuckoo search and MLP-PSO

6. Conclusion

Data set has been calculated from our own developed multi-modal sensing gadget. Modified cuckoo search has been developed to detect the floods rapidly and precisely with less false alarm rate. Simulation results of proposed algorithm were compared with the novel approach MLP-PSO which was applied in our past researches. The simulated results were compared with the existing MLP-PSO (Combined hybrid algorithm) approach. Results confirmed that ANN Cuckoo search has worked better than the PSO as the accuracy has increased to 96.35 % from 94.69%. Moreover, training time and elapsed time can be used as a yardstick to gauge the algorithm. MATLAB results have been compared with MLP-PSO and it has been proved that our proposed algorithm has performed more accurately and rapidly with 0.0067 mean squared error 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-PSO algorithm can be acknowledged as a novel approach that was proposed in our earlier research paper.

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