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ORIGINAL ARTICLE

Comparative Performance Analysis of Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient for the Prediction of flash Floods

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ABSTRACT

Severe flash floods are the root cause of the increased death toll of humans, cattle, and devastation of infrastructure in various countries. Flash floods can be considered as one of the most horrible unpredictable disasters in the world. Floods may cause due to the severe precipitation velocity, cloud to ground flashes and melting of debris in the ocean. Diversified methodologies were adopted to detect the flash floods rapidly and timely. Almost dozens of sensors have been used to detect all the evaluation parameters concerned to the flash floods like upstream level, precipitation intensity, flood magnitude, run-off velocity, color of the water, precipitation velocity, pressure, temperature, wind speed, wave pattern and cloud to ground (CG flashes). Transducers and sensing elements produce false alarms or irrelevant information as well due to the inadequate algorithms. False alarm rate is the cause of bad forecasting of floods due to the incompetent algorithms. In this research paper comparative analysis of Bayesian regularization, Levenberg Marquardt and scaled conjugate gradient-based neural network learning has been performed to determine the best learning algorithm for solving optimization issues with less false alarm rate. Results showed that Bayesian regularization worked better than the other learning algorithms in terms of better fitness, regression value, mean square error in fewer epochs.

Keywords: Flash floods, Levenberg-Marquardt, natural disaster, Bayesian Regularization, Disaster management, Scaled conjugate gradient

Author`s Contribution	Address of Correspondence	Article info.
[1,2,3,4,5]*Manuscript writing, Data analysis, interpretation, Conception, synthesis, planning of research, Interpretation and discussion, Data Collection*	*M.S Mazliham* *Email: mazliham@unikl.edu.my*	*Received: Jan 11, 2019* *Accepted: Nov 07, 2019* *Published: December 30,2019*

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INTRODUCTION

Severe floods are one of the most classified adversities in countries like China, India, Nepal, Malaysia, Bangladesh, South France and the Philippines which causes a huge amount of death ratio and also damage to buildings and other facilities [1]. The sudden and huge amounts of rain are also frequent in the mentioned countries. A huge amount of work has been done to encounter this salient problem. To calculate authentic and actual analysis of thunderstorms, hurricane and severe floods few sensor devices like precipitation magnitude sensor, water upstream level indicator, wind speed (anemometer), precipitation velocity sensor, pressure and temperature of the run-off and oceanic bottom pressure via acoustic link have been applied. A few research also involved direct calculation and measurement using gauges, few of them applied the aggregation of satellite and Radar based results [1-3]. In contrast to the last research work, authors calculated the integrated geomagnetic field and estimated the flood prediction for controlling the flood disasters during the adversity [2]. A few investigations used high definition X-band pictures captured with the help of Radar to analyze Tsunamis and floods [4]. A layout was implemented using Partial Differential Equation (PDE) for the estimation of different aspects of these adversities. A considerable amount of studies and evaluation have been done using Fuzzy Logic Controller (FLC), Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Interference Systems (ANFIS), Fuzzy Interference System (FIS), ANN and NNARX, Kalman Filtering, Bayesian Classifier, Particle Swarm Optimization (PSO) and Extended Kalman Filtering (EKF). Due to these techniques, huge standards have been set to estimate and predict the events on an early basis [5-8]. This research includes five segments. The first segment consists of the introduction of the paper. Segment II is composed of on-going research trends. Segment III elaborates methodology and proposed solutions. Segment IV discusses results comparison

LITERATURE REVIEW

A few pieces of research have been developed like (NISTARA) composed of multiple sensors (temperature, fire, rainfall, and pressure) was introduced to estimate and predict floods. Among different sensors, smoke detectors have a very huge percentage of fake alarms as compared to temperature sensors. So, the merger of both can be used. The draining path will be determined on the ground of fuzzy logic built upon discrete fire severities [9]. The huge amount of precipitation might forward towards the weather threat with a merger form the water cycle and wind activeness. The low peak of GPS PWV could be proposed as the first-level indicator. As per noticed the severe reduced value of GPS PWV was low during evening time within the span of two to three days earlier the floods and a moderate level of GPS PWV was at peak value during the span of adversity [10]. The proposed solution having the lowest failure rate was preferred to determine the accurate results. Mean square error was adopted to calculate the error and its result was 0.2. A Scheme was flourished by implementing SCADA technique to avoid catastrophe. Both models involved neural network like process. Performance of Radar and rain measurement system was not up to the mark and their results were also inconsistent and they required regular maintenance. Research was implemented at a place named Garden de Mialet a watershed of the Gardon d'Audze. The place was approximately 220 square kilometers and its height varied from 147 to 1170 meters with a 36 percent gradient area. Predicted conclusion proved that in the absence of any preceding data neural networks are efficient enough to calculate the disaster [11-12]. To determine any diverse behaviour in climate radar can be installed as a crucial tool as Radar is very effective in severe conditions [13]. For robust calculation of run-offs variety of different techniques have been used. Fuzzy Logic Controller (FLC), Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Interference Systems (ANFIS), Fuzzy Interference System (FIS), ANN and NNARX, Kalman Filtering, Bayesian Classifier, Particle Swarm Optimization (PSO), Extended Kalman Filtering (EKF) and Machine learning (ML) have been applied for prediction of disaster [1-3].

A sensor node described as a "shock sensor" or piezoelectric transducer. For detecting voice input microphone is installed. They also have a very high percentage of false results [14]. Surrounding data was being captured and analyzed. Sending complete information towards base station was found to be very costly, hence to eliminate fake alarms distributed algorithm techniques were needed. Fuzzy k-means and k-means well-known clustering techniques have been implemented to identify the floods timely. Both techniques have the same working principle but the primitive variation that a fragment was fixed to a specific cluster. Fuzzy logic controller and Bayesian classifier have been used as classifiers [15]. This study aimed to differentiate the false alerts. RR intervals, Invalid blocks and QRS complexes were investigated and if there was a fake alert present and identified the process ended. PPG (photoplethysmograph) and ABP (Arterial blood pressure) were determined when to merge with QRS complexes. The highest and lowest values of standard deviation and heart rate of RRs were correlated to the limits [16]. To certify the assumption SVDD (Support Vector Data Description) and SVDM calculations were investigated. Allotment in machine learning and data analysis is one of the crucial tasks. To perform this crucial task several techniques are being adopted like decision trees to evaluate the performance [17]. Conclusive evidence provide a merger of Extended Kalman filter and SD-CFAR can detect effectively in contrast with other methods used to estimate underground substance and it can provide more accurate results [18]. Diversified process to minimize fake alerts in the estimation of run-off has been proposed with several other techniques that are in practice like Support vector machine (SVM), PSO (Particle swarm optimization), Kalman filtering, Extended Kalman filtering (EKF), Multilayer perceptron (MLP), ImPSO (Improve Particle swarm optimization) and Genetic Algorithm [19].

RESEARCH METHODOLOGY

A. Levenberg-Marquardt

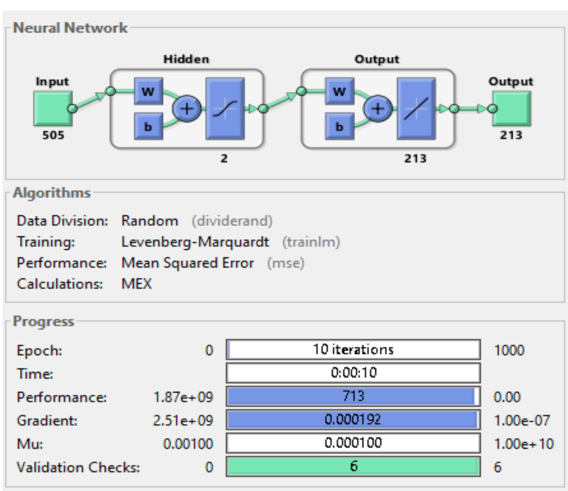


Figure 1. Levenberg-Marquardt Neural Network

Levenberg-Marquardt learning algorithm was applied to the collected data set. The data set has been collected in previous research as well using an appropriate combination of sensors for the thorough identification of flash floods. The data set comprised of six attributes names as Passive infrared sensor (PIR), temperature, wind velocity (pressure), distance, carbon dioxide levels in the environment and altimeter [24]. Actually, it updates the parameter between the Gauss-Newton and Gradient Descent method.

$$F(x) = \frac{1}{2}\sum_{i=1}^{m}[f_i(x)]^2. \tag{1}$$

Fig. 1 shows the neural network configuration using two neurons. After completing the ten iterations it started to achieve good results for training the algorithm.

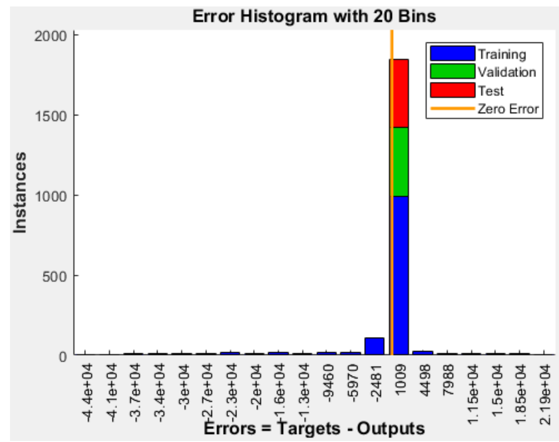


Figure 2. Error Histogram

Fig. 2 shows the error histogram of the Levenberg-Marquardt algorithm. The number of bins represents the vertical number of observed bars while error can be graphically seen from orange-colored vertical bar.

Results

	Samples	MSE	R
Training:	6	59793286.85571e-0	9.67743e-1
Validation:	2	42584.21005e-0	7.39527e-1
Testing:	2	68178.41604e-0	8.68536e-1

The Levenberg-Marquardt can optimize the non-linear data in very little time but takes a lot of memory as it updates the parameter using Gauss-Newton and Gradient Descent. The algorithm stops the epoch if the minimum error is achieved because further epochs may increase the mean square error (MSE) in training, validation and testing.

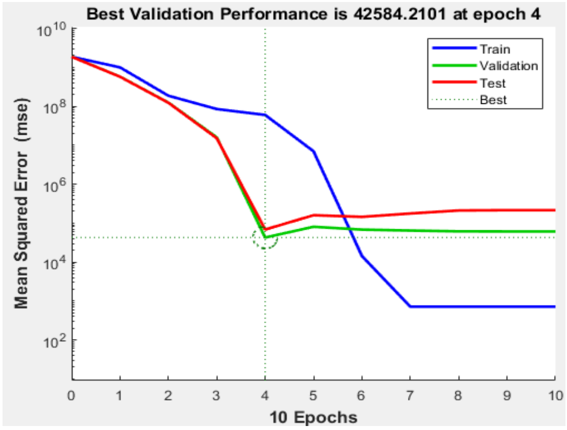


Figure 4. Levenberg-Marquardt Validation Performance

Fig. 4 displays the graphical analysis of the best validation performance achieved by the Levenberg-Marquardt at 10 epochs. After 10 epochs it may easily notice that the mean square error started to increase and fitness was not close enough therefore algorithm stopped at 10 epochs automatically.

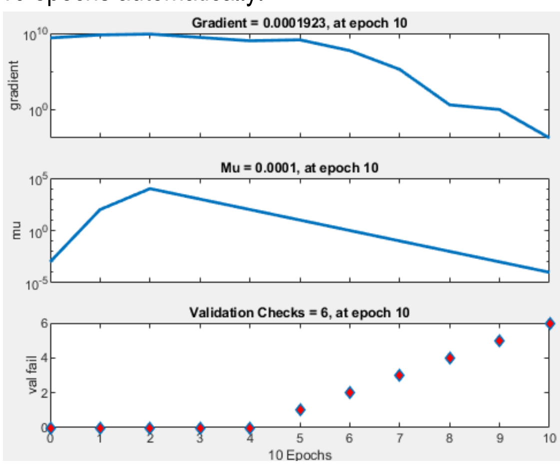


Figure 5. Training Plot

Fig. 5 represents the gradient value of 0.0001923 at the epoch at 10. Mu was achieved 0.0001 at epoch 10. Validation checks failure was found to be 6 at epoch 10.

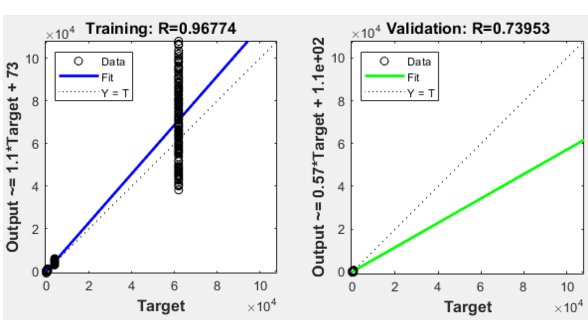


Figure 6. Training and Validation Analysis

Fig. 6 demonstrated the training correlation and validation correlation comparison. Basically, the regression value R is the measurement of correlation the desired and actual output. If the regression value R is equal to one, it can be acknowledged as a close relationship between actual and desired output. If the regression value is zero then it can be considered as a random relationship.

B. Bayesian Regularization

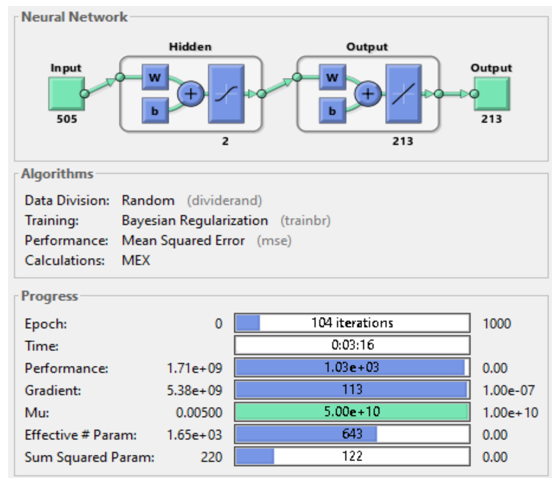
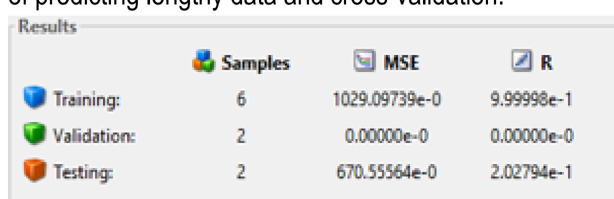


Figure 7. Bayesian Regularization Configuration

Fig. 7 demonstrated the neural network configuration of Bayesian Regularization using two hidden neurons. Approximately 104 iterations were processed. The best validation performance was achieved at epoch 57. Bayesian Regularization neural network works better than then convention back propagation neural network in terms of predicting lengthy data and cross-validation.



Results

	Samples	MSE	R
Training:	6	1029.09739e-0	9.99998e-1
Validation:	2	0.00000e-0	0.00000e-0
Testing:	2	670.55564e-0	2.02794e-1

Figure 8. Bayesian Regularization Results.

Fig. 8 represents that the Bayesian Regularization was applied on the same dataset, the mean square error and regression values can be easily noticed here for the training, validation, and testing which are far better than the Levenberg-Marquardt learning algorithm. Results proved that a neural network with Bayesian regularization deals with the non-linear data more intelligently compared to the Levenberg-Marquardt for the predictive analysis of flash floods. But sometimes Bayesian regularization stuck in a huge datasets due to the regularization computation of data.

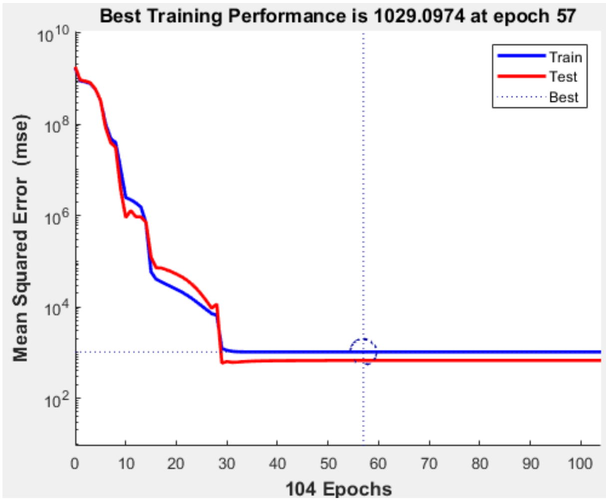


Figure 9. Performance Analysis

Fig. 9 shows the graphical illustration of the Bayesian Regularization performance. Total of 104 epochs were processed by Bayesian regularization. It can be noticed that the best training performance was achieved at the value of 1029.0974 at epoch 57 and the algorithm continued to iterate the process till 104 epochs as the Bayesian regularization neural network doesn't stop automatically after getting the best performance.

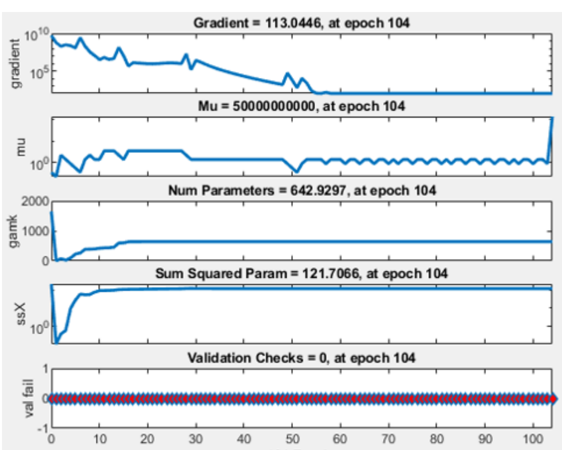


Figure 10. Training plot of Bayesian Regularization

Fig. 10 exhibits the training plots of the Bayesian regularization neural network. Gradient value was found to be 113.0446 at epoch 104. Num parameters and Sum squared parameters were estimated as 642.9297 and 121.7066 at epochs 104 respectively. Validation checks have also been presented in the training plots of the Bayesian regularization neural network.

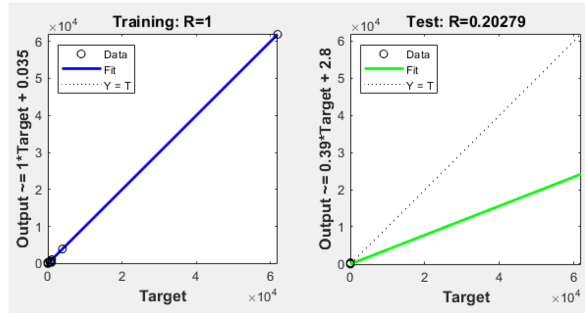


Figure 11. Training and Testing Bayesian Regularization

Fig. 11 exhibits the graphical analysis of the regression values between actual output and desired outputs. In training plot, R regression value has been achieved one that showed training was successful and the relationship is close. On the other hand, in testing the regression value is far away from 1 which means it did not perform up to the mark and the relationship between the desired and actual output would be acknowledged as random.

C. Scaled Conjugate Gradient

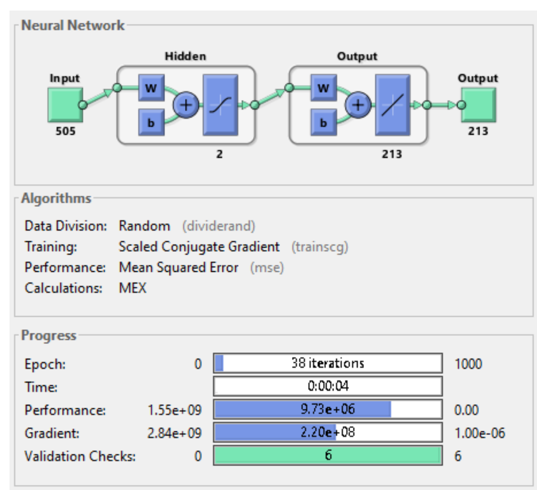


Figure 12. Scaled Conjugate Gradient

The same data set which was collected for the predictive analysis of flash floods was applied to the scaled conjugate gradient to determine the better learning algorithms in terms of the less mean square error in training, testing, and validation. A scaled conjugate gradient algorithm is acknowledged as a supervised learning algorithm. It performs faster in less time compared to the backpropagation.

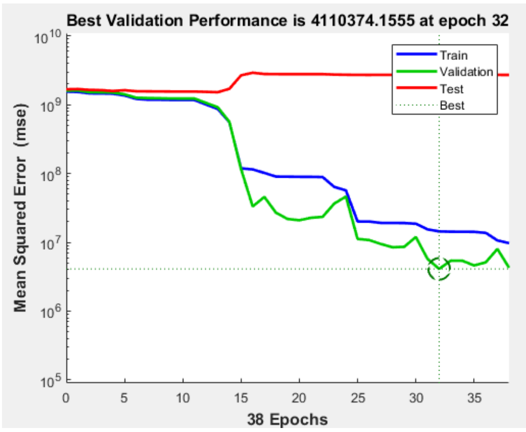


Figure 13. Scaled Conjugate Gradient

Fig. 12 portrays the graphical illustration of best validation performance achieved by the scaled conjugate gradient algorithm. Scaled conjugate gradient (SCG) achieved the best validation performance value of 1440374.1555 at epoch 32. SCG stops iterating the process after MSE starts to increase. It can stop automatically if the increase of MSE is determined.

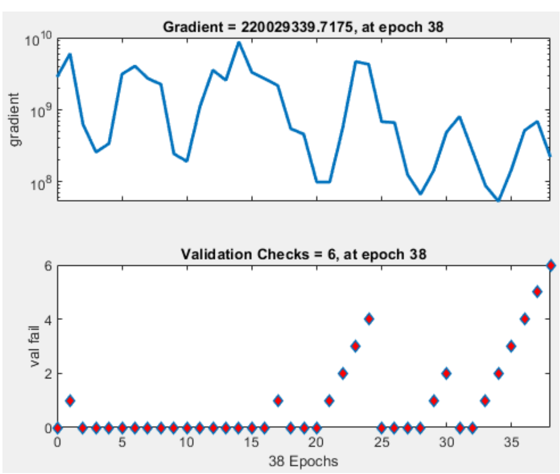


Figure 14. Scaled Conjugate Gradient Training state plot

Fig. 14 shows that the gradient value of 220029339.7175 has been achieved at epoch 38. Validation checks failure was found at the value of 6.

Results

	Samples	MSE	R
Training:	6	14425027.57574e-0	3.33661e-1
Validation:	2	4110374.15554e-0	-5.73873e-2
Testing:	2	2147483647.1905...	-2.74711e-1

Figure 15. Scaled Conjugate Gradient Results

Fig. 15 displays the mean square error and regression values for the training, validation, and testing.

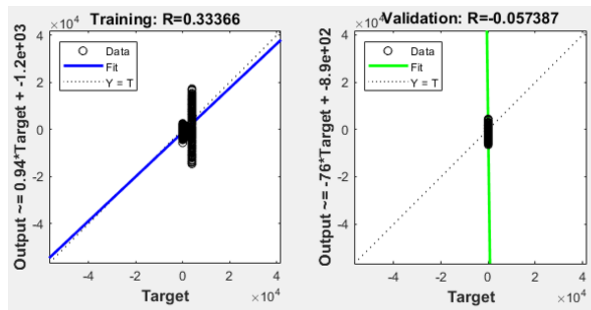


Figure 16. SCG Training and Validation Plots

Scaled conjugate gradient-based training and validation graphs have been plotted to determine the relationship between actual and desired values. Regression values of training and validation were found to be 0.33366 and -0.057387 respectively which is very less and far away from the one. The regression values show that the relationship using SCG was found to be very random and stable.

RESULTS AND DISCUSSION

Comparative analysis has been performed between Leven-Marquardt, Bayesian Regularization and Scaled conjugate gradient to determine the best performance of the learning algorithms for the non-linear data. Results proved that Bayesian regularization performed better as its regression values are better than the other two algorithms. Leven-Marquardt, Bayesian Regularization, and scaled conjugate gradient are benchmarked to the backpropagation neural network. Mean square errors, epochs, processing time and training state have been discussed also for the individual algorithms."

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