Disaster Management System Based on Levenberg-Marquardt Algorithm Artificial Neural Network

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Abstract—**This paper presents Disaster Management System Based on Levenberg-Marquardt Algorithm Artificial Neural Network. Although Malaysia is located outside the "Pacific Rim of Fire" and protected from severe ravages caused by natural disasters, however, Malaysia do still experience other disasters. In Malaysia, the disaster management is laid out under integrated system called the Malaysia National Security Council Directive No. 20 (MNSC No. 20). Unfortunately, the policy introduced in the year 1997 is not enough to help the responders managing disasters efficiently. Study shows, a computerized system was identified as one of the best tools in supporting the responders in Malaysia especially the lead responding agency to manage disasters. Thus, the Disaster Management System Based on Levenberg-Marquardt Algorithm Artificial Neural Network was developed with the aim to help and assisting responders (FRDM first responders) in Malaysia to manage disaster particularly during early stage of response phase. The objective of this paper is to analyse the system in terms of accuracy of system (MLP model). Mean Square Error (MSE) value was used to identify the suitable model for the ANN system. The analysis of the results shows that the best model of ANN is at 15 neurons with the MSE of 0.0159 which will be discussed thoroughly in this paper.**

Index Terms— **MNSC No. 20, FRDM, ANNt, MSE and Levenberg-Marquardt.**

I. INTRODUCTION

DISASTER management is defined as systematic process of using operational skills, administrative decisions, organization, and capacities to implement policies and strategies of the local communities in minimizing the negative impact of disasters [1]. The Red Cross and Red Crescent Societies define the disaster management process as the management of responsibilities, resources and supplies for dealing with all humanitarian aspects of emergencies and disasters including preparedness, response and recovery to lessen the effect of disasters [2]. The disaster management comprise the process of preventing tremendous losses from disasters (including assets and human lives), preparing and response during disasters as well as recovery from disaster [1] [2].

Until early 1990's, Malaysia has no specific disaster management system [3]. The revolution of disaster management in the countrry came after the tragedy of the Bright Sparkles explosion and the collapsed of Luxury Highland Towers in the year 1991 and 1993 respectively [4][3]. Consequently, these major disasters have caused devastation impact to the Malaysian society and left unspeakable traumatic impressions on Malaysian people. Following these disasters, on May 11, 1997, the country developed its first disaster management policy which acts as a framework containing activities that relate to disasters and relief management in Malaysia known as the Malaysia National Security Council Directive No.20 (MNSC No.20): Policy and Mechanism on National Disaster and Relief Management [5][6].

The policy is not only focused on a specific type of disasters. However, it is applicable to all types of disasters which includes natural, man-made as well as hybrid disasters. MNSC No.20 outline a policy on disaster management and has set the

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responsibilities and the role of the agencies involved at the time needed in dealing with disasters. In March 2012, the revised version of the policy were introduced in order to comply to the international framework and conform with the current changes and complexity of disasters [7][3]. The directives have shaped the environment of the disaster management in Malaysia and was referred by many studies in disaster management [3].

Unfortunately, the policy (MNSC N0. 20) alone is not sufficient to support the local authorities, particularly the responding agency in Malaysia to combat disaster [8]. In the event of mega-scale disasters, it will be a huge challenge to the local authorities having jurisdiction in managing disasters themselves [9]. Studies reveals, a computerized system was identified as one of the best tools to support the lead responding agency in Malaysia in managing disasters efficiently and effectively [4][3].

Thus, researchers came with a solution by introducing a computerized system. The system is known as “Disaster Management System Based on Levenberg-Marquardt Algorithm Artificial Neural Network”. A computerized system is referred as a computer software or a program that have a capability to draws upon the knowledge of human captured in a knowledgeable base to solve tasks or any problems that normally require human or expertise to solve [10]. Basically, the system provides solution to store human knowledge and expertise (including experiences) in computers. Some of the computerized system are specifically designed to replace human or experts, while others are designed with the objective to aid them [11], [12].

In this research, researchers focusing on designing an assisting system (aiding system) for lead responding agency in Malaysia (FRDM first responders) in managing disaster during early stage of response phase. Response phase is one of the critical phase in disaster management cycle in Malaysia [12]. One of the challenges faced by responders during disaster (response phase) is to make an effective and accurate decision within a limited time. The timeliness and accurate decision made by the responders shapes the effectiveness of emergency response efforts [21]. During response phase, usually FRDM experts will be the one who is responsible in making the decisions [11]. Effective and accurate decisions made by experts such as determining the level of disaster and type of resources needed is based on years of experience [11]. The problem is that, human expertise not always available at the disaster location to lead and assist responders. This leads to difficulty in finding domain expert with relevant knowledge and experience to manage the disaster [22] especially during initial respond. These difficulties identified, may lead to a longer time taken during decision-making process that is supposed to be done in a short time frame due to the absence of expertise [11]. Due to this, a computerized system with a capability to propose an appropriate type of fire engines and its number, manpower needed as well as the level of disaster is demanded.

It is the objective of this paper to analyse th. optimum ANN model for the computerized system used in this research.

II. Artificial Neural Network (ANN)

An artificial neural network is a computational learning machine (model) based on the structure of biological neural networks for example the human brain and neurons; whereas the information or data are the processing paradigm [13][14]. The ANN has a mental capability which includes the skill to plan and it also can think abstractly. In addition to that, the ANN as well can be used as a problem-solving tool and act as alternative modelling technique to non-physical and physical systems with mathematical or even scientific basis. The main characteristics of ANN are that they have the capability to learn complex nonlinear input-output relationships, can simply adapt themselves to the information or data given and lastly it use a sequential training procedures [15].

Additional, ANN can learn swiftly from any given data or experience through a process, known as the training process. ANN can be trained to perform optimization [16]. The information inserted in ANN is trained to learn characteristic or behaviour to ensure the system is capable in recognizing the input data and can react to it (give output). Learning process is just like a starting point to gain knowledge, in order to success or failure [13].

III. MULTILAYER PERCEPTRON (MLP)

Multilayer perceptron is also known as MLP. It is a unique subset of ANN that has been broadly used in modelling ANN especially when dealing with complex problems. The MLP is a system consisting of vastly distributed parallel processors which comprise of simple processing units known as neurons. It exhibits the natural tendency for storing as well as utilizing experiential knowledge [13]. The MLP comprise of three (3) or in certain cases more than three (3) layers which can be used in solving a complex nonlinear problem.

The units in functional MLP are organised in interconnected layers which comprise of an input layer, an output layer and lastly the hidden layer(s) (one (1) or more layer) in between the input and output layer. Among those three (3) layers, the hidden layers are the most important and crucial layers due to the reason that, they hold the responsibility in extracting underlying patterns from the inputs and enable the MLP to learn complex task or assignment from the inputs, hence producing the desired outputs [17]. The numbers for both input and output units are fixed, since they depend on the input and the desired output(s). However, the number of hidden layers and its units are adjustable. They are problem-specific, besides, can be tuned to ensure the performance of MLP is maximizes. A more complicated problems sometimes might require more than one (1) hidden layers as well as the hidden units [18].

IV. NGUYEN-WIDROW ALGORITHM (NW)

The interconnections between the layers of MLP and its weights are randomly adjusted (initialized) prior to training process. A too small or too large initial weight values of MLP may slowing down the process of ANN’s convergence or even in the worst case, preventing the ANN itself from converging [19]. To avoid this problem from happening, the NW algorithm were utilized in the MLP model. It can be used to generate the initial weight values (bias values) for a hidden layer(s) in the ANN. This is to ensure the active regions of the hidden layer's units will be spread and distributed approximately evenly over the input space or area [20]. These weights values only need minor adjustments during training process, consequently greatly speeding up the training process of MLP [16].

V. EARLY STOPPING

When training neural networks (MLP), there are several decisions must be made. Especially regarding the parameter used in order to obtain a good MLP performance. For instance, the number of training epochs (number of full passes) of the data set should be used during MLP training [21]. A common problem arising during this process (training process) is over-generalization [22][23]. Over-generalization can be express as a situation or state where the MLP has been trained until it has memorized the data given (input) instead of learning. Due to this, the MLP is incapable to adapt and generalise when encounter new cases [16].

Hence, in order to prevent the problem from occurring (over-generalization), the Early Stopping (ES) method is implemented in this research. Additional this method obtain an optimum generalization. Generally, the ES method divides the dataset into three (3) different sets which are training, testing and validation set [16].

The used of training set is to ensure the MLP weights is updated throughout training process. Under this stage, the validation set will be used to monitor an error. Characteristically, during training, the validation set does not participated in updating the MLP weights. Therefore, the set can be used as a performance device in measuring the MLP generalization capabilities. This can be done when it encounters new cases (untrained cases) [15].

Over-generalization occurred when the error in the training dataset (training error) continues to fall, however the error in validation dataset (validation error) has started to climb. This situation indicates that over-generalization has occurred. Hence the training process will be stopped [24].

The ES method is simple to implement and understand. Moreover, in various cases, this method also has been proved to be a better method compared to regularization method and it is as well can avoid the network from overfitting the data. Due to this reason it has been a popular method and broadly used by researchers and academician. [14].

VI. LEVENBERG MARQUARDT ALGORITHM (LMA)

MLP used a various of learning methods. Levenberg-Marquardt Algorithm (LMA) is one of the learning methods that is widely used especially when dealing with ANN modelling [5]. The LMA training method has been chosen in this research. Basically, the LMA is a standard algorithm used in optimizing MLP model and can be used in solving complex non-linear problems [25].

The LMA is a popular method and broadly used in many software applications. It is capable of locating a local minimum of a numerous function which includes real-valued functions as well as sum of squares of several non- linear function by using an iterative techniques [18]. In addition to that, this method act as a combination of two (2) training method which are the Gauss-Newton iteration method (GN) and Vanilla Gradient Descent method (VGD).

The LMA will behave as VGD when it detect the local minimum is far from the current solution. The process is slower. However, this method is definitely to converge. The LMA will behave as the GN method when it detect the local minimum is close to the current solution. In this situation, the GN method will exhibits a fast convergence [18].

In simple terms, the mechanism of LMA technique is that it ensures the performance function of MLP will always being reduced for every iteration. Due to this reason, the LMA has become the fastest training algorithm for MLP with moderate size network.

Unfortunately, LMA function has several weaknesses of memory and computation overhead caused. These problems arise due to the calculation of the gradient and approximated Hessian matrix [14][26]. Though the LMA method spends large memory, but it converges in fewer number of iterations and consumes a less time frame. In many cases, LMA is able to generate and produce a better result with high accuracy (lower MSE) compare to any of other algorithms. It is as well has been proved to have a slightly better advantage in terms of training speed (training iterations) [16].

VII. METHODS

- ***Collecting Data (Past Disaster Record)***

Fire and Rescue Department of Malaysia (FRDM) was chosen as research partner in this project due to their roles as lead responding agency as well as their direct involvement and contribution in Malaysia disaster management [3]. Hence, for this research, the source of information regarding the disaster is mainly came from FRDM including their past disaster records (printed and online data) as well as their procedures used in managing disaster. The data collected is on one (1) type of disaster which is fire only. An online database system called the 'Sistem Pelaporan Insiden (SPI)' from FRDM was used to collect past disaster records. Then, the data being tabulate in a table form consist of ten (10) parameters including six (6) input and four (4) output. These data will be used to develop the disaster management system. The parameters are listed as below:

Table 1: List of Input and Ouput Parameters Used in Developing System

Input	Output
Type of fire (Chemical / Non-Chemical)	Emergency Medical Rescue Services, EMRS (Number of Fire Engines)
Area involve (m^2)	Fire Rescue Tender (Number of Fire Engines)
Height involve (m)	Hazardous Materials Team, HAZMAT (Number of Units)
Percentage of Losses (%)	Turntable Ladder (Number of Fire Engines)
Number of injury	
Number of death	

A total of 1379 dataset has been collected. Prior to the training, the dataset was rescaled to between -1 and 1 before being split into 70:15:15 (training: validation: testing) ratio.

- ***Selecting MLP Layer and Number of Neurons***

A fully-connected MLP structure consist of one (1) input layer, one (1) hidden layer and one (1) output layer was used. The number of hidden neurons is set up as follows:

Table 2: MLP Structure Used

Network	MLP Structure
1	6:5:4
2	6:10:4
3	6:15:4
4	6:20:4
5	6:25:4

The parameters shown in Table 1 and Table 2 were used for LMA training, respectively.

- ***Train MLP***

During this process, the input-output relationships are mapped by altering the interconnected weights. The process is supervised [19], whereas the MLP network being provided with a sample data (data is presented in input-output pairs). Then, the network's output will be compared with the expected responses [27]. Training process continues and repeated until the MLP is able to produce the expected response [27].

- ***Measure the Performance of MLP***

The performance of MLP is measured through the Mean Squared Error value (MSE). After the training process is complete, the value of MSE is monitored. The model with the lowest MSE is selected as the optimum model for this project.

VIII. Results

The optimum MLP model was successfully achieved. Based on Figure 1 below, all the MSE value obtained is less than 0.1. The optimum model of MLP is achived at 15 neurons. This is due to the reason that, at neurons 15 the MSE yield the lowest value which is 0.0159. The highest value is at 5 neurons which show that the MSE is equal to 0.0178. This implies that the model did not learnt properly since the number of neurons is not enough to fit the model.

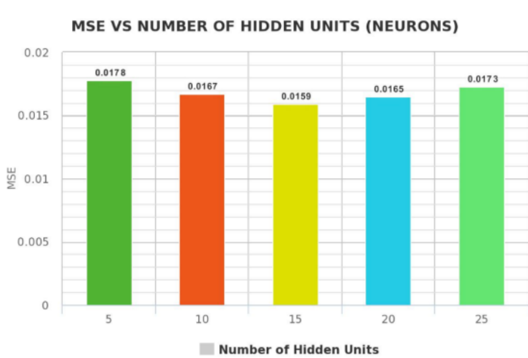

Figure 1: MSE VS Number of Hidden Units

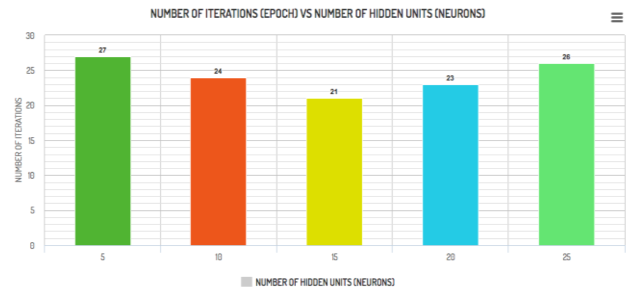

Figure 2: Number of Iterations VS Number of Hidden Units

Based on Figure 2 above, all training runs stopped prematurely when it detected that the MLP model is over fitting the training data. The highest iterations is at neurons 5 which shows 27 iterations. The lowest iterations is 21 at 15 neurons (optimum model). The average iterations obtained from the graph (Figure 2) is around 22 to 24 iterations.

Figure 3 below show the performance plot of MSE for training set (blue line), validation set (green line) and testing set (red line) of the optimum model of MLP (15 neurons).

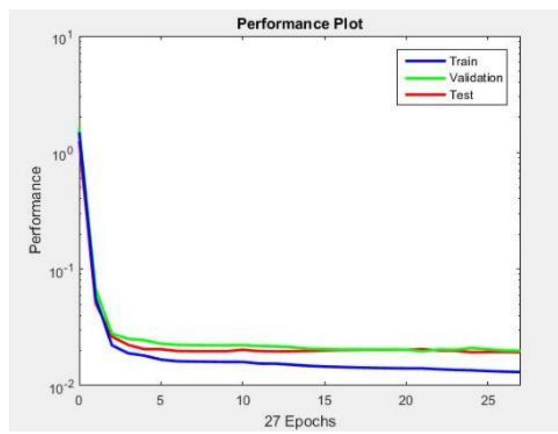

Figure 3: Performance Plot of MSE

The graph shows that MSE performance is abruptly decrease during training process starting from 0 until 5 iterations. The maximum decrease in MSE generally occurred in the first 15-21 iterations. This is due to the reason that, most weight changes occurred during this initial period, which contributed to the dramatically reduction of MSE. Later iterations showed little decrease in MSE (performance gradient is almost equal to zero (0)) as the weight values were refined indicate that the learning process is almost done.

As can be seen from the graph above, the training process stopped prematurely due to the Early Stopping (ES). The ES method stopped MLP training process when it noticed the MLP was starting to over-fit the training data. The training stopped when the validation error increased for six (6) iterations (occurred at iteration 27). The best validation performance occurs at iterations 21 with MSE value of 0.0159 (lowest value). A smaller MSE value signifies that the residuals are small, meaning to say that the MLP model had successfully trained and fitted the data well.

IX. CONCLUSION

Based on the results obtained, it can be conclude that, the Disaster Management System Based on Levenberg Marquardt Algorithm Artificial Neural Network is successfully developed. For this research, the best model (optimum model) of MLP is at iteration 21 with 15 neurons. Since at this iteration, the MSE yield the lowest value (0.0159) which indicate that the model did learnt properly during training process and capable of giving the accurate response (output). Therefore, the MLP model will be used in the computerized system.

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