Defence Science Journal, Vol. 63, No. 5, September 2013, pp. 497-501, DOI : 10.14429/dsj.63.3716

Designing a Battlefield Fire Support System Using Adaptive Neuro-Fuzzy Inference System Based Model

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ABSTRACT

Fire support of the maneuver operation is a continuous process. It begins with the receiving the task by the maneuver commander and continues until the mission is completed. Yet it is a key issue in combat in the way gain success. Therefore, a real-time mannered solution to fire support problem is a vital component of tactical warfare to the sequence that auxiliary forces or logistic support arrives at the theatre. A new method for deciding on combat fire support is proposed using adaptive neuro-fuzzy inference system (ANFIS) in this paper. This study addresses the design of an ANFIS as an efficient tool for real-time decision-making in order to produce the best fire support plan in battlefield. Initially, criteria that are determined for the problem are formed by applying ANFIS method. Then, the ANFIS structure is built up by using the data related to selected criteria. The proposed method is illustrated by a sample fire support planning in combat. Results showed us that ANFIS is valid especially for small unit fire support planning and is useful to decrease the decision time in battlefield.

Keywords: Fire support, adaptive neuro-fuzzy inference system, ANFIS, fuzzy logic, neural network

1. INTRODUCTION

Combat fire support plays an important role in the success of troops in battlefield. Changing security needs, military technology and new international agreements make the combat fire support more complex and significant for armies. Today's armed forces, which have a new perspective for war fighting, are trying to use high-end technologies to improve their fire support capabilities. Command and control of Military operations requires leaders who are able to make decisions and respond in an appropriate, timely manner even in highly uncertain situations. It can be said that complexity is the real word to define the future war environment, which will need more information about fire support decision.

Jwo and Chen[1] studied on the design of radar target tracking and global positioning system (GPS) navigation based on the ANFIS. In another study, the image fusion technique in iterative fashion using fuzzy and neuro fuzzy approach has been used[2]. This technique very useful in medical imaging and other areas, where quality of image is more important than the real time application. Although neural network and ANFIS has been applied in many studies, few of these have contributed to research in the military science area[3-4]. This study contributes to the field of combat fire support research. The main goal of this study is to maintain better fire support for troops in comparison to traditional ones.

2. COMBAT FIRE SUPPORT

Decision making is an important part of today's battlefield[5-9]. Planning fires in support of a maneuver operation is a complex task that requires both the maneuver commander and fire support coordinator (FSCOORD) to work together throughout the entire process to ensure the commanders intent is realized[10]. The FSCOORD must follow the events on the battlefield and anticipate fire support requirements before they are requested. There is no stem in the planning process that can be done without the linking of the fire support plan to the maneuver plans[11] .

Fire support is the collective and coordinated use of indirect-fire weapons, armed aircraft, and other lethal and nonlethal means in support of a battle plan[12]. Fire support includes different types of fire like field artillery, mortars, naval gunfire, air defense artillery in secondary mission, and air-delivered weapons[13]. The force commander employs these means to support his scheme of maneuver, to mass firepower, and to delay, disrupt, or destroy enemy forces in depth. An efficient fire support should destroy, neutralize, and suppress enemy weapons, enemy formations or facilities, and fires from the enemy rear area[13].

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

An adaptive-network-based fuzzy inference system is one of the earliest and most popular unified models of artificial neural network (ANN) and fuzzy inference system (FIS)[14]. Jang first introduced the ANFIS method by embedding the FIS into the framework of adaptive networks[15-16]. The ANFIS is used in many areas such as financial prediction[17-18], classifying[19], controlling[20], recognition[21] and strategic planning[22].

Received 20 January 2013, revised 16 July 2013, online published 25 September 2013

The ANFIS can simply be defined as the combination of ANNs and fuzzy logic[23]. This combined system has the abilities of deducing knowledge from given rules (which come from the ability of fuzzy inference systems[24]), learning, generalization, adaptation and parallelism[25-26] (which come from the abilities of ANN). FIS is a framework based on fuzzy set theory and fuzzy if-then rules[27]. The structure of FIS has three main components: a rule base, a database, and a reasoning mechanism[28]. The rule base contains fuzzy if-then rules[29]. The model is called a first-order Sugeno fuzzy model when *f(x,y)* is a first-order polynomial as shown below[30-31]

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1 x + q_1 y + r_1$
Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 x + q_2 y + r_2$ (1)

Layer 1: This layer consists of input variables (membership functions-MF). Here, triangular or bell shaped MF can be used. Triangular MF is used in this study. To simplify the structure x and y are assumed to be the input nodes, A and B are the linguistic labels, μ_{A_i} and μ_{B_i} are the membership functions. Outputs obtained from these nodes are expressed below[23] ;

$$O_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1,2 \text{ or}$$
$$O_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for } i = 3,4 \tag{2}$$

$O_{1,i}$ is the output of the node i in the first layer. A typical membership function is bell function with

$$\mu_A(x) = \frac{1}{1 + |(x-c)/a|^{2b}} \tag{3}$$

where a, b, c are referred to as the premise parameters[14,32].

Layer 2: This layer is called membership layer. It checks for the weights of each MFs., receives the input values x_i, y_i from the 1st layer and act as MFs to represent the fuzzy sets of the respective input variables. Further, it computes the membership values which specify the degree to which the input value x_i belongs to the fuzzy set, which acts as the inputs to the next layer (Fig.1).

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2. \tag{4}$$

Figure 1 represents a sample adaptive network, which has two inputs (x and y), one output (f) and five nodes; each circle represents a node, each arrow between two circles denotes a connection. Each node performs a function (called node function) on the node's input and produces the node's output[16].

Layer 3: Every node is a fixed node labeled N and calculates the ratio of the i^{th} rule's firing strengths to the sum of all rule's firing strengths in this layer. The output of each node is called normalized firing strength given in Eqn. (5).

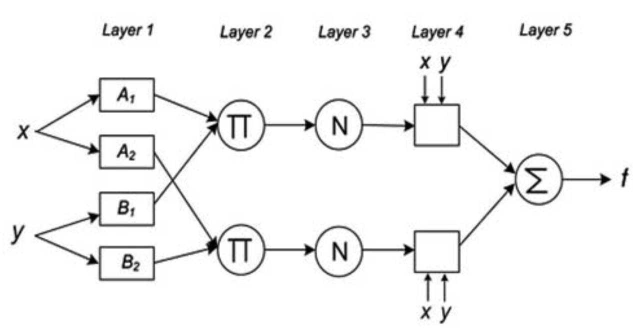


Figure 1. Adaptive neuro-fuzzy inference system[16].

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{5}$$

Layer 4: All nodes are adaptive nodes with a node function in this layer.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad i = 1,2 \tag{6}$$

where w_i is the output of layer 3; p_i, q_i and r_i are the parameters set. Parameters in this layer are referred to as the consequent parameters.

Layer 5: This node computes the overall output of ANFIS as the summation of all incoming signals from the 4th layer.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i = 1,2 \tag{7}$$

The final output of adaptive neuro-fuzzy inference system is expressed as

$$f_{out} = \overline{w}_1 f_1 + \overline{w}_2 f_2 = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1$$
$$+ (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2 \tag{8}$$

4. PROPOSED FIRE SUPPORT MODEL USING ANFIS

Herewith is proposed an ANFIS system for planning the fire support of available friendly troops to help the field commander for the optimal allocation of fire resources in this section. The proposed model applies sufficient information about enemy gained from detection equipment. Then, it decides on fire power and rate of the response with respect to the fighting features of weapons in hand.

Stage 1: Defining Model

Step 1: Identify inputs and output of fire support model: First stage of model includes two steps. In the first step, inputs and output of fire support model are identified. The proposed inputs are obtained from combat experience and arms technical characteristics used as the inputs for the ANFIS.

Three criteria (input) are selected by fire support planners to increase combat fire effect. These are speed of target (input1=speed= β), distance of target (input2=distance= δ) and activity of target (input3=activity= ϕ). Membership functions of β are slow, speedy and very speedy (sSL, sSP, sVS). Membership functions of δ are very near, near and far (dVN, dNR, dFR). Membership functions of ϕ are static target, moving target and unidentified target (aST, aMV, aUN). Model output has six different degree of fire support. These are 'destroy now', 'fire', 'fire when ordered', 'cease-fire', 'wait' and 'identify target'. Criteria of proposed model is given in Fig. 2. Figure 2 demonstrates three inputs, their membership functions, rules of model, output membership functions and one output.

Step 2: Choose model parameters: In this step, model parameters to evaluate the criteria are defined. Back propagation method has been selected for fuzzy inference system (FIS) optimization method and the training dataset is trained for 56 epochs. Three membership functions are assigned to each input. Triangular membership function (trimf) is chosen to train the model criteria.

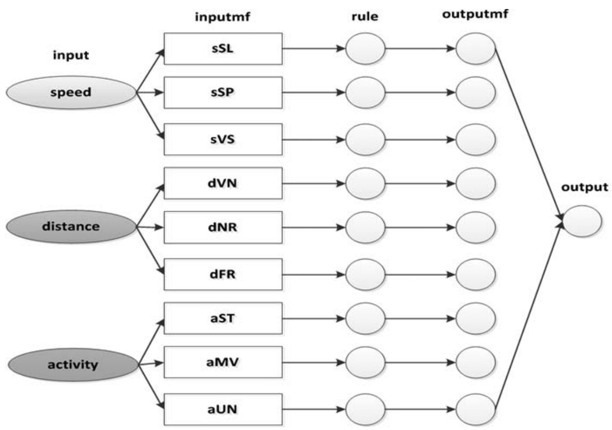


Figure 2. Structure of proposed model.

Stage 2: Input Stage

Step 1: Input fire support training data into ANFIS model: Training data have placed to ANFIS model using Matlab ANFIS editor.

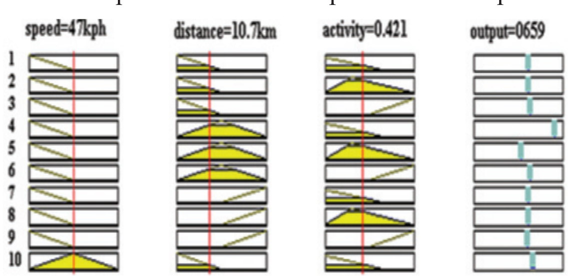
Membership functions are assigned to each input for the training purpose. Each input has three membership functions. The rules are generated by the grid partition method.

Step 2: Obtain trained results: The rule structure of the model is obtained after training, as seen in Fig. 3(a). The rule viewer displays a roadmap of the whole fuzzy inference process and allows fire support planners to change input values and obtain output values., If speed of target is 47 kph, distance is 10.7 km and its' activity is moving then output result is 0.659 which means 'identify target' according to Fig. 3(a).

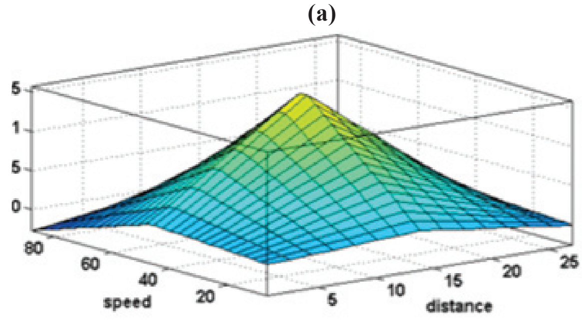
Step 3: Input test data into ANFIS model: Test data is placed to model using Matlab ANFIS editor.

Stage 3: Check results

Step 1: The 3D surface plot shown in Fig. 3(b) depicts the relationship between certain inputs and the output obtained by the developed ANFIS system, where other inputs are fixed at a certain value. Figure 3 (b) illustrates the relationship between the two inputs, target speed (Membership functions of speed are slow, speedy and very speedy = sSL, sSP, sVS) and distance of target (Membership functions of distance are very near, near and far = dVN, dNR, dFR). In this figure, we can see that there is a pattern such as: when distance is nearer then 10 km, and when speed is between 20-80 km, then fire support commander's decision should be 'destroy now the target'.



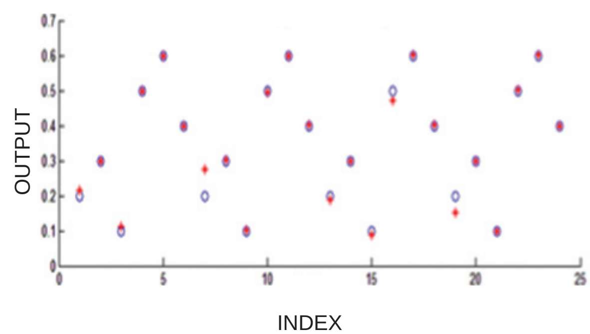
(a)



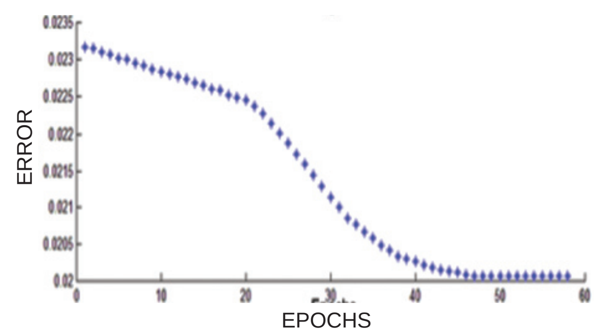
(b)

Figure 3. (a) ANFIS rule structure and (b) the relationship between speed, distance and fire support.

Step 2: Test developed fire support model: Testing and training data are used to test the model performance. Figure 4 presents the comparison of real values and corresponding output values proposed by the ANFIS model. ANFIS can be trained to learn some pattern from input and the outputs (known as training data) of the target system. After the training is completed, the values of the parameters of ANFIS have been tuned. Then, given the new input data sets, ANFIS can approximate or predict the output. FIS outputs are plotted with asterisk (*) symbols, and data is plotted as (o) symbols. The plot demonstrates a correspondence between the FIS output and the data, indicating that the developed ANFIS model is accurate.



(a)



(b)

Figure 4. (a) Real and output values (b) Training error.

4.1 Model Usage

ANFIS method has been used to develop combat fire support planning in this study. A data set was obtained by asking fire support needs of different army units in combat. There are three input for fire support planners to increase combat fire effect. These are speed, distance, and activity of target. Output has six different degree of fire support as mentioned is *Stage 1*. Proposed model evaluates real time combat situation and offers a fire type using ANFIS fire support predicter (Fig.5).

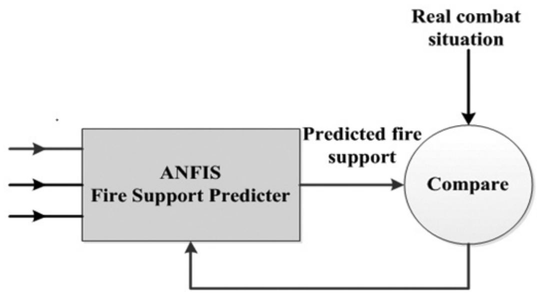


Figure 5. Fire support prediction process.

ANFIS model gives a predicted fire type to fire combat unit here. Operation commander evaluates ANFIS output with real combat situation. Then operation commander gives his final order to fire.

Fire support planners have to take into consideration info comes from a troop. Let say an unnamed target is approaching to a friend troop. If β is speedy, δ is near and ϕ is moving then commander's decision would be 'fire when ordered' according to proposed ANFIS model (Fig. 6).

Model usage samples are given in Table 1. It can be seen different fire support decision for commander according to varient inputs.

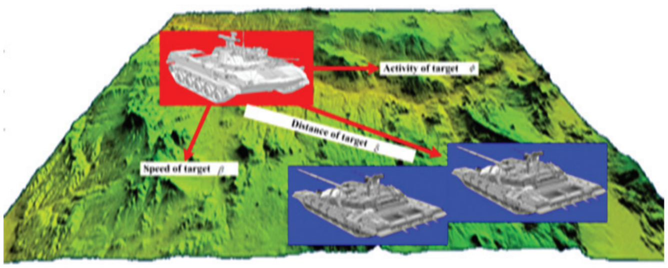


Figure 6. Sample fire support scenario.

From combat fire support angle, an ANFIS based fire support provides a natural means of conducting the fire support operation, enabling the fire support commander to:

- Customize the fire support behavior of the (espicially artillery) units according to their own criteria and expertise.
- Define a fire support rule-set for a battlefield and operation area. This can provide details of fire support rules representing the behavior of army units.

Table 1. Sample fire support scenarios

Target Type	Speed (β)	Distance (δ)	Activity (ϕ)	Result (Output)
Armoured Vehicle	Slow	Near	Moving	Fire when ordered
Combat Unit	Slow	Very near	Static	Fire
Unidentified Vehicle	Speedy	Near	Moving	Identify target
Armoured Vehicle	Very speedy	Near	Moving	Destroy now
Unidentified Unit	Slow	Far	Static	Wait

- Increase existing fire support process with new fuzzy rules.

5. CONCLUSION

A fire support plan depicts what action each unit will be performing, and when. Deciding for combat fire support is important and of great interest because succesful fire support may prevent troops' casualties. It is clear that many component affects battle field commander decision to fire or not. These are highly complicated and very difficult-to-know issues for a commander because there are a lot of variables that may determine fire support management.

A new method for deciding on combat fire support is proposed using ANFIS in this paper. The proposed Combat Fire Support System has been performed on MATLAB 7.8 (The MathWorks Inc., USA) environment by using the fuzzy toolbox. From the ANFIS simulation results, we found that the performance of the model outperformed classic fire support approach based on the comparisons of the computational time and predominance values for cases with a small number of targets. ANFIS based fire support is a feasible decision aid to help military decision makers to respond to combat incidents. Results showed us that ANFIS is valid especially for small unit fire support planning and is useful to decrease the decision time in battlefield. Applying the proposed model to the operational and strategic combat level is a topic for further work.

Furthermore, it has been found that a system works well when applied with a given battlefield simulation scenario. The model's goal is not to control whole battlefield fire support system; however, it aims at warning fire support commander for expected or real threats. The proposed model shows its superiority in the areas of development flexibility and fast response for battlefield threats. The model can be used by fire support commander in order to support army units in theater.

Comparing the performance of ANFIS with other meta-heuristics may be interesting for researchers (e.g. Artificial Neural Network, Genetic Algorithm) or regular statistical methods (Linear/Nonlinear Regression). A special interest would be on testing whether ANFIS approach has any advantage in dealing with battlefield fire support.

ACKNOWLEDGEMENTS

The work was supported by War Colleges Command. We thank to War Colleges Command, Army War College, Dept. of Combat Tactic staff officers for their valuable contribution.

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