Investigate of Linear Response of Vehicle Arm Based on Artificial Intelligence Technique

Hemin M. M, Rahman M. M and Omar R.M.
Faculty of Mechanical Engineering, Universiti Malaysia Pahang, Malaysia.
Automotive Engineering Centre, Universiti Malaysia Pahang, Malaysia.
Universiti Tenaga Nasional, Malaysia.
hemin_hm@yahoo.com

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ABSTRACT

Neural networks have emerged as a field of study within artificial intelligent AI and engineering via the collaborative efforts of engineers, physicists, mathematicians, computer scientists, and neuroscientists. This study deals with intelligent technique's modeling for a linear response of suspension arm. The finite element analysis and Radial Basis Function Neural Network (RBFNN) technique is used to predict the response of suspension arm. The neural network model has three inputs representing the load, mesh size and material while three output representing the maximum principal stress, Von Mises and Tresca. Regression analysis between finite element results and values predicted by the neural network model was made, and RBFNN proposed approach was found to be highly effective with least error in identification of stress of suspension arm. Simulated results show that RBF can be very successively used for reduction of the effort and time required to predict the stress response of suspension arm as FE methods usually deal with only a single problem for each run.

Keywords: **RBFNN; FE; Vehicle suspension arm; neural network**

1. Introduction

Modeling and simulation are indispensable when dealing with complex engineering systems. It makes it possible to do an essential assessment before systems are built. It can alleviate the need for expensive experiments, and it can provide support in all stages of a project from conceptual design, through commissioning and operation. RBFNN is a robust and versatile computational method that can simulate the physical behavior of suspension arm. The growth of neural networks has been heavily influenced by the RBFNN. The application of the RBF network can be found in pattern recognition (Musavi et al., 1992). The two most important parameters of RBFNN, the center and the covariance matrix, have been researched thoroughly (Musavi et al., 1992). RBFNN models are the popular network architectures used in most of the research applications in medicine, engineering, mathematical modeling, etc. (Coccorese et al., 1994; De Alcantara et al., 2002). RBFNN is based on supervised learning. RBF networks were independently proposed by many researchers (Ramuhalli et al., 2002; Chady et al., 2001) and RBFNN are also good at modeling linear data and can be trained in one stage also learn the given application quickly.

Neural networks have been used in mechanical engineering problems since the early 1990's. To minimize error factors, neural networks containing radial basis functions, can be used in many of the same situations in which back-propagation networks (Akeel and mohammed, 2008; Abdullah, 2009) are used but the edge goes to RBFNN because RBFNN provide fast learning & straight forward implementation (Rautenberg et al., 2006). To properly train the network, the necessary suitable independent training, testing and valid data sets in shape of maps are collected, synthesized and applied to the network.

These software packages contain computationally efficient numerical simulation routines for executing realistic full-motion behavior of complex mechanical systems and provide quick analysis for multiple design variations toward an optimal design (Erdman et al., 2001). This paper includes the study on the influences of the artificial intelligent on the response suspension lower arm by using RBFNN. MSC Nastran finite element techniques have been used as a tool to model the mechanical properties of the suspension arm in conjugation. Three-dimensional linear tetrahedral solid elements (TET10) used for the initial analysis based on the loading conditions.
The model is constructed through the use of the neural network design (nntool) toolbox in MATLAB. The comparison results with other traditional methods also prove its superiority. The proposed approach was found to be highly effective in identification stress of lower arm. In contrast to this work, we focus on the issue of enhancing reliability of RBFNN in the presence of gross errors.

2. Model Description

Vehicle suspension is a mechanism locating between the sprung mass (vehicle body) and the unsprung masses (wheels) of the vehicle. The suspension provides forces between these two masses of the vehicle according to certain state variables of the vehicle. A good car suspension system should have a satisfactory road holding ability, while still providing comfort when riding over bumps and holes in the road. When the bus is experiencing any road disturbance the bus body should not have large oscillations, and the oscillations should dissipate quickly. A simple three-dimensional model of suspension arm was modeling by used Solid Works software. Fig.1 shows the structural model.

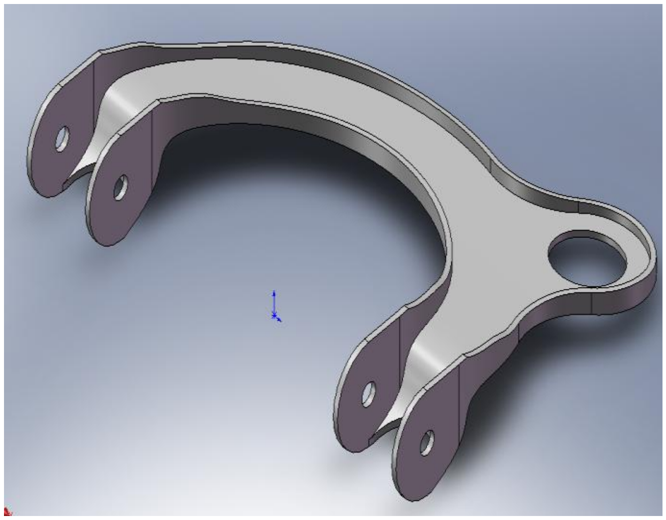

Fig.1. Structural Model

The overall dimensions are shown in Fig.2.

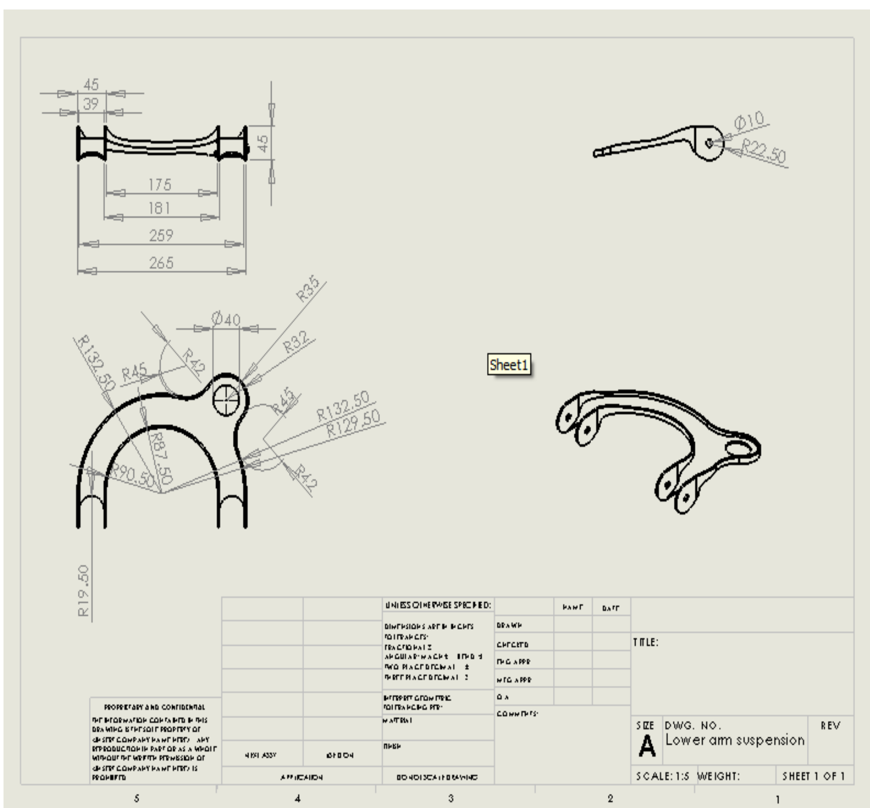

Fig.2. Overall Dimension

3. Mechanical Properties

Material model and material properties play an important role in the result of FE method. The material properties are one of the major inputs, which is definition of how the material behaves under the cyclic loading conditions. The materials parameters required depend on the analysis methodology being used. The mechanical properties of 7075-T6 aluminum alloy are shown in Table 1.

Table 1: Mechanical properties of aluminum alloy 7079-T6

Material	Young's Modulus (GPa)	Poisson's ratio	Tensile strength (MPa)	Yield strength (MPa)
Aluminum alloy AA7079-T6	72	0.33	503	572

4. Artificial Neural Network

RBFNN have increasingly attracted interest for engineering applications due to their advantages over traditional multilayer perceptrons, namely faster convergence, smaller extrapolation errors, and higher reliability. Over the last few years, more sophisticated types of neurons & activation functions have been introduced in order to solve different sorts of practical problems (Satish, 2005; Kurban and Besdok, 2009).

In particularly, RBFNN (Satish, 2005) have proved very use full for many systems and applications. RBFNN is defined in the literature as a kind of ANN that has radial activation functions on its intermediary layer. The function approximation problem has been tackled many times in the literature by using RBFNN. RBFNN were robust used in the context of neural networks as linear and nonlinear function estimators and indicated their interpolation capabilities by Broomhead and Lowe (Broomhead and lowe, 1988).

The neural network is a mapping between its inputs and outputs based on a number of known sample input-output pairs. In general, the more samples available to train the network, the more accurate the representation of the real mapping will be. These samples are obtained by solving the direct problem (times), in its simplest form, a Radial Basis Function Neural Networks (RBFNN) consists of three layers of neurons are shown in Figure 3.

The first layer acts as the input layer of the ANN. The second layer is hidden layer as a high-scale dimension, which promotes a linear transformation of input space dimension by computing radial functions in their neurons. And the third one, the output layer, outputs the ANN response, promoting a linear transformation of the intermediary layer high-scale dimension to the low-scale dimension (Pandya, 1995).

For effective predicting of suspension arm, the simulation data from MSC Nastran-Patran software has been used for training and testing. In the present study, inputs are selected as load, Mesh size and material. The NN outputs have been termed as four output node representing the maximum principal stress, von Mises and Tresca as shown in Figure 4.

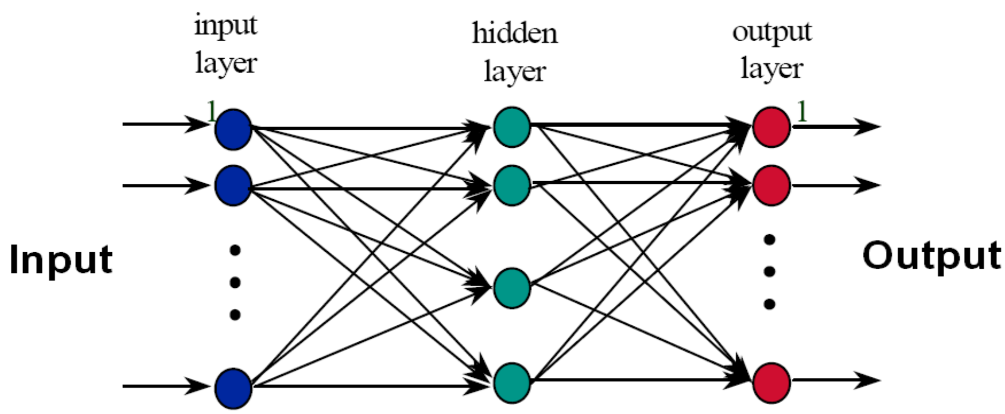

Fig.3. Radial Basis Function Neural Networks

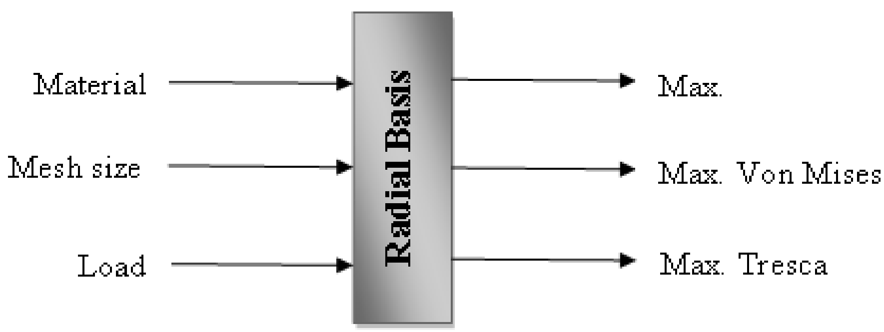

Fig.4. Model of RBFNN approach for suspension arm

One of the advantages in the RBFNN use is the training speed, taking into account that this process involves, usually, two distinct stages: an unsupervised training and a supervised training. In the unsupervised training the centers are created for the intermediary layer. Commonly, this stage employs means algorithm (Rautenberg et al., 2006).

In supervised training, a linear method is employed to minimize the established error measure. However, it is important to note that the RBFNN performance measure is intrinsically linked to the intermediary layer determination. A characteristic feature of radial function (Simon, 2002) is that its response decreases or increases monotonically with distance from a central point named as center of the radial function. These neurons are so called Radial basis activation function. The above equation presents the most often used form for such a function.

$$f(x) = \exp(-\|x - t\|^2) \tag{1}$$

where, x is the n-dimensional vector of input signal, t is a constant vector in the same direction while $\|$ is Euclidean norm in the n-dimensional space and Practically $f(x)$ shows how close vector *'x'* is to vector *'t'* in n-dimensional space. The choice of $\|$ and t plays a critical role in the training algorithm and stability of the Neural Network system. There are no theoretical guidelines found for choosing these constants so they are chosen on heuristic grounds by experimental or trial and error techniques. The performance of the Neural Network system is not very sensitive to this choice in the convergence region. In (Chiang et al., 2009), the output of a RBF network has been written as:

$$\hat{y} = \begin{bmatrix} W_{11} & \cdots & W_{1j} \\ \vdots & \ddots & \vdots \\ W_{i1} & \cdots & W_{ij} \end{bmatrix} . \begin{bmatrix} 1 \\ \sigma\left(-\|x - t_1\|^2\right) \\ \sigma\left(-\|x - t_i\|^2\right) \end{bmatrix} \tag{2}$$

$$\hat{y} = W.H \tag{3}$$

where the weight matrix is represented as W and ‖ matrix is represented as H. GD algorithm can be implemented to minimize the error after defining the error function:

$$E = \sum (Y - \hat{Y})^2 \tag{4}$$

where Y is the desired output. RBF can be optimized with adjusting the weights and center vectors by iteratively computing the partials and performing the following updates (Kurban and Besdok, 2009):

Various methods have been used to train RBF networks (Satish, 2005; Kurban and Besdok, 2009). One approach first uses K-means clustering to find cluster centers which are then used as the centers for the RBF functions. However, K-means clustering is a computationally intensive procedure, and it often does not generate the optimal number of centers.

Another approach is to use a random subset of the training points as the centers. Now training (Simon, 2002) of the RBFNN in general can be divided into two stages, that is, training in the hidden layer followed by training in the output layer. Training in the hidden layer is unsupervised and it involves determination of the centers and spread of the Gaussian functions of the hidden nodes utilizing an appropriate clustering algorithm. On the other hand, training in the output layer uses a supervised method like the Least Mean Square (LMS) algorithm.

The centers of the Gaussian functions are determined with the K-means clustering algorithm and the spreads are calculated using the second order nearest neighbor heuristic. The weights between the hidden and output layers are determined by minimizing the square error of the network output with the LMS algorithm

5. Results And Discussion

5.1 Modeling And Simulation

The lower arm suspension is one of the important parts in the suspension system. A specific area of constraint has been set into the design in order to get a precise result. TET10 has been used in the finite element modeling using MSC. PATRAN. These analyses were preformed iteratively at different mesh global length until the appropriate accuracy obtained.

The convergence of the stresses was studied as the mesh global length was refined in the analysis. The mesh global length of (0.1-1.5) mm was chosen and the pressure of 8 MPa was applied at the end of the bushing that connected to the tire. The other two bushing that connected to the body of the car are constraint. The pressure that has been applied is based on (Al-Asady et al. 2008). The three-dimensional FE model, loading and constraints of suspension arm is shown in Fig.5.

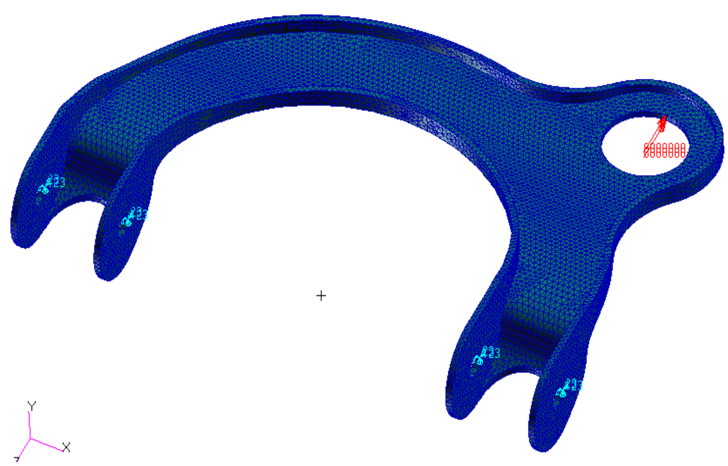

Fig.5. Three-dimensional FE model, loading and constraints

5.2 Effects of the Mesh Types

The stress histories calculated using the linear static analysis method are usually the most accurate and are commonly used by members of the finite element community as a reference to evaluate the response of RBFNN. The linear static stress analysis was performed utilizing MSC.NASTRAN to determine the stresses result from finite element model. The material models utilized of elastic and isotropic material. The tetrahedral element TET10 was use for the mesh analysis Fig.6. The convergence of the finite element model of the structure was tested for TET10 and 5 different mesh sizes. Fig.7 shows the von Mises stress contour for TET10 element. The linear elastic analysis results including maximum principal stress, von Mises stress, and Tresca stress are tabulated in Table 2. The convergence of the stress was considered as the main criteria to select the mesh type. The finite element mesh was generated using TET10 for various mesh global length.

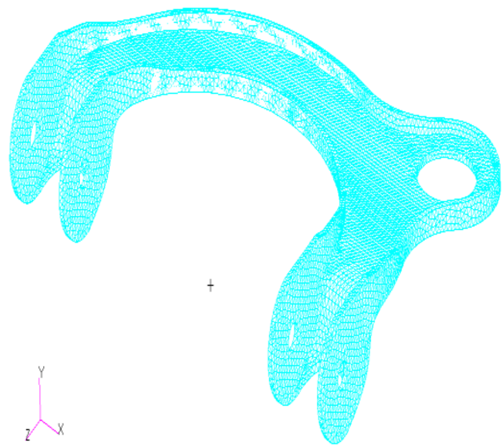

Fig.6. TET10, 54178 elements and 96080 nodes

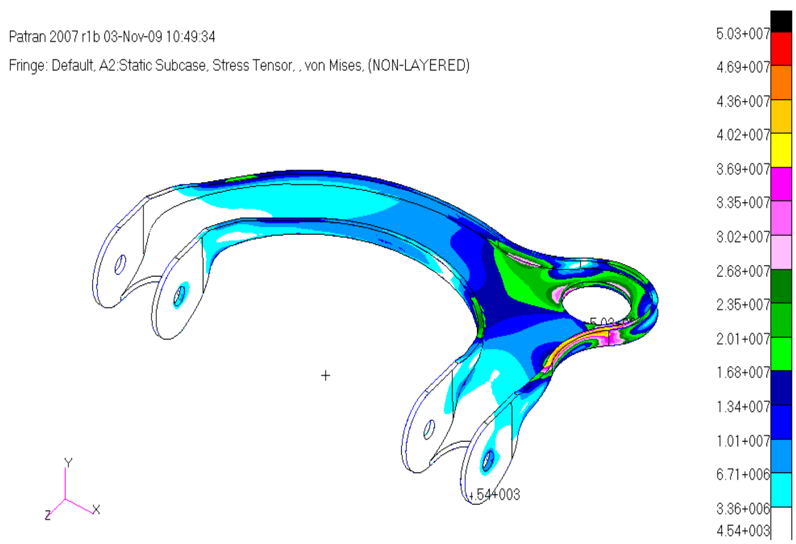

Fig.7. Von Mises stresses contour for TET10

It can be seen that the smaller the mesh size capture the higher predicted stresses. It is also observed that mesh size of 0.1 mm (54178 elements) has obtained the maximum stresses, which is almost flatter in nature. The maximum stress obtained of 50.3, 52.2 and 56.3 MPa for von Mises stress, Tresca and Maximum principal stress method respectively. The maximum principal stress method occurred through the highest stresses along the global length range.

The mesh convergence is based on the geometry, model topology and analysis objectives. comparison result between FEM and RBFNN techniques based on von Mises, Tresca, and maximum principal stresses is tabulated in Table 3 for output (FEM and RBFNN), according to the result and comparison between FEM and RBFNN the (ANN) prediction is much less as compared with the FEM; it means RBFNN can often obtain results in almost negligible time as compared to similar works using the FE methods. The finite element against corresponding RBFNN prediction is shown in Fig.8.

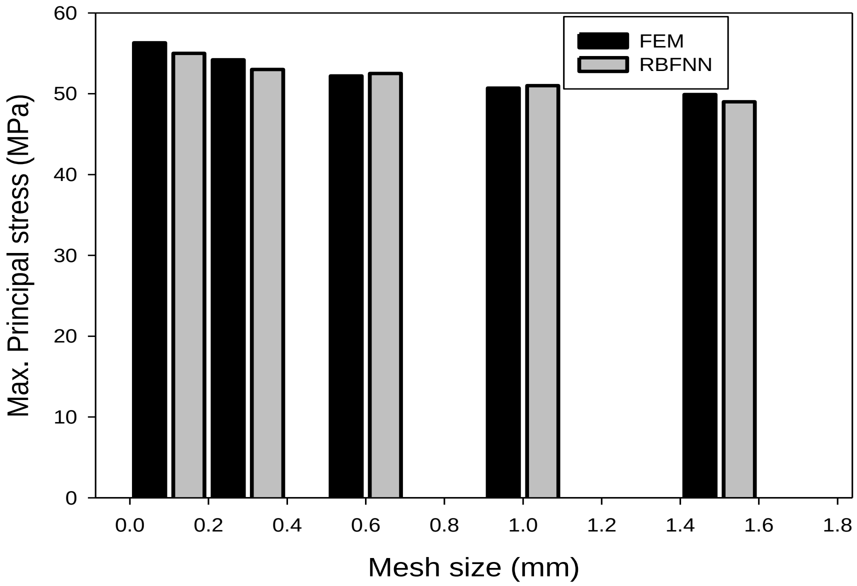

Fig.8. FEM and RBFNN Maximum principal stress

Finally, it can be concluded from table 3 and Fig.8, that this technique shows the following:

1. Highly effective (depends upon its accuracy, speed and memory requirements.) in identification stress of suspension arm
2. RBF can be very successively used for the enhanced navigational performance and error reduction of the effort and time required determining the stress response of lower suspension arm as the FE methods usually deal with only a single problem for each run.
3. Also the method can solve many problems that have mathematical and time difficulties

Table 2: Variation of stresses concentration at the critical location of the suspension arm for TET10 mesh

Mesh size (mm)	Total nodes	Total Elements	Von Mises (MPa)	Tresca (MPa)	Max Principal Stress (MPa)
0.1	96080	54178	50.3	52.2	56.3
0.3	10041	4676	50.2	51.3	54.2
0.6	5889	2665	48.9	50.6	52.2
1.0	5436	2465	47.4	48.2	50.7
1.5	3186	1409	45.3	35.7	49.9

Table 3: output from FEM and RBFNN techniques

	FEM			RBFNN		
Mesh Size (mm)	**max. principal stree (MPa)**	**Tresca (MPa)**	**Von Mises (MPa)**	**max. principal stree (MPa)**	**Tresca (MPa)**	**Von Mises (MPa)**
0.1	56.3	52.2	50.3	55	53	52
0.3	54.2	51.3	50.2	53	52	51
0.6	52.2	50.6	48.9	52.5	49	48
1.0	50.7	48.2	47.4	51	48	47
1.5	49.9	35.7	45.3	49	36	46

6. Conclusion

This paper investigated and presented a method which provides a simple way to predicting linear response of lower suspension arm, the previous work has been show the efficiency of neural networks (NN), coupled with the finite element method (FEM). In this study we provide an introduction to Radial Basis Function Neural network. RBFNN have very attractive properties such as localization, functional approximation, interpolation, and cluster modeling. These properties made it attractive in many applications. We provide some of their properties and few training algorithms to evaluate linear response of lower suspension arm. We focus on the issue of enhancing reliability of RBFNN. Also the method has been used of more realistic finite element problems, computer parallel programming, in order to get quickly solutions and with few workload of processing, this technique is quite feasible.

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