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Predict Dynamic Response of Suspension Arm Based on Artificial Neural Network Technique

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Abstract: Modeling and simulation are indispensable in researching on complex engineering systems. This study attempts to improve the modeling of dynamic response of suspension arm by applying intelligent techniques. The structural model of the suspension arm utilizes the solid works and aluminum alloys (AA7079-T6) as a suspension arm material. The finite element analysis and Radial Basis Function Neural Network (RBFNN) technique are used to predict the response of suspension arm. By utilizing the finite element analysis code, the dynamic analysis is performed. And in the neural network model, there are three inputs represent the load, material and natural frequency, with three outputs representing the Max, Dynamic-displacement T1, T2, T3. Finally, the regression analysis is performed between finite element results and the values predicted by the neural network model. The simulation outcomes show that the proposed RBFNN approach seems highly effective with least error in identification of dynamic-displacement of suspension arm. Also the RBFNN can be very successively used for reducing the effort as well as the time required to predict the dynamic-displacement response of suspension arm, compared with FE methods which usually deals with only one single problem for each run.

Key words: Suspension arm, redial basis function neural network, aluminum alloy, dynamic analysis

INTRODUCTION

Recently, there is an increasing interest within the automotive industry in the ability to produce designs that are strong, reliable and safe, while also light in weight, economic and easy to produce. The vehicle suspension system is responsible for driving comfortably and safely as suspension carries the vehicle-body and transmits all forces between body and road. And this study will focus on suspension arm more exactly the dynamic response of suspension arm.

One of the basic tasks in dynamic analysis of the various constructions is to evaluate the displacements of the construction from the time dependent functions given the time varying loads. But before the equations of motion are defined one should assume that the corresponding system is linear (its dynamic forces are bonded with acceleration, velocity or displacement vectors by means of linear coefficients) or nonlinear (mechanical properties of the system are not constants).

For mechanical engineering problems, neural networks have been used since the early 1990's, with the main areas of concentration on control, identification and damage detection. But the growth of neural networks has been heavily influenced by the RBFNN, which is a robust and versatile computational method that can simulate the physical behavior of suspension arm (Wannas and Abd, 2008). It is also good at modeling linear and nonlinear data. And the two most important parameters of RBFNN, the center and the covariance matrix have been researched thoroughly.

Actually to minimize error factors, many neural networks containing radial basis functions, can be used because of the back-propagation networks (Wannas and Abd, 2008; Abdullah, 2009) used but the edge goes to RBFNN because RBFNN provide fast learning and straight forward implementation (Rautenberg, 2006). However, for more complex structures, finite element modeling is useful to analyze and optimize these structures (Archambeault *et al*., 2006).

So this study shows the influences of the artificial intelligent on the response of suspension arm by using RBFNN to predict dynamic response and by using finite element technique as a tool to model the mechanical properties of the suspension arm in conjugation with RBFNN modeling. Three-dimensional tetrahedral solid elements (TET10) are used for the initial analysis based on the loading conditions. The model is constructed through the use of the neural network design toolbox in MATLAB.

The simulation results find that the proposed approach is of rapid processing and good performance in the target identification of predicting dynamic response of suspension arm. Also through comparison with other traditional methods, the superiority of the proposed approach has been proved.

ROBUST RADIAL BASIS FUNCTION NEURAL NETWORK TECHNIQUE

RBFNN has increasingly attracted interest for engineering applications due to their advantages over traditional multilayer perceptions, namely faster convergence, smaller extrapolation errors and higher reliability. Over the last few years, more sophisticated types of neurons and activation functions have been introduced in order to solve different sorts of practical problems (Erdman *et al*., 2001). In particularly, RBFNN had proven to very use full for many systems and applications (Erdman *et al*., 2001). RBFNN is defined in the literature as a kind of ANN that has radial activation functions on its intermediary layer. RBFNN was robust used in the context of neural networks as linear and nonlinear function estimators and indicated their interpolation capabilities by Broomhead and Lowe (1988). Hartman *et al.* (1990) were proven that RBFNN is capable of approximating any function with arbitrary accuracy. 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 RBFNN consists of three layers of neurons (Fig. 1). 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. Third layer, 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 dynamic analysis has been used for training and testing. In the present study, inputs are selected as load, material and natural frequency. The NN outputs have been termed as three output node representing the maximum displacement T1, T2, T3 as shown in Fig. 2.

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 (Frimpong and Li, 2007). 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 is that its response decreases or

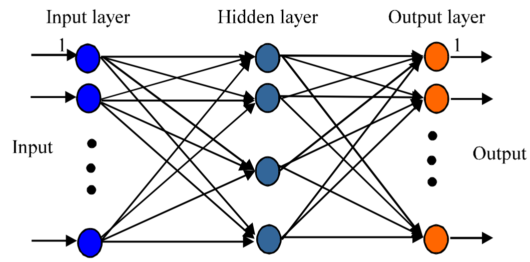

Fig. 1: Radial basis function neural networks

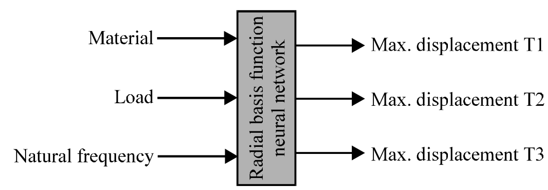

Fig. 2: Model of RBFNN approach for suspension arm

increases monotonically with distance from a central point named as a center of the radial function (Simon, 2002). These neurons are so called Radial basis activation function. The Eq. 1 presents the most often used form for such a function.

$$f(x) = \exp(-\|x - t\|^2)...... \quad (1)$$

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 Chiang *et al.* (2009). The output of a RBF network has been written as:

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

$$\hat{y} = W.H \quad (3)$$

where. the weight matrix is represented as the 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 Besdo, 2009).

Various methods have been used to train RBF networks (Kurban and Besdo, 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 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 (Simon, 2002). Training in the hidden layer is unsupervised and it involves a 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.

MOTION FOR SUSPENSION SYSTEM OF AUTOMOBILE

Natural frequency: Natural frequency is the rate of energy interchange between the kinetic and the potential energies of a system during its cycle motion. As the mass pass through the static equilibrium position, the potential energy is zero (Dimarogonas, 1996). The natural frequency is expressing as Eq. 5:

$$w_n = \sqrt{\frac{k}{m}} \tag{5}$$

Where:
w = Natural frequency
k = The coefficient of spring
m = Mass

The chassis natural frequency is used the suspension rate and chassis mass and expressed as in Eq. 6:

$$w_n = \sqrt{\frac{k_s}{m_c}} \tag{6}$$

Where:
w_n = Natural frequency for the car
k_s = The coefficient of spring
m_c = Mass of the car

For the wheel natural frequency ω_w, it is necessary to take into account Ks and Kt because the wheel oscillates between the suspension and tire springs Eq. 7. Although, these two springs are on an opposite side of the wheel/hub/knuckle mass, the mass would feel the same force if the two springs were in parallel on one side of the mass. In other words, the two springs Ks and Kt, are in parallel and their composite rate is their sum.

$$w_w = \sqrt{\frac{(k_s + k_t)}{m_w}} \tag{7}$$

Where:
w_w = The natural frequency of the wheel
k_s = The coefficient of spring
k_t = The coefficient of tire
m_w = Mass of the wheel

Automobile suspension arm is two-degree of freedom system. The two-degree of freedom car suspension model is illustrated in Fig. 3 (Milliken, 2002; Milliken and Milliken, 2002).

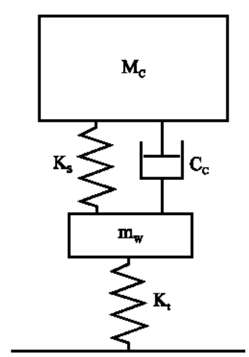

Fig. 3: Quarter car passive suspension arm. C_C is Damping coefficient, k_t is Tire deflection stiffness, K_S is the suspension stiffness, M_C is the mass of the car and m_w is the unsprung mass

Dynamic analysis: One of the basic tasks in the dynamic analysis of the various constructions is to evaluate the displacements of the construction as the time dependent functions when the time varying loads are given. Before the equations of motion are defined one should assume that the system for which those equations are to be defined is linear (it is dynamic forces are bonded with acceleration, velocity or displacement vectors by means of linear coefficients) or nonlinear (mechanical properties of the system are not constants). The forces imposed on the vehicle from the tires, gravity and aerodynamics determine the dynamic behavior. In a real car, the wheel loads are constantly changing. These loads may be in the longitudinal direction such as acceleration and braking forces, in the lateral direction such as cornering forces and in the vertical direction.

RESULTS AND DISCUSSION

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 three-dimensional model of suspension arm was modeling utilizing Solid Works software as shown in Fig. 4a. The overall dimension as shown in Fig. 4b.

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 a definition of how the material behaves under the cyclic loading conditions. The materials parameters required to depend on the analysis methodology being used. The mechanical properties of 7079-T6 aluminum alloy are shown in Table 1.

Modeling and simulation: The suspension control arms are important parts in a vehicle. It should provide ride comfort to the driver by isolating irregular vibrations from road surface effectively and must secure the maneuverability. The suspension arm was modeled using, MSC. Nastran, Finite element analysis software. The premise was to model a lower arm structure and verify that the two techniques theoretical and computer provided the same answer. If this was true, then one could use the computer analysis to solve for more difficult structures that might pose a problem using theoretical analysis. A 10 node tetrahedral element (TET10) was used for the solid mesh. Sensitivity analysis was performed to determine the optimum element size. Stress analyses considering the ultimate load condition applied to the parts during the driving were performed. The strength and the stress analyses were performed with PATRAN/NASTRAN commercial software. A data file of information on parts designed with Solid Works software was converted to a STEP file. Several constraints on the model imported into the MSC. Software program was set up and the stress analysis was performed after mesh generation. The mesh global length of 5.3 mm was considered and the force (X = -549.7 N, Y = 12218.3 N, Z = 845.9 N) was applied one

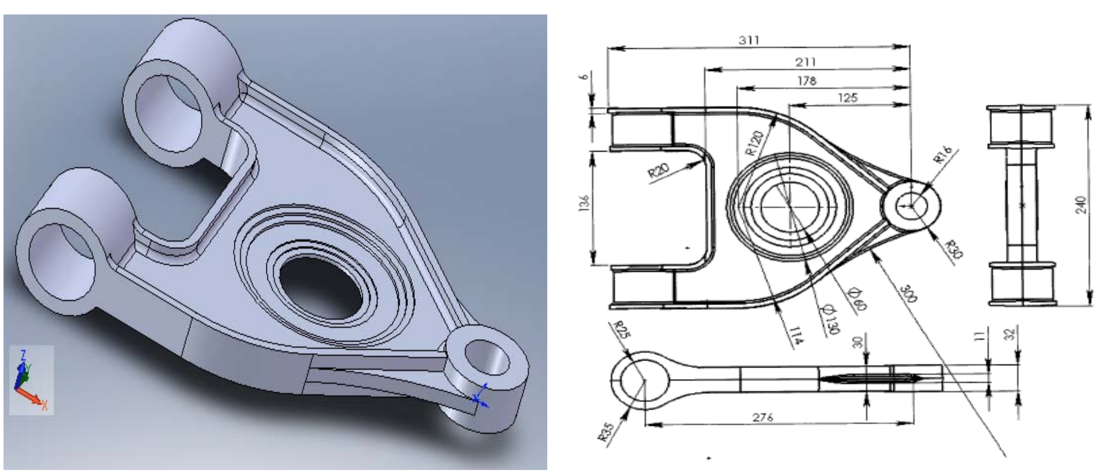

Fig. 4: Structural model and overall dimensions of suspension arm (a) Structural model and (b) Overall dimension

Table 1: Mechanical properties of aluminum alloy 7079-t6

Material (Aluminum alloy)	Young's modulus (GPa)	Poisson's ratio	UTS (MPa)	YS (MPa)
AA7079-T6	70	0.33	540	450

Table 2: Maximum displacements from modal analysis

	T1	T2	T3
Mode No.	(μm)		
1	5.9362769	1.1423386	66.325012
2	9.1471920	18.2595330	58.596310
3	18.282864	24.3536160	65.195534
4	10.549701	18.6380370	10.567502
5	8.2864723	44.2262920	10.115671
6	20.041723	20.6486510	98.877060
7	20.919615	36.8801080	62.914886
8	12.581594	34.3640820	122.164530
9	35.766823	21.4692920	116.340580
10	45.454102	14.0304320	34.420017

end of the bushing that connected to the tire. The other two bushing that connected to the body of the car are constraints. These preload are based on Seo *et al.* (2007).

Dynamic analysis of lower arm: Dynamic analysis is focused on the eigen-frequencies and mode shapes. From a physical point of view, an initial excitation of an undamped system causes to vibrate and the system response is a combination of eigenmodes, where each eigenmode oscillates at its associated eigen-frequency (Amako *et al.*, 2008). The natural frequency histories calculated using the dynamic analysis method are usually the most accurate and are commonly used by members of the finite element community as a reference to evaluate the accuracy of the stochastic design improvement. Modal analysis is usually used to determine the natural frequencies and mode shapes of a component. It can be used as the starting point for dynamic analysis. The finite element analysis codes usually used several mode extraction methods. The Lanczos mode extraction method is used in this study. Lanczos is the recommended method for the medium to large models. In addition to its reliability and efficiency, the Lanczos method supports sparse matrix methods that significantly increase computational speed and reduce the storage space. This method also computes precisely the eigenvalues and eigenvectors. The number of modes was extracted and used to obtain the suspension arm stress histories which is the most important factor in this analysis. Using this method to obtain the first 10 modes of the suspension arm and the shape of the mode are shown in Fig 5a-j. It can be seen that the working frequency (80 Hz) is far away from the natural frequency (205.26 Hz) of the first mode. A sample of the resulting eigenvalue/eigenvector from the suspension arm is shown in Table 2 in which three output node representing the maximum displacement in x-axis (T1), maximum displacement in the y-axis (T2) and maximum displacement in z- axis (T3).

Table 3: Sample of training data

		Dynamic analysis (FEM)		
	Natural frequency	T1	T2	T3
Mode No.	(Hz)	(μm)		
1	205.26	5.9362769	1.1423386	66.325012
2	879.23	9.1471920	18.2595330	58.596310
3	997.58	18.282864	24.3536160	65.195534
4	1900.1	10.549701	18.6380370	10.567502
5	1948.5	8.2864723	44.2262920	10.115671
6	2349.2	20.041723	20.6486510	98.877060
7	2524	20.919615	36.8801080	62.914886
8	2800	3.703614	14.7455360	54.896472
9	3079.3	12.581594	34.3640820	122.164530
10	3300	3.914717	15.2364720	56.945495
11	3619.4	35.766823	21.4692920	116.340580
12	3800	6.945832	15.2782320	61.019631
13	4187.4	45.454102	14.0304320	34.420017

Technique RBFNN: This technique investigated and presented a new method which provides a simple way to predicting linear response of lower suspension arm. The previous work has been showing the efficiency of Neural Networks (NN), coupled with the Finite Element Method (FEM). For effective predicting of suspension arm, the simulation data from MSC Nastran-Patran software has been used for training and testing.

The NN outputs have been termed as three output node representing the maximum displacement in the x-axis (T1), maximum displacement in the y-axis (T2)and maximum displacement in the z-axis (T3) are tabulated in Table 3. To train RBFNN model from the MSC Nastran-Patran software, network architecture was required; first the entire training data file was randomly divided into training and testing data sets. About 90% of the data 84 patterns were used to train the different network architectures where remaining 8 patterns were used for testing to verify the prediction ability of each trained NN model. This neural network was simulated using the scientific and engineering package MATALB® 10. Table 4 shows comparative results of maximum displacement obtained using dynamic analysis against corresponding RBFNN prediction. This study presented a method which provides a simple way for predicting the dynamic response of lower suspension arm. Table 4 has been showing the efficiency of Neural Networks (NN) and also show can be very successively used for the enhanced navigational performance, error reduction and time required predicting the dynamic-displacement response of suspension arm with few workloads of processing (test and training). According to the result and comparison between dynamic analysis and

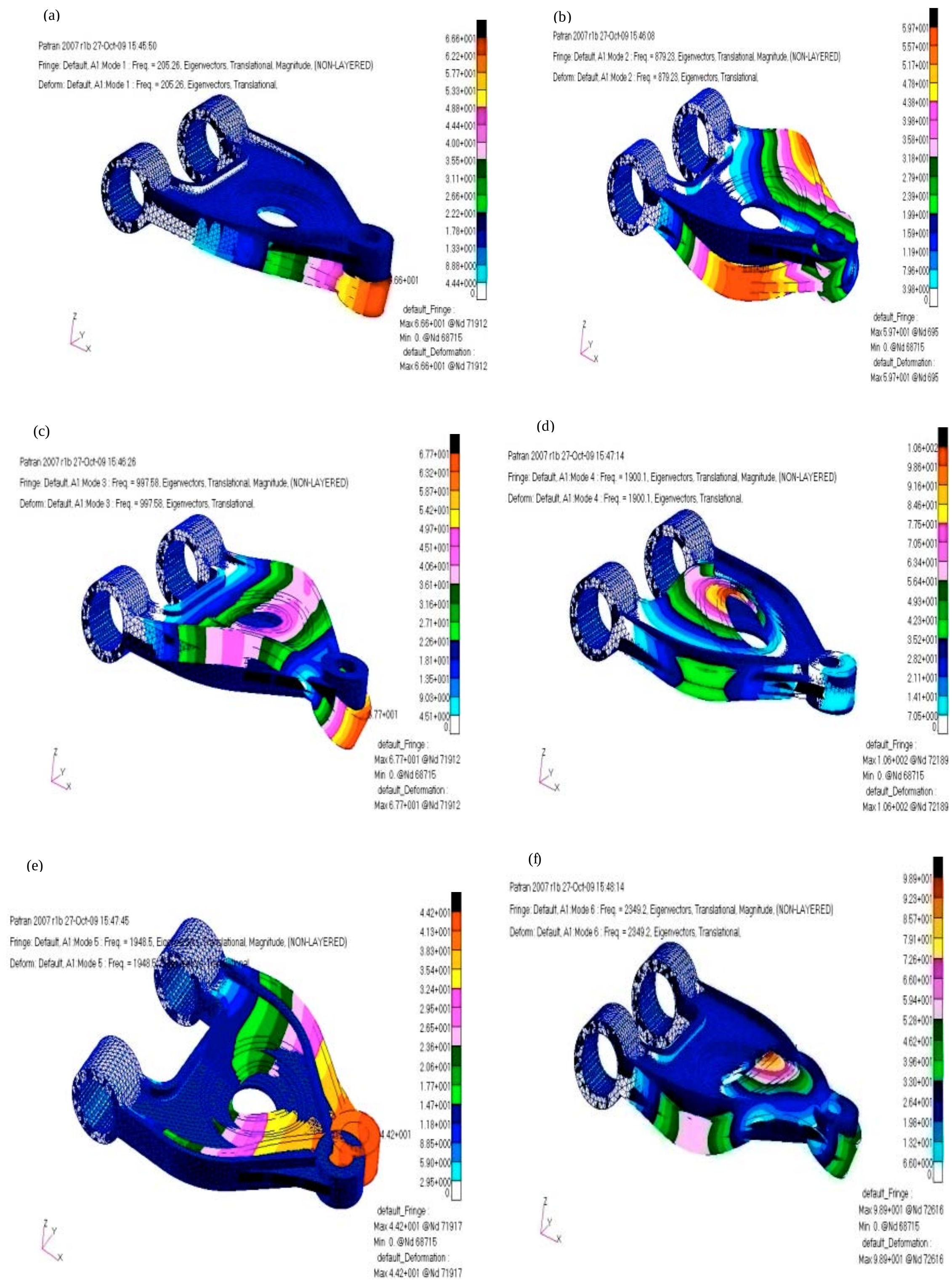

Fig. 5: Continue

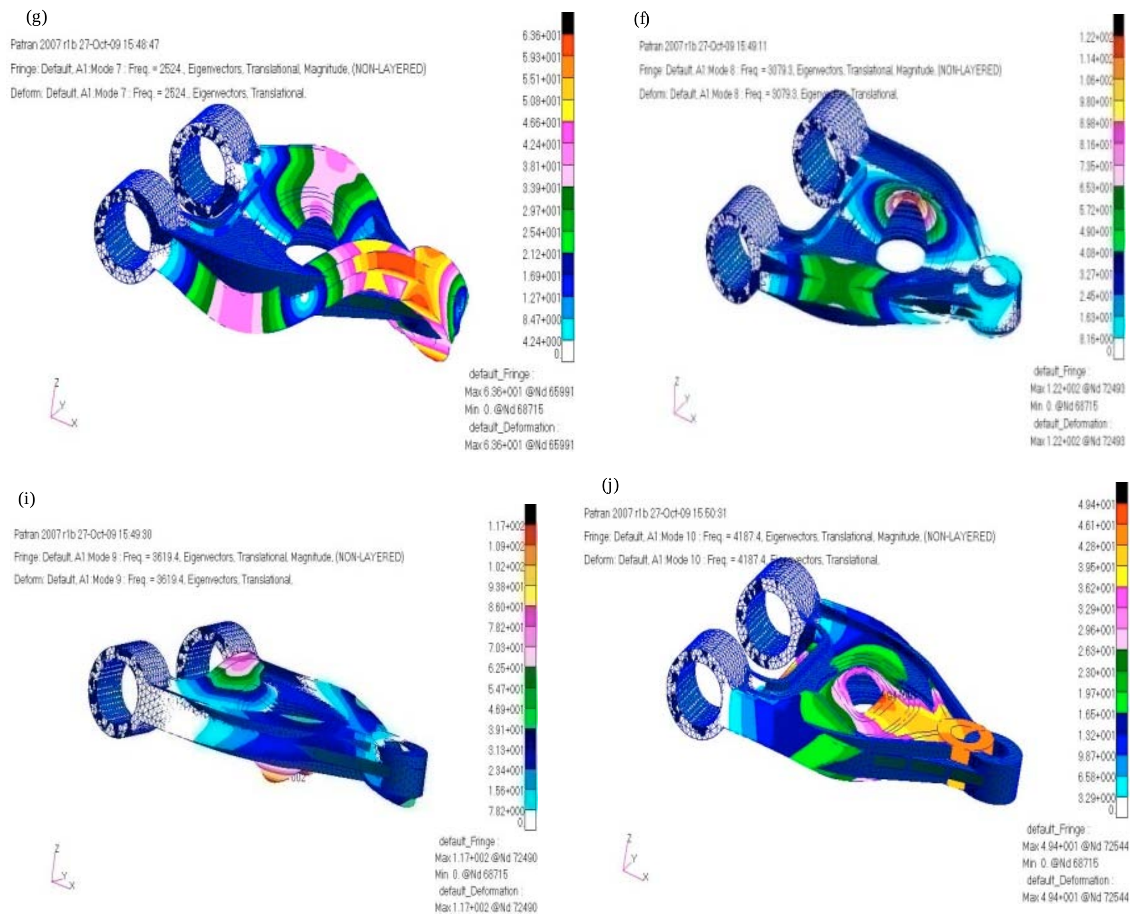

Fig. 5: Frequency mode of lower arm (a) Mode 1; Natural frequency = 205.26, (b) Mode 2; Natural frequency = 879.23, (c) Mode 3; Natural frequency = 997.58, (d) Mode 4; Natural frequency = 1900.1, (e) Mode 5; Natural frequency = 1948.5, (f) Mode 6; Natural frequency = 2349.2, (g) Mode 7; Natural frequency = 2524, (h) Mode 8, Natural frequency = 3079.3, (i) Mode 9; Natural frequency = 3619.4 and (j) Mode 10; Natural frequency = 4187.4

Table 4: Comparison between dynamic analysis and RBFNN techniques

Mode No.	Natural frequency (Hz)	Dynamic analysis (FEM) T1 (µm)	T2 (µm)	T3 (µm)	RBFNN T1 (µm)	T2 (µm)	T3 (µm)
1	500	3.585362	14.521961	54.625630	3.58	14.51	54.60
2	1000	18.28816	24.355831	65.193620	18.28	24.35	65.19
3	1500	3.556752	14.541624	54.572560	3.58	14.54	54.57
4	1920	9.845671	29.694552	8.766357	9.84	29.69	8.76
5	2200	6.629148	16.344712	63.624730	6.67	16.33	63.61

RBFNN in Table 4, the ANN prediction is much less as compared to dynamic analysis. It means that the RBFNN can often obtain results in almost negligible time as compared to similar works using the dynamic analysis. This approach found to be highly effective in identification Dynamic-displacement of suspension arm and it has been used of more realistic finite element problems, computer parallel programming, in order to get quickly solutions and with few workloads of processing, this technique is quite feasible (Abdullah, 2009).

CONCLUSION

In this study, we provide an introduction to Radial Basis Function Neural network. A detailed model of suspension arm has been developed using finite element techniques. The tetrahedral elements (TET 10) are used for the initial analysis. The results of the frequency are shown 10 modes and several deformation shapes and from the results proved that the model has been predicted the dynamic behavior. RBFNN has very attractive properties such as localization, functional approximation, interpolation and cluster modeling. These properties made it attractive in many applications. Highly effective (depends upon its accuracy, speed and memory requirements) in identification dynamic-displacement of suspension arm. RBF can be very successively used for the enhanced navigational performance and error reduction of the effort and time required to determine the dynamic-displacement response of lower suspension arm as the FE method usually deals with only a single problem for each run. The method can solve many problems that have mathematical and time difficulties.

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