



# Finite element model updating of a space vehicle first stage motor based on experimental test results



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## ABSTRACT

This paper discusses about a procedure to minimize the differences between analytical and experimental results of a space vehicle model by applying the finite element model updating procedure, in order to optimize the structures and processes before hardware is acquired. The material and geometric parameter set is formed for modal updating based on sensitivity analysis. Optimal values of experimental model parameters are determined using orthogonal array method. The updated finite element model produces more reliable results with the measured values. The method avoids irregularity and mismatch between the experimental and analytical model data sets, allowing flexible but automated model updating using neural network predicted parameters. The numerical results are compared with the experimental measurements and the divergences are measured by natural frequency difference and modal assurance condition. By training the neural network model based on the results and simultaneously adjusting the structural parameters, it is possible to reduce the difference between the measured and the predicted frequency values.

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## 1. Introduction

The uncertainty in the results between the Finite Element Analysis (FEA) and the Experimental Modal Analysis (EMA) is due to the assumptions made in defining unsuitable element material property and geometrical property [1]. The effects of errors due to be short of data's and information are analyzed using FEA and improvements must frequently be made to trim down the errors related with the FEM model. Model updating is done by correcting, improving or modifying the damping parameters, mass properties and stiffness of the FE model in anticipation of a better conformity between FEA values and EMA test results is achieved [1,2]. A better contest between analysis data and test results by constructing actual significant changes to the structural model parameters which correct imprecise finite element modeling assumptions is the objective of Finite element model updating [3,4]. The benefit of updated Finite element model is that, it is capable of modeling other loads and boundary conditions without go for any additional experimental testing [1,5]. The focus of model updating is constructed for analyzing the dynamics behaviors of a structure can be

developed and corrected using experimental test results measured on the actual structure of a space vehicle. It becomes the most demanded and challenging applications for testing [6]. An important requirement in dynamic analysis is to establish an analytical model capable of reproducing the experimental results. For this purpose, EMA and FEM that describe the behaviors of the structure in terms of frequencies and mode shapes were compared [7]. Many model updating methods [8,9] have been developed, but model updating by Artificial Neural Network (ANN) has been developed in the last decades only. One unique feature of the Neural Network (NN) is that they have to be trained to the functions. The experiment results and the FEA results from the software will be considered for updating. The selection of the parameters for updation is crucial because the FE model of the real structure is affected by updating the selected parameters [10]. The important issues are the number of preferred and selected parameters from the set. Physically, the selected updating parameters must be uncertain in the model. Mathematically, it if the estimation of too many parameters is attempted, then the problem can become visible and the values are difficult to find out. It is necessary to select those updating parameters that will be most effective in producing a genuine improvement in structure modeling. The quantity of updating parameters should be kept minimum and such parameters should be selected with the intend of converting predictable improbability in the model and ensuring that the data is perceptible to them. The

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parameters which are extensively used for model updating based on the sensitivity analysis are Young's modulus, Poisson's ratio, shear modulus and density. All these parameters come under material properties of the structure. Geometrical properties like plate thickness, structural cross sectional properties and spring stiffness were also consider for model updating [11].

After selecting the material and geometric properties taken as the parameters, next step is to develop an iterative NN methodology, it has been shown that the number of training samples required increases exponentially as the number of parameter to be updated increases [12,13]. To minimize the number of training samples and to obtain a well trained neural model, orthogonal array method has been implemented [14]. The random generation of training samples will also produce best updated parameters [15]. The investigations of selection of training samples for updating the numerical model also addressed. Numerical implementation of NN material model and geometric model are developed to learn the material response data and the structural behaviors of the model. So that, finite element model need not be analyzed to know the sensitivity of the structure [16].

Another important issue is the training of the sample, such that the network should reflect the dynamic uniqueness of the composition [17,18]. For that the NN model would need to be re-trained during the updating process. Re-training is achieved by removing

the original sample from the sample domain and by replacing it by newly predicted sample from the network [19,20].

This updating procedure is applied on Functionally Graded Material also. The work is motivated by the recent research activity on Functionally Graded Materials (FGMs), i.e., linear elastic isotropic materials with spatially varying properties tailored to satisfy particular engineering applications [21,22]. The special case of a body with Young's modulus depending on the radial coordinate only, and with constant Poisson's ratio, is examined in various research. It is shown that the stress response of the inhomogeneous cylinder (or disk) is significantly different from that of the homogeneous body [23]. For example, the maximum hoop stress does not, in general, occur on the inner surface in contrast with the situation for the homogeneous material. The results are illustrated using a specific radially inhomogeneous material model for which explicit exact solutions are obtained [24]. The main objective of the FEA-based design of heterogeneous objects is to simultaneously optimize both geometric shapes and material distributions over the design domain (e.g., Homogenization Design Method). However, the accuracy of the FEA-based design wholly depends on the quality of the finite element models generated [25]. Therefore, there exists an increasing need for developing a new mesh generation algorithm adaptive to both geometric complexity and material distributions. Here we used adaptive mesh generation al-

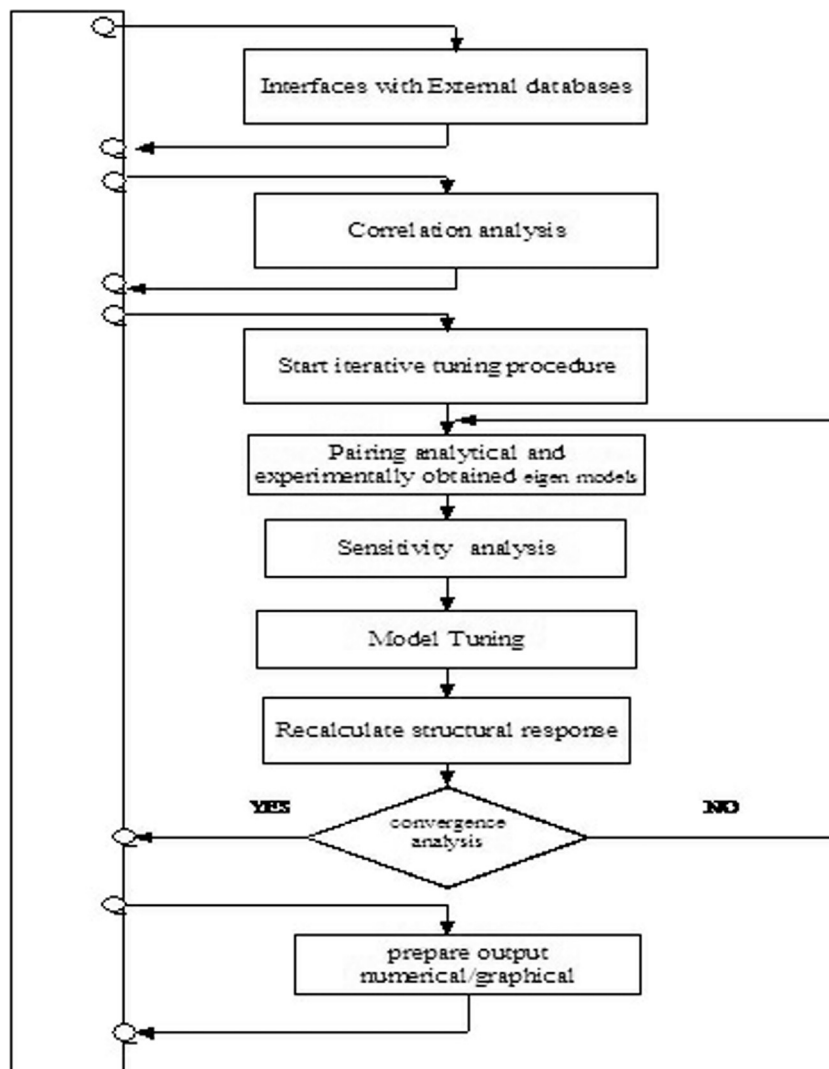


Fig. 1. General updating scheme.

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