

Developing a Transfer Function for Vehicle Ride Performance

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ABSTRACT

The purpose of this paper is to develop the transfer function for the ride and handling performance for military tracked vehicle. This transfer function will be used in place of the expensive physical hardware or simulation model for further study for robust design and optimization studies. Response Surface Methodology (RSM) approximation technique was used to develop the transfer functions. The RSM comprises of a group of statistical techniques for empirical model building and exploitation. RSM uses Design of Experiment (DOE) and multiple linear regression techniques for fitting of a response surface model that relates the output response to the design variables. The general form of the transfer function is a second order polynomial with unknown parameters to be identified. These unknown parameters were determined using the Central Composite Design (CCD) design of experiments.

1 INTRODUCTION

Approximation concepts were introduced in structured design optimization by Professor L.A Schmit and coworkers in the late 1970s to reduce the number of computer intensive detail analysis through the use of mathematical approximation of the design optimization objective and constraint function to reduce the number of independent design variables, and to perform constraint detection. Most approximation-based optimization methods make step-by-step improvements to the approximation model by adjusting the limits of the design variables [13]. Today's engineering design frequently involves complex and large systems. Complex computer models, computation-intensive numerical analyses/simulations, and Computer-Aided Design and Engineering (CAD/CAE) techniques are often used to analyze the system behavior from many angles and to facilitate design improvements. However, the high computational cost related to these engineering analyses and simulations restricts them from being used as performance measurement techniques in the design optimization. For instance, Ford Motor Company reports that one single crash evaluation using simulation on a passenger car requires 36 to 160 hours [11]. The design optimization process requires several numerical iterations, each with at least one analysis call, before the optimal solution is determined. Simulation-based analysis tools are finding increased use

during preliminary design to explore design alternatives at the system level.

2 BACKGROUND

Approximation method can be applied locally or globally. Polynomial response surface methodology is an example of the local approximation and are defined over a specific region of interest, namely about the current best design [14]. Optimization performs over the region where the model is valid and proceeds using the move limit or a trust region strategy. However, global approximation tries to capture the behavior of the response over the entire domain of interest. Artificial Neural Networks (ANN), Radial Basis Function (ABF), and Kriging are among many approximation methods that can be used to capture the behavior of the overall design space.

A variety of approximation models and techniques are available for constructing "surrogates" of simulation codes. A comprehensive review of using approximation models in structural optimization, in mechanical and aerospace systems application, in multidisciplinary design optimization can be found in recent literatures. At this point, an examination of the current uses of approximation in the context of the optimization can be conducted. This section reviews the state-of-the-art, as well as, the more classical uses of approximation. It is not meant to be a comprehensive list, rather, it serves to observe what areas of design optimization are taking advantage of approximation methods. Below is a brief description of different types of statistical approximation techniques which are most prevalent in the literatures:

Response Surface Methodology (RSM) was first developed through the collaboration of a statistician and chemist [3]. As Myers and Montgomery [14] define it, "RSM is a collection of statistical and mathematical techniques useful for developing, improving and optimizing processes." RSM incorporates the Design of Experiments, response surface model building, and model exploitation to explore a factor space and seek optimal factor settings. The general form of response surface models is a polynomial function [8]. Since this is a linear model (in parameters), the usual linear model tools may be applied.

Thus, RSM model is very easy to use. The drawback is that the rigid structure of a pre-selected polynomial model may not be flexible enough to represent the true response [7, 8, 14]. RSM was initially developed to create smooth approximations of response data with random error present [96]. Due to lack of error in computer model, response surface approximations may not be perfect, when approximating deterministic computer analyses. Therefore, a large number of sample points may be necessary to approximate all of the polynomial terms [1]. Many researchers used sequential response surface modeling approaches using move limits or trust region methods [17]. The literature contains several examples of RSM applied successfully to computer experiments.

Kriging is also known as Design and Analysis of Computer Experiments (DACE). Kriging method is used more frequently for approximating deterministic computer experiments [2, 16, 18]. Kriging evolved in the field of geostatistics and has recently become popular in the area of spatial statistics [5]. Kriging models are flexible, because a wide range of correlation functions can be selected for construction the model. Based on the selected class of correlation function, a Kriging model can either accept the data, providing an exact estimation of the data or leveling the data in the existence of analytical noise [6].

Artificial Neural Network (ANN) is a famous approach for building simple and fast approximations of highly complex computer analyses [4]. A neural network is inspired by cognitive and data processing capabilities that are characteristics of biological neural networks. An ANN model is represented by a diagram of nodes in various layers with weighted connections between nodes in different layers. As illustrated in Figure 1, a basic network is comprised of nodes. The nodes can be broken down into three different units, input, output, and hidden units. The nodes in the input unit receive the input data and the output unit provides the output responses. In between, there is usually at least one “hidden” layer, which induces flexibility into the modeling. Activation functions define transformations between layers (the simplest is linear function). Back propagation to previous layer is possible, except for function approximation. The typical ANN is feed forward only with one hidden layer and uses sigmoidal activation functions.

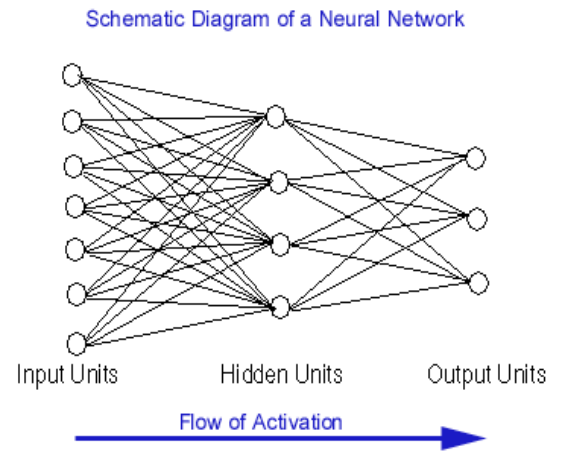


Figure 1 Artificial Neural Network concept [22]

The general function of a feedforward ANN with one hidden layer and activation functions $b_1(.)$ (input to hidden) and $b_2(.)$ (hidden to output) is in the equation below.

$$g_k(x; w; v; \theta; \tau) = b_2\left(\sum_{h=1}^H w_{hk} \cdot b_1\left(\sum_{j=1}^p v_{jh}x_j + \theta_h\right) + \tau_k\right)$$

where $k=1, \dots, K$

K is the number of response variables

P is the number of the inputs variables

H is the number of hidden nodes

Weights v_{jh} link input nodes j to hidden nodes h

W_{hk} link hidden nodes h to output nodes k

θ_h and τ_k are constant terms called “bias” nodes

The number of coefficients to be estimated is $(p+1)H + (H+1)K$.

Multivariate Adaptive Regression Splines (MARS): MARS constructs approximation models through a forward/backward iterative approach. Multivariate Adaptive Regression Splines is relatively new in the engineering design application. The computational cost to construct an approximation model using MARS is very low and the accuracy of the model is adequate.

Radial Basis Function (RBF): Radial basis functions have been developed for scattered multivariate data interpolation [12]. Radial basis function approximations have been proven to produce good model fits to for both stochastic and deterministic response functions [21].

Curve-fitting techniques use the data obtained experimentally to understand the relationships between the dependent and independent variables and construct models for future prediction of behavior.