Design Optimization for Suspension System of High Speed Train Using Neural Network*

Young-Guk KIM**, Chan-Kyoung PARK**, Hee-Soo HWANG*** and Tae-Won PARK****

Design optimization has been performed for the suspension system of high speed train. Neural network and design of experiment (DOE) have been employed to build a meta-model for the system with 29 design variables and 46 responses. A combination of fractional factorial design and D-optimality design was used as an approach to DOE in order to reduce the number of experiments to a more practical level. As a result, only 66 experiments were enough. The 46 responses were divided into four performance index groups such as ride comfort, derailment quotient, unloading ratio and stability index. Four meta-models for each index group were constructed by use of neural network. For the learned meta-models, multi-criteria optimization was achieved by differential evolution. The results show that the proposed methodology yields a highly improved design in the ride comfort, unloading ratio and stability index.

**Key Words**: Design of Experiment, Neural Network, Differential Evolution, Design Optimization, Ride Comfort, Derailment Quotient, Unloading Ratio, Stability

1. Introduction

The role of optimization becomes more and more important in current engineering design. For today's complex engineering problems, which spread over almost every engineering field, it is frequently a matter of utmost concern to apply the multi-disciplinary or multi-criteria optimization to real systems and to obtain an optimum efficiently.

Many of the current optimization methods for engineering design depend on numerical techniques which employ complex computer analysis codes.

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Optimization design, using these techniques, needs a vast amount of information for the system. Despite continual advances in computing power and speed, however, the cost and time necessary to run the large analysis set still remains non-trivial. It is very difficult or may be impossible to generate a globally optimal design over a full design space in the case of complex design problems with many design variables and criteria.

Therefore, it is worthwhile to obtain an improved design under real constraints on computational time and resource in such cases. For this purpose, approximation of real system, so-called meta-model, is widely used in engineering design[1].

A common way to build a meta-model is to apply response surface methodology (RSM)[2,3]. In this methodology, algebraic regression approximations of object functions and design variables, which consist of quadratic polynomial equations, are generally constructed. The approximations are responses to data that are carefully distributed by design of experiment (DOE)[4,5,6] over the design space.

However, if the system has highly nonlinear behavior, a quadratic, or even cubic polynomial fit
would have difficulty in accordance with the generated data. One possible solution is to use as high order polynomials as possible. If there are, for example, ten data points that have been sampled for 1 design variable, then a ninth order polynomial, composed of ten regression coefficients, can be determined by the least squares method. This solution, however, is not a good one. High order polynomials tend to oscillate wildly between data points at the extremes of the range. For this reason, they are not considered appropriate meta-models in the case of highly nonlinear systems like the suspension system of railway vehicles.

As an alternative method, neural network\(^{(13)(4)-(6)}\) is used frequently to build meta-model for highly nonlinear systems. It is composed of neurons which are multiple linear regression models with nonlinear transformation.

Firstly, this paper will describe the methodologies used such as DOE, neural network and differential evolution (DE). Then, the above methodologies will be employed for the design optimization of the suspension system of the Korea High Speed Train (KHST), which is a nonlinear multi-degree system and has 29 design variables and 46 responses. The dynamic simulations are performed using a commercial analysis code called VAMPIRE\(^{(7)}\). DOE and neural network are applied to build the meta-models. In order to exploit improved design variables of meta-models, design optimization for KHST suspension system is accomplished by DE. The multi-criteria optimization procedure, based on the neural network model and the differential evolution, is presented in Fig. 1.

2. Overview of Methodologies

In this chapter, the methodologies used in this study such as DOE, neural network and differential evolution (DE) will briefly be described. The following methodologies are devoted to searching the optimal design variables of the suspension system of KHST.

2.1 Design of experiments (DOE)

A large variety of DOE, such as central composite design, D-optimality design, full factorial or fractional design, and orthogonal array\(^{(10)(9)}\) are widely used in engineering analysis. Properly designed experiments are essential for effective computer utilization. The number of experiments increases exponentially as a function of the number of design variables.

For example, the KHST suspension system has 29 design variables and the resulting number of experiments, decided by DOE, may amount to \(2^{29}\) in case that 2 level full factorial design is applied. It is really nonsensical, from an engineering point of view, because it may take a number of years to acquire all data from experiment.

In order to reduce the number of experiments to a more practical level, a combination of fractional factorial design and D-optimality design is used as an approach to the design of the experiment. Firstly, 32 experiments are selected by using Taguchi's \(L_{32}\) orthogonal array. This is chiefly used in industry because orthogonal array is the smallest fractional factorial design. Secondly, 33 experiments, which have 5 levels, are added by means of the D-optimality design to get effective information from inside the design space. To these 65 experiments, the mid-point of all design variables is added and the resulting number of experiments becomes 66.

2.2 Neural network

Neural network\(^{(10)(4)-(6)}\) is created into an architecture by assembling neurons that are multiple linear regression models with a nonlinear transformation on the output \(y\). The most prevalent architecture is the multi-layer feed-forward network. Training of the network is accomplished most commonly through back-propagation.

One of the problems, which occur during training, is the fact that a great amount of computation time is consumed. The second is that the regression can be over-fitting at specific points. There are several high performance methods which can converge from ten to one hundred times faster than the typical back-propagation method and are also enough to provide an adequate fit for practical problems\(^{(8)}\). Another problem that arises in the process of building network is how to determine an appropriate network configuration. This is because the number of neurons can be too large or too small to represent the approximations properly over all the design space\(^{(9)}\).

As will be explained in the following chapter, the KHST suspension system has 46 responses which are divided into four performance index groups such as ride comfort, derailment quotient, unloading ratio and
stability index. Four neural networks have been constructed for each index group. The Baysian Regulation with Levenberg-Marquardt has been used as training algorithm to avoid over-fitting at given points. In this study, each network is composed of an input layer, a hidden layer and an output layer. The numbers of neurons in the input layer and output layer are set to the number of design variables and responses, respectively. In order to decide the number of neurons in the hidden layer, the fuzzy clustering method has been employed.

Cluster analysis is a technique used for grouping data and finding structures within data. The most common application of clustering methods is to partition a data set into clusters or classes, where similar data are assigned to the same cluster, whereas dissimilar data should belong to different clusters. In real applications there is very often no sharp boundary between clusters. Therefore, fuzzy clustering is often better suited to the data. Fuzzy clustering can be applied as an unsupervised learning strategy in order to group data. The number of groups can be used to estimate the number of necessary neurons in the hidden layer of the network.

2.3 Differential evolution (DE)

Differential evolution, suggested by Rainer Storn and Kenneth Price is an optimization algorithm which obtains the minimum in the design space. It is a novel parallel direct search method which utilizes NP parameter vectors of Eq. (1) as a population for each generation G,

\[ x_{i, c} = x_{i, c}^{G} \quad i = 1, 2, \ldots, NP \quad j = 1, 2, \ldots, NS \]  (1)

where NP is population size, and NS is the number of parameter to search. NP does not change during the minimization process. If nothing is known about the system, the initial population is chosen randomly. As a rule, we will assume a uniform probability distribution for all random decisions. If a preliminary solution is available, the initial population often generates by adding normally distributed random deviations to the nominal solution \( x_{nom} \).

The crucial idea behind DE is a new scheme for generating trial parameter vectors. DE generates new parameter vectors by adding the weighted difference vector between two population members to a third member. If the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector replaces the vector with which it was compared. For each vector, the trial vector \( u_{i, c} \) is generated according to Eq. (2),

\[ u_{i, c} = x_{i, c} + F \cdot (x_{i, c} - x_{r_1, c}) \]  (2)

with \( r_1, r_2, r_3 \in [1, NP] \), integer and mutually different, and \( F > 0 \).

The mutually different integers \( r_1, r_2 \) and \( r_3 \) are chosen randomly with uniform distribution from the interval (1, NP), and also different from the running index \( i \). \( F \) is a real and constant factor which controls the amplification of the differential variation \((x_{r_1, c} - x_{r_3, c})\). In order to increase the diversity of the parameter vectors, the vector is formed as in Eq. (3),

\[ u = (u_1, u_2, \cdots, u_{NP})^T \]  (3)

with \( u_j = u_{j, c} = \begin{cases} u_j & \text{if } (rand \leq Cr) \\ x_{j, c} & \text{otherwise} \end{cases} \quad j = 1, \ldots, NP \]

\( i = 1, \ldots, NS \)

where rand is a random number generated with uniform distribution in the range from 0 to 1, and \( Cr \) is a crossover rate.

3. Design Problem

The objective of the present study is to reach design optimization on the dynamic behavior of KHST. In this section, the KHST suspension system and the cost function will be described.

3.1 KHST suspension system

The model and coordinate system of KHST is shown in Fig. 2. KHST is composed of six cars including 1 power car (1 in Fig. 2), 2 motorized trailer cars (2 and 6 in Fig. 2) and 3 trailer cars (3, 4 and 5 in Fig. 2). Also, it has eight Bogies including 2 power motor bogies (PMB, 7 and 8 in Fig. 2), 2 motorized trailer bogies (MTB, 9 and 14 in Fig. 2) and 4 articulated trailer bogies (ATB, 10, 11, 12 and 13 in Fig. 2). The detailed figure of MB and ATB is shown in Fig. 3 (a) and (b).

As shown in Figs. 2 and 3, a bogie frame is connected to a body via the 2nd suspension, and a wheelset is connected to a bogie frame via the 1st suspension. The suspension elements are coil springs, air springs, hydraulic dampers, rubbers, stabilizers and so forth.

The 29 design variables, selected from engineer’s experiences, are summarized in Table 1 and 46 responses are selected from dynamic performances. The 46 responses are composed of 10 responses for ride comfort, 12 for derailment quotient,
Table 1 Design variables for suspension system of KHST

<table>
<thead>
<tr>
<th>No</th>
<th>Name</th>
<th>Design variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>Primary suspension of MTB and ATB</td>
<td>Elastic joint Ks, Kr</td>
</tr>
<tr>
<td>X2</td>
<td>Primary suspension of MTB</td>
<td>Elastic joint Ky</td>
</tr>
<tr>
<td>X3</td>
<td>Primary suspension of MTB</td>
<td>Elastic joint Kt, Kw</td>
</tr>
<tr>
<td>X4</td>
<td>Primary suspension of MTB</td>
<td>Double coil spring Ks</td>
</tr>
<tr>
<td>X5</td>
<td>Primary suspension of MTB</td>
<td>Vertical oil damper Cx</td>
</tr>
<tr>
<td>X6</td>
<td>Secondary suspension of MTB</td>
<td>Air spring Ks, Ky</td>
</tr>
<tr>
<td>X7</td>
<td>Secondary suspension of MTB</td>
<td>Air spring Ky</td>
</tr>
<tr>
<td>X8</td>
<td>Secondary suspension of MTB</td>
<td>Vertical oil damper Cx</td>
</tr>
<tr>
<td>X9</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g1</td>
</tr>
<tr>
<td>X10</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g2</td>
</tr>
<tr>
<td>X11</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g3</td>
</tr>
<tr>
<td>X12</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g4</td>
</tr>
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<td>X13</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g5</td>
</tr>
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<td>Anti-yaw oil damper g6</td>
</tr>
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<td>X15</td>
<td>Secondary suspension of MTB</td>
<td>Double coil spring Ks</td>
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<tr>
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<td>Secondary suspension of MTB</td>
<td>Vertical oil damper Cx</td>
</tr>
<tr>
<td>X17</td>
<td>Secondary suspension of MTB</td>
<td>Air spring Ks, Ky</td>
</tr>
<tr>
<td>X18</td>
<td>Secondary suspension of MTB</td>
<td>Air spring Ky</td>
</tr>
<tr>
<td>X19</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g1</td>
</tr>
<tr>
<td>X20</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g2</td>
</tr>
<tr>
<td>X21</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g3</td>
</tr>
<tr>
<td>X22</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g4</td>
</tr>
<tr>
<td>X23</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g5</td>
</tr>
<tr>
<td>X24</td>
<td>Secondary suspension of MTB</td>
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<td>Anti-yaw oil damper g9</td>
</tr>
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<td>X28</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g10</td>
</tr>
<tr>
<td>X29</td>
<td>Secondary suspension of MTB</td>
<td>Anti-yaw oil damper g11</td>
</tr>
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</table>

Fig. 3 Bogies, (a) Motorized trailer bogie, (b) Articulated trailer bogie

12 for unloading ratio, and 12 for stability index. These 48 responses are also summarized in Table 2.

Each performance index group is defined as the following: ride comfort is defined as root mean square (RMS) of frequency-weighted acceleration according to UIC 513R(4), derailment quotient according to UIC 518(32) as standard deviation for ratio of lateral force to vertical force at the wheel/rail contact point, unloading ratio as maximum for ratio of dynamic vertical force to static vertical force at the wheel/rail contact point and stability index as standard deviation of the body’s lateral displacement at the track center.

3.2 Definition of cost function for KHST suspension system

In general, optimization is to maximize or minimize the cost function under some constraints. In the present design problem, decrease of response means increase of performance, i.e. as each response for KHST becomes smaller, the dynamic behaviors of KHST become better. Therefore, the cost function is defined as the sum of responses of Eq.(4) and the optimization is conducted to minimize the cost function.

\[
\text{Cost} = \sum_{i} p(x) i
\]

Constraints for the present optimization are presented in Eqs.(5) and (6),

\[
k(x)_i = p(x)_i - p(x),_{\text{init}} < 0, \quad i = 0, 1, 2, \ldots, n \quad \text{(5)}
\]

\[
-1 < p(x)_i < 1 \quad \text{(6)}
\]

where \( p(x)_i \) and \( p(x),_{\text{init}} \) are \( i \)th responses for KHST after and before optimization, respectively, and \( n \) is the number of responses (=46). The first constraint in Eq.(5) prevents all the optimized responses from increasing relative to the initial response. The second constraint in Eq.(6) restricts the range of optimized responses between -1 and 1. Both the constraints play an important role in preventing some specific response prevailing over the others in respect of cost function.

For differential evolution, the first constraint in Eq.(5) is included into the cost function in Eq.(4). The resulting cost function is defined as Eq.(7),

\[
\text{Cost} = \sum_{i} p(x) i \text{ if } (k(x)_i < 0) \\
\sum_{i} \rho y_i \text{ otherwise}
\]

where \( \rho y \) is penalty coefficient, and \( w_i \) is weight of \( i \)th response for KHST.

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4. Results and Discussion

4.1 Representation of neural network for KHST suspension system

Four networks for ride comfort, derailment quotient, unloading ratio, and stability index have been created. The networks for derailment quotient, unloading ratio, and stability index have 29 neurons for the input layer and 12 neurons for the output layer. The network for ride comfort has 29 neurons for the input layer and 10 for the output layer.

In order to determine the number of neurons in the hidden layer, fuzzy clustering has been performed by use of the design variables and the responses of each network obtained from 66 DOEs. As shown in Fig. 4, the overall trends for all networks are very similar and the objective functions decrease with increasing number of neurons ranging from 2 to 20.

In particular, the gradient of the objective function is far steeper when the number of neurons is smaller than 10, which means that at least 10 neurons are needed to build a proper network. From the above result, Ten has been chosen as the initial number of neurons in the hidden layer. The number of neurons was increased if the proper network had not been constructed in the tolerance. Ten neurons in the hidden layer are enough for the ride comfort, unloading ratio and stability index, while those needed for the derailment quotient are 13.

Figure 5 presents the result of regression analysis for r1 response between true model using the VAMPIRE code and network model. The correlation coefficient for r1 is 0.998, which means that the network response is in accordance with the true response. For more extensive analysis, the absolute mean errors, as well as the correlation coefficients of all the indices, are plotted in Fig. 6. The absolute mean error is defined as Eq. (8).

\[
\text{Error}_{\text{mean}} = \frac{\sum_{i=1}^{n} |y_{\text{true}}(x_i) - y_{\text{network}}(x_i)|}{n}
\] (8)

The absolute mean errors are less than 3% and the correlation coefficients are almost 1 at all responses. The results show that the learned neural network models seem to be satisfactory in dealing with the design problem.

4.2 Optimization for KHST suspension system

Design variables to minimize the cost function defined in chapter 3 have been searched using differential evolution for 100 cases, in which the initial 30 (NP) parameter vectors were randomly chosen. For the chosen 5 arbitrary cases, the convergence curves of cost function defined in Eq. (7) are presented in Fig. 7. The cost functions seem to remain constant after about 800 iterations, and thus, we iterated the DE processes 2 500 times for all cases. This seems enough to be considered as convergence criteria.

For all of the 100 cases, the optimized cost functions are presented in Fig. 8 and the initial and the optimized value of each response are presented in Fig. 9. As shown in Fig. 8, the cost function is −3.97 under the initial condition, where all the normalized design variables are 0, and the average of the optimized cost function is −26.91, i.e. the cost function decreased by 22.94 after optimization on average. The optimized cost function distributed from −24.63 to −29.32 with a standard deviation of 0.936, which seems to be reasonable considering the average decrease of cost function is 22.94. The optimized values of response in Fig. 9 are smaller than the initial value and are in the range between −1 and 1 for all cases. This means that the constraints are successfully satisfied, preventing any response to prevail over the others in the cost function.

Figure 10 compares the cost functions of network
Fig. 6 Correlation coefficient and absolute mean error for each performance index, (a) Ride comfort, (b) Derail quotient, (c) Unloading ratio, (d) Stability index

Fig. 7 Convergence curve of cost function

Fig. 8 Cost function after optimization for 100 cases

model and true model for the best 10 cases and the worst 10 cases out of 100 cases. The cost functions of true model have been calculated using the VAMPIRE code. After optimization, the cost function for network model and true model decreased by 22.90 and 21.65, respectively, which conveys that the optimizations were conducted successfully to improve the performances because the cost functions decreased by a similar amount in both cases.

For more extensive investigation, an arbitrary case is chosen and the optimized design variables of the case are presented in Table 3. Figure 11 shows
Table 3  Optimized design variables for an arbitrary case

<table>
<thead>
<tr>
<th>No.</th>
<th>Normalized design variable</th>
<th>No.</th>
<th>Normalized design variable</th>
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<tr>
<td>X15</td>
<td>-0.001</td>
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</table>

Fig. 9  Initial and optimized value of each response for 100 cases

Fig. 10  Cost function of network model and true model for the best 10 and the worst 10 cases

The responses of the network model and the true model to the design variables before and after the optimization. In both cases, most of the responses to the optimized value decrease according to those of the initial value. The efficiency of optimization is very good for the ride comfort, the unloading ratio and the stability index. In the case of derailment quotient, however, the performance is improved to a small extent or it even deteriorated for some responses of true model.

The improvement of performance (IoP) for each response is evaluated using the parameter defined in Eq.(9) and shown in Fig. 12.

\[
\text{IoP} = \frac{\mathcal{R}(x)_{\text{optimized}} - \mathcal{R}(x)_{\text{initial}}}{2}
\]  \hspace{1cm} (9)

As indicated in the Fig. 12(a), (c) and (d), the performances are remarkably improved in the stability index, ride comfort and unloading ratio by up to 88%, 38% and 15%, respectively, in both cases of the network model and the true model. Moreover, the true model yields a good agreement with the network model for each performance index group. In the case of the derailment quotient, as shown in Fig. 12(b), the maximum IoP is 24% in the network model and 16% in the true model at d11 response. The IoP is negative at d1, d3, d5 and d6 response in the true model, while there are no negative IoP's in the network model. The negative IoP in the true model seems to originate from the fact that the overall performance improvement in derailment quotient is relatively small or practically zero. However, the prediction errors of the network model for derailment quotient are not larger than, but the same as the other three cases.

From the results, it can be concluded that the present differential evolution, using the network model, is a successful optimization method for the optimal design of the suspension system of high speed train that has many design variables and design objectives.

Figure 13(a) and (b) show the normalized values of optimized design variables for 100 cases and the averages and the standard deviations of the 100 cases, respectively. In the Fig. 13(b), the standard deviations of some optimized design variables is near to 0.6 and this means that the optimized design
variables are scattered throughout a wide range, but the optimized cost functions are within a narrow range as in Fig. 8. From the above result, it also can be concluded that the present optimization problem of the KHST suspension system has various local optima in the full design space.

5. Conclusion

The following conclusions can be made from the optimization of the KHST suspension system using...
the neural network and differential evolution.

1) Reliable optimization results could be attained for the nonlinear multi-variable and multi-criteria system that has 29 design variables and 49 responses.

2) Only 66 experiments were enough to build a proper neural network.

3) The fuzzy clustering method was successfully applied to the determination of the neural network architecture and, as a result, the iterative learning time taken to get the final neural network can be diminished.

4) There seems to be many local optimums in the present design space from the fact the optimized values of the design variables from 100 cases with different initial condition are scattered throughout a wide range even though the optimized cost functions are within a narrow range.

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