Multi-Objective Design Optimization of High-Speed Train Nose*

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Abstract

This paper presents a novel design technique for high-speed trains using a multi-objective optimization method to balance plural aerodynamic properties. The technique involves the use of an evolutionary algorithm, a shape parameterization technique that uses B-spline curves and Coons patches, and a computational simulation that uses a Message Passing Interface. To demonstrate the capability of the method, a train nose is designed that has optimized aerodynamic drag and aerodynamic forces with respect to affecting other trains. A 10th generation evolutionary calculation with 512 individuals was conducted, and physically reasonable Pareto solutions were successfully obtained.

Key words: Railway, High-Speed Train, Multi-Objective Shape Optimization, Evolutionary Algorithm, Aerodynamic Property

1. Introduction

In designing the shape of a train, many factors have to be taken into consideration, such as mechanical structures, intensities, aerodynamic properties, driver visibility, manufacturing cost, and ease of maintenance. Amongst these, a critical design factor for a high-speed train is its aerodynamic properties, for which one must take into consideration parameters such as tunnel micro-pressure waves, aerodynamic drag, flow-induced car vibrations in tunnels, response to crosswinds, and aerodynamic forces affecting the other trains and trackside structures. Amongst them, tunnel micro-pressure wave has been considered to be the most important factor in designing the nose of high-speed trains in Japan. A tunnel micro-pressure wave is an impulsive pressure wave that is radiated from a tunnel exit with an explosive sound when the train nose enters the tunnel at a high speed. Since Iida et al.1) obtained the optimum cross-sectional area variation (but not three-dimensional shape) of a train nose for reducing the tunnel micro-pressure wave by using a flow simulation and a nonlinear optimization method, several studies have been conducted pertinent to this design2,3). The latest Shinkansen trains have been designed on the base of these studies. As for aerodynamic drag, wind tunnel experiments and on-track tests have been conducted and a guide principle for reducing the drag has been proposed4). It has been reported that pressure fluctuations on the sides of a train cause flow-induced car vibration in a tunnel and several train shapes have been examined using wind tunnel and on-track tests to reduce these pressure fluctuations5). Because the aerodynamic forces acting on a train under a crosswind depend not only on the vehicle shape but also on wayside structures, wind tunnel experiments with systematic classification of trains and wayside...
The optimum nose configuration of a train for reducing pressure variations during the passage of the train, which causes the aerodynamic forces affecting the other train and the trackside structures, was obtained by using an axisymmetric flow simulation combined with nonlinear programming, and was confirmed by a model experiment.

As stated above, extensive studies have been conducted in order to improve each individual aerodynamic property of a high-speed train. However, it is not an easy task to meet the requirements of multiple aerodynamic properties simultaneously. In the field of aerospace and aeronautical engineering, multi-objective optimization has been extensively studied and applied in designing an actual aircraft. However, only a few studies have been conducted on the topic of multi-objective optimization in the field of railways. Although Tyll et al. proposed the concept of multi-objective optimization for a magnetic elevated vehicle, they examined only an optimum two-dimensional nose shape, but not an optimum three-dimensional one. Therefore, in this study, we develop a multi-objective optimization method for the three-dimensional shape of a train with the aim of supporting the train design process.

2. Method

2.1 Outline of the method

A flowchart showing the multi-objective optimization process is presented in Fig. 1. First, initial values of design variables defining initial train shapes are randomly given. Then the flow field around the train is calculated and the aerodynamic properties are estimated. Next, new possible design variables are established by the use of an evolutionary algorithm, before returning to the flow simulation stage. The process is repeated until the objective functions converge.

Fig. 1  Flowchart of proposed method
2.2 Definition of train shape

The shape parameterization techniques are a very important aspect of optimization, and a higher degree of flexibility in representing shapes by fewer parameters is required. In this study, cross-sectional shapes are first defined by B-Spline curves, which is one of the most popular approaches for airfoil designs\(^{(10)}\). Next, the surfaces between the cross-sectional shapes are determined by bilinear Coons patches\(^{(11)}\) (Fig. 2). Here, we define the cross-sectional shape by using a third-order B-Spline curve with four control points as an example (Fig. 3). In order to reduce the computational cost, the distance \(d\) from the corner to the control points \(V_1\) and \(V_2\) is set to be constant. This means that the curvature of corners is constant. In addition to the constraint condition of the maximum height and width of the train, the cross-sectional area is set to be in accordance with the optimum cross-sectional area variation for the purpose of reducing the tunnel micro-pressure wave. The optimum cross-sectional area \(A\) is defined by the following equation\(^{(1)}\):

\[
\frac{A(x)}{\pi b^2} = (1 - \alpha_2) \left[ (1 - \alpha_1) \frac{x}{a} + \alpha_1 \sqrt{\frac{x}{a}} \right] + \alpha_2 \left( \frac{x}{a} \right)^2.
\]  

\(1\)
where $x$: the distance from the front end, $a$: the length of the train nose, $\pi b^2$: the area of the maximum part of the nose, which is set at 11 m$^2$ in this study. The design variables $\alpha_1$ and $\alpha_2$ are 4.18 and 0.75, respectively, when $a/b = 5$. Adding this as the constraint condition reduces the number of design variables of each cross-section to one, which is the aspect ratio.

After defining a set of cross-sections along the nose by using the B-Spline curves, the surface between each cross-section is interpolated by using the bilinear Coons patch. In this study, we use five cross-sections to represent the nose shape. Therefore, the number of design variables for creating the train shape is five.

2.3 Multi-objective evolutionary algorithm

An optimization problem lies in maximizing or minimizing an objective function under a constraint condition. If we have multiple objective functions, this is called as a multi-objective optimization problem. Multi-objective optimization presents not a unique solution, but a set of compromised solutions called Pareto-optimal solutions, which represent a trade-off information of the competing objectives\(^{(12)}\) (Fig. 4).

![Fig. 4 Pareto solution](image)

Optimization methods are generally categorized into two groups: deterministic methods and stochastic ones\(^{(13)}\). If one wants to search the maximum values of the objective functions and these functions have a single peak in their solution space, the deterministic method is suitable. In cases where the objective functions have plural peaks, the deterministic method entails the risk of getting stuck in a local optima, and the stochastic method is better suited in these cases. In general, aerodynamic problems have plural peaks.

Among the stochastic approaches, there is an evolutionary algorithm that mimics biological evolution. In the evolutionary algorithm, first an initial population of design candidates called individuals is randomly generated. A fitness function of each individual, which is related to the objective function, is evaluated. Mating pairs of individuals with higher fitness values are selected to produce offspring for the next generation by exchanging and mutating their design parameters. Then the fitness functions of the new generation are evaluated and the mating pairs are selected to reproduce the next generation again. In the process, one can expect to have individuals with better objective values. The evolutionary algorithm can sample as many solutions as the number of individuals during
the alternation of generations and is suitable to find Pareto-optimal solutions. Moreover, the algorithm is easily programmed for parallel computation. Each process of the evolutionary algorithm is explained as follows.

**Selection:** One may say that the individuals with parents of higher fitness values possibly have higher fitness values compared with the ones that have parents of lower fitness values. Then the individuals to be parents are selected in a stochastic process corresponding to their fitness values. Several selection methods have been proposed, such as roulette selection, ranking selection, and tournament selection\textsuperscript{10}. We employ Stochastic Universal Sampling (SUS)\textsuperscript{13} to prevent the loss of population diversity. SUS uses a roulette, that is divided into sections in proportion to their fitness values, with plural indicators to select a certain number of parents for each spin of the wheel (Fig. 5). We have two indicators in this study.

The fitness values are evaluated by the Pareto ranking method\textsuperscript{14}. In this method, ranks of Pareto-optimal solutions are assigned one value, and the ranks of the other are assigned values in response to their locations in the solution space (Fig. 6). In the population of a generation, if an individual is dominated by (inferior to) $p$ pieces of individuals, the rank of the individuals is assigned $1 + p$. For instance, because individual D in Fig. 6 is inferior to individuals A, B, and C, the rank of individual D is 4. The fitness value is set to be an inverse number of the rank.

![Fig. 5  Stochastic universal sampling](image)

![Fig. 6  Pareto ranking method](image)
It is preferable that Pareto-optimal solutions are uniformly distributed in the solution space to maintain population diversity. Thus the fitness values of the individuals in the densely populated area of the solutions are lowered and the ones in the depopulated area are raised. The modified fitness value is as follows:

\[ f'_i = \frac{f_i}{\sum_{j=1}^{N} s(d_{i,j})}. \]  

where \( N \) is the size of the population. \( s \) is a function of the population density as follows:

\[ s(d_{i,j}) = \begin{cases} 1 - \left(\frac{d_{i,j}}{\sigma_{share}}\right)^\kappa, & d_{i,j} < \sigma_{share} \\ 0, & d_{i,j} \geq \sigma_{share} \end{cases}. \]

where \( d_{i,j} \) is Euclidean distance between the individuals \( i \) and \( j \) in the space of the objective functions. \( \kappa \) is set to 0.25. \( \sigma_{share} \) is a parameter that controls the increase or decrease in the fitness values in response to the population density, and is determined by solving the following equation:

\[ N\sigma_{share}^{q-1} - \prod_{i=1}^{q}(M_i - m_i + \sigma_{share}) - \prod_{i=1}^{q}(M_i - m_i) = 0. \]

where \( M_i \) and \( m_i \) are the maximum and minimum values of each objective function, respectively and \( q \) is the number of objective functions. In the case of two objective functions, Equation (4) becomes

\[ (N - 1)\sigma_{share}^2 - (M_1 + M_2 - m_1 - m_2)\sigma_{share} - 2(M_1 - m_1)(M_2 - m_2) = 0. \]

Crossover: Genes are exchanged between selected individuals. In this case, genes mean design parameters. Although there are two ways of representing the design parameters, binary representation and floating-point representation, we adopt the floating representation, which is conceptually close to the real design space. BLX-\( \alpha \) Method, which has a wide exploring area, is employed for combining the design parameters of two parents.

\[ x_{child1} = \gamma \cdot x_{parent1} + (1 - \gamma) \cdot x_{parent2}. \]

\[ x_{child2} = (1 - \gamma) \cdot x_{parent1} + \gamma \cdot x_{parent2}. \]

where \( x_{child1} \) and \( x_{child2} \) are the design parameters of the children, and \( x_{parent1} \) and \( x_{parent2} \) are those of the parents. And \( \gamma = (1 + 2\alpha)u - \alpha \), where \( u \) is a uniform random number between 0 and 1. According to \( \alpha \), the design parameters of the children are assigned to be outside between the parents’ design parameters in a stochastic manner. \( \alpha \) is set to 0.5.
**Mutation:** In order to explore the wider area where the crossover of the present population cannot reach, parts of the genes are forcedly mutated in a stochastic manner. There are two basic methods of mutation. One is a uniform mutation that adds a uniform random number to each design parameter at a probability called a mutation rate. The other is a Gaussian mutation that adds a number with a unit normal distribution. Because the former is generally employed in the evolutionary algorithm with the floating-point representation, we adopt the uniform mutation method. The mutation rate is set to 0.1.

**Alternation of generations:** A simple way of alternating generations is that the parent population is always replaced by the offspring population. The lifetime of each individual is one generation in this system. The offspring, however, do not always have better fitness values than the parents. Thus, the parents and the children compete with each other. The individuals with higher fitness values within the population size survive to the next generation.

### 2.4 Objective functions and numerical simulation

In this study, we adopt two aerodynamic properties as the objective functions: the aerodynamic drag on the front nose of the train, and the pressure variation around the car, which causes the aerodynamic forces affecting other trains and trackside structures. To estimate these properties, we need to accurately analyze the flow around the train nose. Although high-speed trains have streamlined noses and there are no large flow separations around them, we should consider the boundary layer. Thus, a steady three-dimensional viscous flow simulation is conducted in which the Baldwin–Lomax model is employed as a turbulence model. The numerical scheme is based on the MAC method. The Reynolds number, based on the train height, is set to $10^7$.

As the computational flow simulation places a heavy burden on computational resources and time, the reduction of these costs is the key to making optimization feasible. This study reduces the computational cost by parallel computation using a Message Passing Interface (MPI). By allocating each processor to each individual in the process of the evolutionary algorithm, the aerodynamic estimations of all individuals are conducted simultaneously.

The grid system used in the flow simulation is generated by the following procedure. First, a surface grid is created on the surface, which is represented by Coons patches with the B-Spline curves, as described before, by using a surface grid generation method based on unstructured grid. Then a grid for the whole area is created by a parabolic–hyperbolic hybrid scheme. The train has a length of 2.5 cars (front and tail cars, and half of intermediate car); however, the gaps between the cars are not considered. The numbers of meshes in the surface grid on the train are 141 in the flow direction and 56 in the circumferential direction. The numbers of meshes in the whole grid in each direction are (192, 55, 46) and the total amounts to approximately 490,000 points. Figure 7 shows an example of the grid system. A previous computation using the same numerical scheme and a grid system with almost the same grid spacing around the train nose as this one showed good agreement with experiments in the pressure distribution.

The aerodynamic drag of the nose is evaluated by the pressure drag acting from the top edge to the end of the nose. The pressure variation around the car is estimated by the difference between the maximum and the minimum pressures along a line where the side of the on-coming train (but in the absence of it in the computation) is located (Fig. 8).
3. Example of optimization

In order to show the feasibility of this method, the train shape was optimized using the above described two objective functions. The evolutionary calculation was implemented until the 10th generation with 512 individuals. The computation was conducted on Cray XT-4 and the computational time was approximately 3 h per generation.

Figure 9 shows the objective value distribution at each generation. The horizontal axis is the aerodynamic coefficient and the vertical axis is the pressure coefficient, which indicates the magnitude of the pressure variation. In the first generation, the individuals are widely distributed because the train shapes are randomly given. As the generation moves on, the individuals congregate in the neighborhoods of the Pareto front. Figure 10 shows Pareto-optimal solutions and examples of their train shape. We found 109 Pareto-optimal solutions. The train with minimum drag has a two-dimensional wedge shape. This agrees qualitatively with the result of comparing 16 classified train shapes\cite{24}. The train with minimum pressure variation along the car has a three-dimensional shape that gradually expands in both the upward and sideward directions.

Figure 11 shows a comparison between the Pareto-optimal solutions and simulated aerodynamic properties for a real Shinkansen train in our study of 1996\cite{23}. The aerodynamic properties of the optimal shapes are much smaller than those of the previously used Shinkansen train.
Fig. 9 Objective value distribution at each generation

1st generation

3rd generation

5th generation

10th generation

Fig. 10 Pareto solutions and examples of nose shapes

Shape of the minimum aerodynamic drag

Shape of the minimum pressure variation
4. Concluding remarks

We developed a method of optimizing the three-dimensional shape of a train to meet the requirements of plural aerodynamic properties simultaneously using an evolutionary algorithm and a numerical flow simulation. An example optimization with two objective functions aerodynamic drag and the pressure variation along the car demonstrated its feasibility.

In this study, we optimized relatively simple train shapes using the two objective functions. More practical shapes with more objective functions can be employed, and in a future study, this method will be applied to the design process of an actual train.

References


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