Springer

Journal of
Mechanical
Science and
Technology

Journal of Mechanical Science and Technology 22 (2008) 1121~1131

www.springerlink.com/content/1738-494x

Design of the intake system for reducing the noise in the automobile using support vector regression

Hyoun-Jin Sim, Sang-Gil Park, Yong-Goo Joe and Jae-Eung Oh*

Dept. of Mechanical Engineering, Hanyang University, 17 Haengdang-Dong, Seongdong Gu, Seoul, 133-791, Korea

(Manuscript Received July 20, 2007; Revised January 27, 2008; Accepted March 11, 2008)

Abstract

This paper proposes an optimal design scheme to reduce the noise of the intake system by using support vector regression techniques. For this, as a measuring tool for the performance of the intake system, the performance prediction software was used. Then, the length and radius of each component of the current intake system were selected as input variables and the L_{18} table of orthogonal arrays was adapted as a space-filling design. The simulation of parameter design utilized an orthogonal array design, $L_{18}(2^1 \times 3^7)$. In order to evaluate the above design and levels, the experiments satisfying the condition were done. With these simulated data, we can estimate parameters in support vector regression by solving a nonlinear problem and finding an optimal level for the intake system by using support vector regression.

This optimal design scheme gives noticeable results and is a preferable way to analyze the intake system. Therefore, an optimal design for the intake system is proposed by reducing the noise of its system.

Keywords: Intake system; Noise reduction; Support vector regression; Transmission loss

1. Introduction

Increasingly restrictive regulation of vehicle noise problems, according to the enhanced perception of the environment, makes a vehicle's silence more essential. Especially, the reduction of noise from the intake system of an automotive vehicle, one of the major sources of the vehicle's noise, has been studied for many years. The noise from automotive vehicles has an uncomfortable effect on passenger ride quality and generates environmental noise. In addition, with the increasing number of vehicles, quietness in the passenger compartment becomes one of the most important characteristics of high quality vehicles, and the intake noise is being considered as the important object of research.

In general, the intake noise is low frequency noise below 500Hz. The booming noise generated by the intake noise transferred to the interior of the vehicle has an uncomfortable impact on riding quality. However, it is difficult to reduce the time and the cost for the development of a low noise intake system, because the method to reduce the intake noise is applied by means of trial and error after the design of the engine compartment is finished. In addition, methods for excessive noise reduction have worse effects rather than reducing the intake noise.

It is difficult to design an optimal automotive intake system because the design of the intake system affects the engine performance and the space of the engine compartment is limited. Recently, various methods of analysis (the transfer matrix method, the acoustic finite element method and so on) and the experimental method using a simulator have been proposed.

However, analysis methods require considerable time and cost for optimal design of the intake system, because these depend on trial and error. Further, experimental design methods are inadequate in computer experiments because these are considered along

*Corresponding author. Tel.: +82 2 2220 0452, Fax.: +82 2 2299 3153
E-mail address: jeoh@hanyang.ac.kr
DOI 10.1007/s12206-008-0306-z

with the error term.

A way to overcome this problem is to generate an approximation of the complex analysis code that describes the process accurately enough, but at a much lower cost. Such approximations are often called meta-models in that they provide a model of the model. Common meta-modeling techniques include response surface methodology, Kriging, radial basis functions, and multivariate adaptive regression splines. SVR is a particular implementation of support vector machines (SVM), a principled and very powerful method that in the few years since its introduction has already outperformed most other systems in a wide variety of applications. In this paper, we investigate support vector regression (SVR) as an alternative technique for approximating complex engineering analyses. Therefore, we consider support vector regression, which is suitable for computer experiments, to improve the performance of the system with a low cost and time savings.

The SV algorithm is a nonlinear generalization of the generalized portrait algorithm developed in Russia in the sixties. As such, it is firmly grounded in the framework of statistical learning theory, or VC theory, which has been developed over the last three decades by Vapnik, Chervonenkis and others. Briefly, VC theory characterizes properties of learning machines that enable them to generalize well to unseen data. In its present form, the SV machine was developed at AT&T Bell Laboratories by Vapnik and coworkers. Due to this industrial context, SV research has to date had a sound orientation towards real-world applications. Initial work focused on OCR (optical character recognition). Within a short time, SV classifiers became competitive with the best available systems for both OCR and object recognition tasks. A comprehensive tutorial on SV classifiers has been published by Burges. But also in regression and time series prediction applications, excellent performance was soon obtained. A snap shot of the state of the art in SV learning was recently taken at the annual Neural Information Processing Systems conference. SV learning has now evolved into an active area of research, and it is in the process of entering the standard methods toolbox of machine learning.

In this paper, support vector regression is proposed for an optimal design scheme to reduce the intake noise. The characteristics of the noise reduction are evaluated by using the intake system as shown in Fig. 1. For this, as a measuring tool for the performance of the intake system, the performance prediction software, which was developed by Oh, et al., is used. Then, the length and radius of each component of the current intake system are selected as input variables. The experimental design we used is the L_{18} table of orthogonal arrays. The orthogonal array is adapted as a space-filling design, which gives one confidence that the design is "infiltrating" the design space well, and so is suitable for support vector regression.

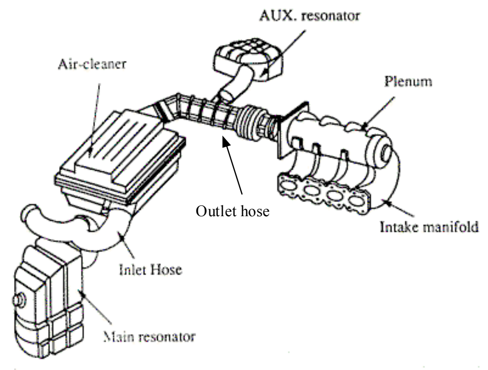

Fig. 1. Overview of an intake system.

In Section 2, we describe the simulator and experiments of noise reduction for an intake system. To do this, experimental design, support vector regression and simulated annealing are introduced in Section 3. In Section 4, we perform support vector regression with simulated data and find the optimal level for the intake system to minimize the intake's noise. Section 5 contains the conclusions of this study and ideas for ongoing work.

2. Prediction of transmission loss by using the transfer matrix method

2.1 Modeling of intake noise by the transfer matrix method

As a method of modeling the transfer characteristic of acoustics, the transfer matrix method, which introduces the concept of impedance, is used. Widely used for acoustic systems for its computational simplicity, this method makes design easy since modeling for each factor makes up the whole system.

Adopting acoustic pressure, p, and mass velocity, v, as the two state variables in the transfer matrix method, we found the four-pole parameters from the conditions of both sides, which can be written as Eq. (1), where $\{p_r\ v_r\}^T$ is called the state vector at the upstream point, r and $\{p_{r-1}\ v_{r-1}\}^T$ is called the state vector at the downstream point $r-1$.

$$\begin{Bmatrix} p_r \\ v_r \end{Bmatrix} = \begin{bmatrix} \textit{Transfer matrix} \\ 2\times 2 \end{bmatrix} \begin{Bmatrix} p_{r-1} \\ v_{r-1} \end{Bmatrix} \tag{1}$$

The transmission loss is independent of the source and presumes an anechoic termination at the downstream end. It is defined as the difference between the power incident on the acoustic element and that transmitted downstream into an anechoic termination. So it makes the evaluation and prediction easy to leave the reflected pressure due to radiation impedance out of consideration. The transmission loss is an energy loss of acoustic elements, so the ratio of sound pressure between the inlet and outlet of acoustic elements can be expressed in dB scale. Eq. (2) shows the ratio between incident and reflective pressures through acoustic elements. Also, a two-microphone method is used at the end of the acoustic element to remove the influence of reflected waves.

$$TL(dB) = 10\log_{10}\left|\frac{w_i}{w_t}\right| = 20\log_{10}\left|\frac{p_1^+}{p_2^-}\right| \tag{2}$$

where w_i is the energy of inlet, w_t is the energy of outlet, p_1^+ is an inlet sound pressure, and p_2^- is an outlet sound pressure. Here, p_1^+ and p_2^- are derived from Eq. (1). Fig. 2 shows schematics of transmission loss measurement. Transmission loss obtained from Eq. (2) is used to interpret an improved intake system.

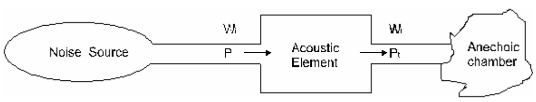

Fig. 2. Schematics of transmission loss measurement.

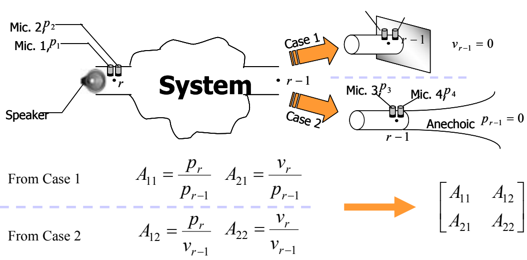

Fig. 3. Experimental 4-pole measurement system.

The 4 – pole parameter method based on plane wave theory is very popular for the analysis of the acoustic behavior of the vehicle intake system. But this method is applicable only for the simple shape of the intake. Moreover, the principal part that was designed by engine performance is used like an unchangeable design factor, such as manifold and air cleaner. Therefore, by way of measurement, a transfer matrix was composed of acoustic pressure p and acoustic velocity v at manifold and air-cleaner. Acoustic velocity v can be obtained by two microphones as in (3).

$$p_r = \frac{p_1+p_2}{2},\ p_{r-1} = \frac{p_3+p_4}{2},$$
$$v_r \cong \frac{-1}{\rho\omega\Delta r_{12}}(p_2-p_1),\ v_{r-1} \cong \frac{-1}{\rho\omega\Delta r_{34}}(p_4-p_3) \tag{3}$$

Finally, the whole system is composed of several matrixes that were obtained by theoretical and experimental method.

2.2 *Analysis of experimental results with the two-microphone method*

The two-microphone method separates the incident wave and the reflected wave in the pipe. The transmission loss can be written as in Eq. (4) and Eq. (5) by using two-microphones.

$$TL(dB) = 10\log_{10}\frac{S_{aa}}{S_{cc}} \tag{4}$$

$$S_{aa}(f) = [S_{11}(f)+S_{22}(f)-2C_{12}(f)\cos k(x_1-x_2) + 2Q_{12}\sin k(x_1-x_2)]/4\sin^2 k(x_1-x_2) \tag{5a}$$

$$S_{bb}(f) = [S_{11}(f)+S_{22}(f)-2C_{12}(f)\cos k(x_1-x_2) + 2Q_{12}\sin k(x_1-x_2)]/4\sin^2 k(x_1-x_2) \tag{5b}$$

$$S_{cc}(f) = [S_{33}(f)+S_{44}(f)-2C_{34}(f)\cos k(x_3-x_4) + 2Q_{34}\sin k(x_3-x_4)]/4\sin^2 k(x_3-x_4) \tag{5c}$$

$$S_{dd}(f) = [S_{33}(f)+S_{44}(f)-2C_{34}(f)\cos k(x_3-x_4) + 2Q_{34}\sin k(x_3-x_4)]/4\sin^2 k(x_3-x_4), \tag{5d}$$

where S_{aa} is an incident spectrum for inlet, S_{bb} is a reflected spectrum for inlet, S_{cc} is an incident spectrum for outlet, and S_{dd} is a reflected spectrum for outlet. Also, c_{12} is a real part of the cross spectrum for inlet, Q_{12} is an imaginary part of cross spectrum for inlet, and k is wave number.

Fig. 4 is a block diagram of the experimental setup.

We installed a non-reflected part (Anechoic terminator) in the outlet for complete separation of the reflected wave. Incident pressure and reflecting pressure are measured at the same time when measuring pressure amplitude. We used anechoic terminator at the outlet to reduce error. Anechoic terminator prevents the reflection of wave phenomena. The anechoic terminator typically uses fiberglass to absorb incoming sound waves. The acoustic energy is converted to heat at the anechoic terminator. Because Eq. (4) is constructed excluding the information in the reflected spectrum, the experiment is performed to get S_{aa} and S_{cc}. This experimental value is used to evaluate the performance of an intake system.

2.3 Verification of transmission loss simulation for the intake system

The intake system consists of the manifold, plenum, air cleaner, pipe and resonator. The manifold and plenum are not considered as design parameters because the manifold and plenum are designed by considering the engine performance in the early stage.

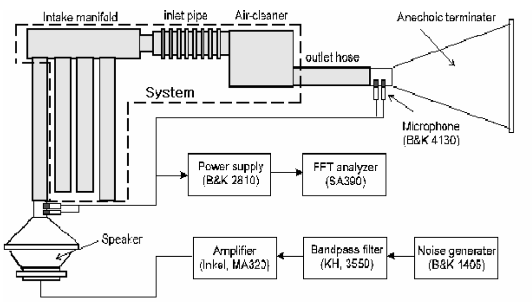

Fig. 4. Block diagram of the experimental set-up using the two microphone method.

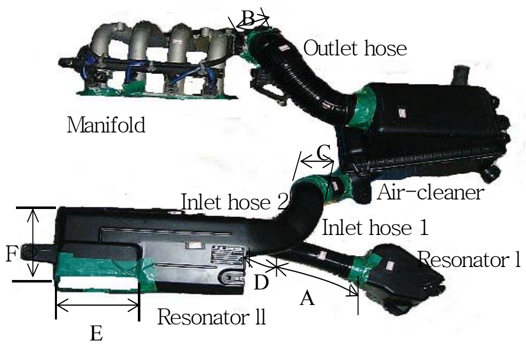

Fig. 5. Factors of intake system.

The simplified intake system is represented in Fig. 5 and control factors and levels are represented in Table 1. Table 1 shows six factors that are chosen as the control factors to apply to the preliminary experiment and the boldfaced numbers are values of the current level. These control factors, which are expected to contribute to the characteristic value, are chosen by experience so that the experiment can be easily modified and the total size of experiments can be kept to a minimum in the design process as well.

In this study, we predicted transmission loss (TL) of the intake with the transfer matrix methods. The experiment shows the TL of intake for verification of confidence in intake performance software as in Fig. 6.

From the results of Fig. 6, we know that intake performance software estimated the TL well. To verify the predicted TL, the simulation results obtained for the acoustical transfer matrix were compared with the experimentally obtained results from a two-microphone arrangement. Favorable agreement between the calculated and measured the TL was obtained. The difference between simulation and experimental results has a little error at the low frequency range. Also, the difference between the TL

Table 1. Control factors and levels.

Control factors		Levels		
		0	1	2
A	Reso. 1 neck length	0.42	0.32	
B	Outlet hose diameter	0.055	0.065	0.075
C	Inlet hose 1 diameter	0.048	0.056	0.064
D	Inlet hose 2 length	0.1	0.05	0
E	Fresh Air Duct length	0.07	0.075	0.08
F	Fresh Air Duct Dia.	0.14	0.15	0.16

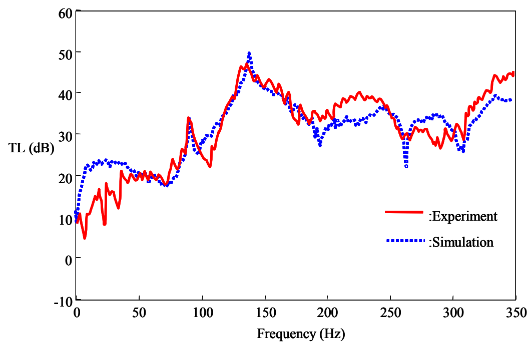

Fig. 6. Comparison between simulation and experimental results.

Table 2. Parameter design using $L_{18}(2^1 \times 3^7)$ orthogonal array.

	Inner array ($L_{18}(2^1 \times 3^7)$)								Outer array ($L_4(2^3)$)				
Factor layout	A	B	C	D	E	F	G	H	Original data				The overall of TL value
Factor name									No. of experiment 1	2	3	4	Uncontrollable factor
Level 1	Main factor layout												
Level 2									0	0	1	1	U
Level 3									0	1	0	1	V
No. / No. of Exp.	1	2	3	4	5	6	7	8	0	1	1	0	W
1	1	1	1	1	1	1	1	1	y11	y12	y13	y14	TL1
2	1	1	2	2	2	2	2	2	y21	y22	y23	y24	TL 2
3	1	1	3	3	3	3	3	3	y31	y32	y33	y34	TL 3
4	1	2	1	1	2	2	3	3	y41	y42	y43	y44	TL 4
5	1	2	2	2	3	3	1	1	y51	y52	y53	y54	TL 5
6	1	2	3	3	1	1	2	2	y61	y62	y63	y64	TL 6
7	1	3	1	2	1	3	2	3	y71	y72	y73	y74	TL 7
8	1	3	2	3	2	1	3	1	y81	y82	y83	y84	TL 8
9	1	3	3	1	3	2	1	2	y91	y92	y93	y94	TL 9
10	2	1	1	3	3	2	2	1	y101	y102	Y103	y104	TL 10
11	2	1	2	1	1	3	3	2	y111	y112	y113	y114	TL 11
12	2	1	3	2	2	1	1	3	y121	y122	y123	y124	TL 12
13	2	2	1	2	3	1	3	2	y131	y132	y133	y134	TL 13
14	2	2	2	3	1	2	1	3	y141	y142	y143	y144	TL 14
15	2	2	3	1	2	3	2	1	y151	y152	y153	y154	TL 15
16	2	3	1	3	2	3	1	2	y161	y162	y163	y164	TL 16
17	2	3	2	1	3	1	2	3	y171	y172	y173	y174	TL 17
18	2	3	3	2	1	2	3	1	y181	y182	y183	y184	TL 18

overall values of the calculated and measured spectra was 1.5dB. The overall value of TL was used as the characteristic value and the large better characteristic was also applied because the larger value implies better performance.

3. Support vector regression based on design of computational experiments

3.1 Space filing design using L_{18} orthogonal array experimental design

The eight variables are arranged on a L_{18} table of orthogonal arrays, which is given in Table 2.

Input variables (A, B, C, D, E, F) shown in Table 2 are placed in the inner array and uncontrollable factors (U: temperature, V: humidity, W: noise) are placed in the outer array. G and H are dummy variables for using an orthogonal array. When the Kriging is preceded, the TL value is used as the response value. The characteristic value, y_{ij}, is the transmission loss, which is used to evaluate the acoustic characteristics and the performance of the reduction of acoustic elements. The transmission loss is an energy loss of acoustic elements, so the ratio of sound pressure between the inlet and outlet acoustic elements can be expressed in dB scale. The overall value, which is the average value of TL in the frequency region of interest, is used as the characteristic value, and the larger-the-better characteristic is also applied because the larger value implies better performance.

3.2 Estimation of the model parameters

To determine the influences of the selected design factors and find the optimal values, we performed an analysis of variance and a factorial effective analysis. The analysis of variance is shown in Table 3.

As can be seen in Table 4, the number of degrees of freedom of a sum of squares is equal to the number of independent elements in that sum of squares. Generally, the number of degrees of freedom for the factors is the number of level-1; for total the sum of squares it is the number of experiments-1 and for the error sum of squares, it is the difference between the total degrees of freedom and the sum of degrees of

Table 3. TL overall & S/N ratio.

Exp. No	Overall Of TL	S/N ratio	Exp. No	Overall Of TL	S/N ratio
1	36.27	3.12	10	36.49	3.12
2	35.77	3.11	11	35.97	3.11
3	35.26	3.09	12	35.61	3.10
4	35.31	3.10	13	35.60	3.10
5	34.82	3.08	14	35.22	3.09
6	34.60	3.08	15	34.66	3.08
7	34.79	3.08	16	34.98	3.09
8	34.23	3.07	17	34.28	3.07
9	33.70	3.06	18	34.12	3.06

Table 4. Analysis of variance for TL.

Source	DF	SS	Mean Square	F-Value
A	1	1.63e-4	1.63e-4	962.30
B	2	4.41e-3	2.20e-3	12982.25
C	2	1.54e-3	7.72e-4	4541.60
D	2	2.44e-5	1.22e-5	71.80
E	2	3.84e-5	1.92e-5	113.08
F	2	2.56E-7	1.28e-7	0.75
Total	15	6.18e-3	4.12e-4	

freedom of the factors. The total sum of squares is

$$SS_T = \sum_{i=1}^{18} y_i^2 - \frac{\left(\sum_{i=1}^{18} y_i\right)^2}{N} \quad (6)$$

where y_i is the response variable and N in the number of experiments.

The mean square of factor C is found as follows:

$$SS_C = \frac{b}{n}\left[C_0^2 + C_1^2 + C_2^2\right] - \frac{\left(\sum_{i=1}^{18} y_i\right)^2}{N} \quad (7)$$

Where $C_0 = \sum_{at\,C_{level0}} y_i$, $C_1 = \sum_{at\,C_{level1}} y_i$, $C_2 = \sum_{at\,C_{level2}} y_i$ and b is the number of levels of factor C. Mean squares of other factors are expressed by this formula.

The sum of squares of error is the difference between the total sum of squares and the sums of squares of factors. The mean square of each factor can be calculated as sum of square / degree of freedom and F ratio, F_0, is the mean square of factor / mean square of error.

3.3 Support vector regression

The experimental data $\{(x_1, y_1), \cdots, (x_l, y_l)\} \subset \chi \times \mathbf{R}$ were given, where χ denotes the space of the input patterns for instance, $\mathbf{R}^d$. In ε-SV regression Vapnik, the objective in this study is to find a function $f(x)$ that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time, is as flat as possible. In other words, we do not care about errors as long as they are less than ε but will not accept any deviation larger than this. This may be important if one wants to be sure not to lose more than ε money when dealing with exchange rates, for instance.

For pedagogical reasons, we begin by describing the case of linear functions f, taking the form

$$f(x) = \langle w, x \rangle + b \quad \text{with } w \in \chi, b \in \mathbf{R} \quad (8)$$

where $\langle \cdot , \cdot \rangle$ denotes the dot product in χ. Flatness in the case of (8) means that one seeks small w. One way to ensure this is to minimize the Euclidean norm, i.e., $\|w\|^2$. Formally, we can write this problem as a convex optimization problem by requiring:

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}\|w\|^2 \\ &\text{subject to} \quad \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon \\ \langle w, x_i \rangle + b - y_i \le \varepsilon \end{cases} \end{aligned} \quad (9)$$

The assumption in (9) was that such a function f actually exists that approximates all pairs (x_i, y_i) with ε precision, or, in other words, that the convex optimization problem is feasible. Sometimes, however, this may not be the case, or we also may want to allow for some errors. Analogously to the "soft margin" loss function in Cortes and Vapnik, one can introduce slack variables ξ_i, ξ_i^* to cope with otherwise infeasible constraints of the optimization problem (9). Hence, we arrive at the formulation stated in Vapnik.

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ &\text{subject to} \quad \begin{cases} y_i - \langle w, x_i \rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \end{aligned} \quad (10)$$

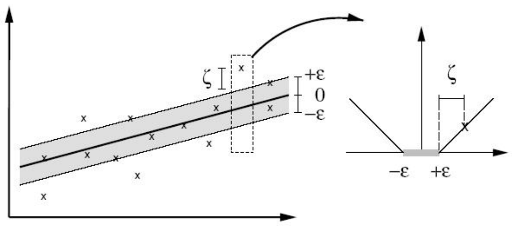

Fig. 7. The soft margin loss setting corresponds for a linear SV machine.

The constant $C > 0$ determines the tradeoff between the flatness of f and the amount up to which deviations larger than ε are tolerated. The formulation above corresponds to dealing with a so-called ε -insensitive loss function $|\xi|_\varepsilon$ described by

$$|\xi|_\varepsilon = \begin{Bmatrix} 0 & \text{if} |\xi| \le \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{Bmatrix} \tag{11}$$

Fig. 1 depicts the situation graphically. Only the points outside the shaded region contribute to the cost insofar, as the deviations are penalized in a linear fashion. It turns out that the optimization problem (10) can be solved more easily in its dual formulation. Moreover, the dual formulation provides the key for extending an SV machine to nonlinear functions. Hence, we will use a standard dualization method utilizing Lagrange multipliers.

3.4 Dual formulation and quadratic programming

The key idea is to construct a Lagrange function from both the objective function (it will be called the primal objective function in the rest of this article) and the corresponding constraints, by introducing a dual set of variables. It can be shown that this function has a saddle point with respect to the primal and dual variables at the optimal solution. Hence, we proceed as follows:

$$\begin{aligned} \mathrm{L} = & \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) - \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i - y_i + \langle w, x_i\rangle + b) \\ & - \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* + y_i - \langle w, x_i\rangle - b) - \sum_{i=1}^{l}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned} \tag{12}$$

It is understood that the dual variables in (12) have to satisfy positivity constraints, i.e., $\alpha_i, \alpha_i^*, \eta_i, \eta_i^* \ge 0$. It follows from the saddle point condition that the partial derivatives of L with respect to the primal variables (w, b, ξ_i, ξ_i^*) have to vanish for optimality.

$$\partial_b \mathrm{L} = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \tag{13}$$

$$\partial_w \mathrm{L} = w - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i = 0 \tag{14}$$

$$\partial_{\xi_i^*} \mathrm{L} = C - \alpha_{ii}^* - \eta_i^* = 0 \tag{15}$$

Substituting (13), (14) and (15) into (12) yields the dual optimization problem.

$$\begin{aligned} &\text{maximize} \quad \begin{Bmatrix} -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle x_i, x_j\rangle \\ -\varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \end{Bmatrix} \\ &\text{subject to} \quad \begin{Bmatrix} \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ \alpha_i, \alpha_i^* \in [0, C] \end{Bmatrix} \end{aligned} \tag{16}$$

In deriving (16) we already eliminated the dual variables η_i , η_i^* through condition (15) as these variables did not appear in the dual objective function anymore but only were present in the dual feasibility conditions. Eq. (14) can be rewritten as follows:

$$\begin{aligned} & w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i \text{ and therefore} \\ & f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\langle x_i, x_i^*\rangle + b \end{aligned} \tag{17}$$

This is the so-called support vector expansion, i.e., W can be completely described as a linear combination of the training patterns x_i . In a sense, the complexity of a function's representation by SVs is independent of the dimensionality of the input space χ , and depends only on the number of SVs. Moreover, the complete algorithm can be described in terms of dot products between the data. Even when evaluating $f(x)$ we need not compute w explicitly, although this may be computationally more efficient in the linear setting. These observations will come in handy for the formulation of a nonlinear extension.

So far we have neglected the issue of computing b. The latter can be done by exploiting the so-called Karush Kuhn Tucker (KKT) conditions. These state that at the optimal solution the product between dual variables and constraints has to vanish. In the SV case this means

$$\begin{aligned} &\alpha_i(\varepsilon + \xi_i - y_i + \langle w, x_i \rangle + b) = 0 \\ &\alpha_i^*(\varepsilon + \xi_i^* + y_i - \langle w, x_i \rangle - b) = 0 \end{aligned} \quad (18)$$

and

$$\begin{aligned} &(C - \alpha_i)\xi_i = 0 \\ &(C - \alpha_i^*)\xi_i^* = 0 \end{aligned} \quad (19)$$

This allows us to make several useful conclusions. First, only samples (x_i, y_i) with corresponding $\alpha_i^* = C$ lie outside the ε-insensitive tube around f. Second, $\alpha_i \alpha_i^* = 0$, i.e., there can never be a set of dual variables α_i, α_i^* which are both simultaneously nonzero as this would require nonzero slacks in both directions. Finally, for $\alpha_i^* \in (0, C)$ we have $\xi_i^* = 0$ and the second factor in (16) has to vanish. Hence, b can be computed as follows:

$$\begin{aligned} &b = y_i - \langle w, x_i \rangle - \varepsilon \quad \text{for } \alpha_i \in (0, C) \\ &b = y_i - \langle w, x_i \rangle + \varepsilon \quad \text{for } \alpha_i^* \in (0, C) \end{aligned} \quad (20)$$

Another way of computing b will be discussed in the context of interior point optimization. There, b turns out to be a by-product of the optimization process, so further considerations shall be deferred to the corresponding section.

A final note has to be made regarding the sparsity of the SV expansion. From (18) it follows that only for $|f(x_i) - y_i| \geq \varepsilon$ the Lagrange multipliers may be nonzero, or in other words, for all samples inside the ε-tube (i.e., the shaded region in Fig. 7) the α_i, α_i^* vanish: for $|f(x_i) - y_i| < \varepsilon$ the second factor in (18) is nonzero, hence α_i, α_i^* has to be zero such that the KKT conditions are satisfied. Therefore, we have a sparse expansion of w in terms of x_i.

3.5 Nonlinearity by preprocessing

Non-linear function approximations can be achieved by replacing the dot product of input vectors with a non-linear transformation on the input vectors. This transformation is referred to as the kernel function and is represented by k(x,x'), where x and x' are each input vectors. Table 5 lists common kernel functions where the kernel function substitution maintains the elegance of the optimization method used for linear SVR.

Applying the kernel function to the dot product of input vectors, we obtain:

$$\text{maximize} \begin{cases} -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)k\langle x_i, x_j \rangle \\ -\varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \end{cases} \quad (21)$$
$$\text{subject to} \begin{cases} \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ \alpha_i, \alpha_i^* \in [0, C] \end{cases}$$

Replacing the dot product in Eq. (21), the SVR approximation becomes:

$$\begin{aligned} &w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k\langle x_i, x_i^* \rangle \text{ and therefore} \\ &f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k\langle x_i, x_i^* \rangle + b \end{aligned} \quad (22)$$

The kernel function $k\langle x_i, x_i^* \rangle$ can be pre-processed, and the results are stored in the kernel matrix. The kernel matrix must be positive definite in order to guarantee a unique optimal solution to the quadratic

Table 5. Common kernel functions.

Linear	$k(\mathbf{x},\mathbf{x}') = \mathbf{x}^{\mathrm{T}}\mathbf{x}'$
Polynomial	$k(\mathbf{x},\mathbf{x}') = \langle \mathbf{x} \cdot \mathbf{x}' \rangle^d$
Gaussian	$k(\mathbf{x},\mathbf{x}') = \exp\left(-\frac{\lVert\mathbf{x}-\mathbf{x}'\rVert^2}{2\sigma^2}\right)$
Sigmoid	$k(\mathbf{x},\mathbf{x}') = \tanh(\kappa\langle \mathbf{x} \cdot \mathbf{x}' \rangle + \vartheta)$
Inhomogeneous Polynomial	$k(\mathbf{x},\mathbf{x}') = (\langle \mathbf{x} \cdot \mathbf{x}' \rangle + c)^d$

optimization problem. The kernel functions presented in Table 5 yield positive definite kernel matrices. Thus, by using the kernel function and corresponding kernel matrix, non-linear function approximations can be achieved with SVR while maintaining the simplicity and computational efficiency of linear SVR approximations. This study used the Gaussian kernel function.

4. Statistical analysis of a design process

4.1 Design and experiments

In order to evaluate the above design and levels, experiments satisfying the condition of $2^1 \times 3^7$ are done. The characteristic values of each experiment are obtained from the experiment explained in Table 6. Here, the characteristic values, which are obtained from TL values, are the overall value of the transmission loss from 0Hz to 350Hz.

To distinguish the effectiveness of the factors, the F-value for the factors was compared to the criterion. Accordingly, the null hypotheses for all factors were rejected. The result shows that they affect the intake noise such that B > C > A > E > D > F in sequence. This sequence is determined by the order of the sensitivity (magnitude difference / unit level), that is, the steeper the slope of the factor becomes, the more sensitive. It means that the levels of each factors corresponding to the largest SN ratio become optimal values of the factors. Thus, we can obtain the maximum characteristic value satisfying the low noise performance from the above optimal parameters.

To assist in interpreting the results of this experiment, a factorial effect diagram was used. It is expressed as a graph of the average responses at each treatment combination.

A re-analysis result using the simulation for the performance evaluation of intake system is conducted. The overall level of TL is 1.8dB that is larger than current specification.

This is adapted to extract the effective main factors. But this value is not an optimum value, because DOE uses the selected value in the discrete data and is not considered a nonlinear characteristic of model. Therefore, this model is applied to SVR by using the effective main factor. In Fig. 8, we find the optimal level of B, C and A, because these factors are verified to be the most significant three factors from L_{18} tables of orthogonal arrays. So, D, E and F factors are kept in current levels because these are not significant.

Table 6. Control factors and levels.

Control factors		Levels	
		Initial	Taguchi optimum
A	Reso. 1 neck length	0.42(0)	0.32(1)
B	Outlet hose diameter	0.065(1)	0.055(0)
C	Inlet hose 1 diameter	0.056(1)	0.048(0)
D	Inlet hose 2 length	0.1(0)	0.0(2)
E	Fresh Air Duct length	0.075(1)	0.07(0)
F	Fresh Air Duct Dia.	0.15(1)	0.15(1)

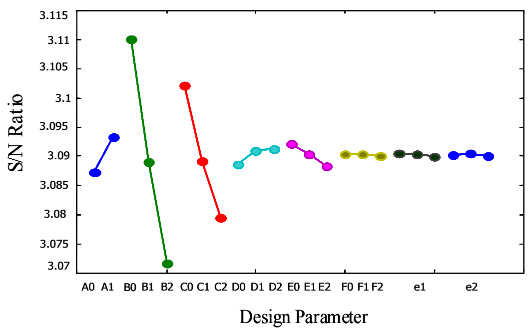

Fig. 8. Factorial effect diagram of intake system.

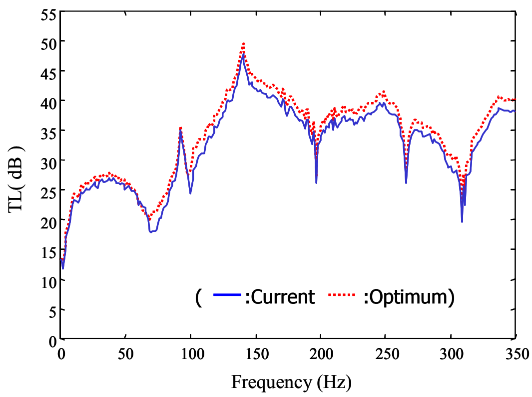

Fig. 9. Comparison of TL Overall for current & optimum Values (DOE) of the objected vehicle intake system.

Fig. 9 shows the comparison of the initial valued (current value) and optimal valued (optimized DOE value) noise spectrum of the TL.

4.2 Finding an optimal level using simulated annealing

Simulated annealing is a technique for combinatorial optimization problems, such as optimizing functions of very many variables. Because many real-world design problems can be cast in the form of such optimization problems, there is intense interest in general techniques for their solution. Kirkpatrick et al. introduced this approach in 1982.

The process of simulated annealing for finding the optimal level in design space by using SVR is given below. Now, a point x_{old} in design space is selected and its SVR estimate value is calculated. Then, x_{new} is selected by perturbing x_{old} and its SVR estimate value is calculated. In the last stage, of the two points, one point remains on the annealing schedule. When a terminate condition is satisfied, this process is ended with an optimal level. In this study, the initial temperature was set by 1, the Boltzmann constant is 0.9999, and the final temperature is 0.9999.

Table 7 shows the optimal level of the intake system. This represents that the maximum value of the SVR estimate in the final temperature might be 38.3.

4.3 The improved noise reduction in the optimal level

Table 8 is a comparison between current conditions and the optimal level resulting from by SVR for over all TL value. As these results show, SVR increases 4.04(dB), as compared to the current condition. Fig. 10 shows a comparison of values between current experiment and SVR. As shown in Fig. 10, the SVR gives better results.

Table 7. Optimum design level for the intake system.

	A	B	C
Optimum design value	0.325	0.045	0.045

Table 8. Comparison current design value and optimum design using SVR.

Condition	Overall TL (dB)
Current	34.83
SVR	38.87

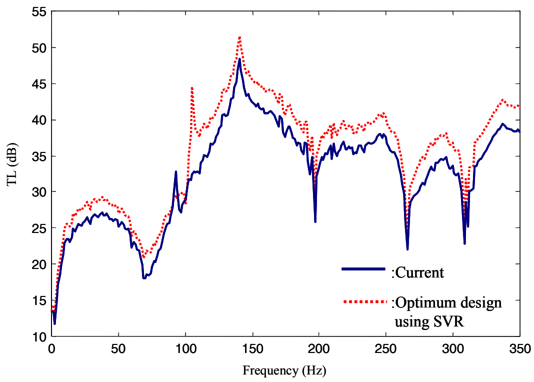

Fig. 10. Comparison of TL Overall for current & optimum Values (SVR).

5. Conclusions

SVR was applied to reduce the vehicle's intake noise. For the preliminary experiment, the L_{18} design was first performed for the six control factors. Statistical analysis was used to detect the effectiveness of the design parameters. The parameters were estimated with SVR and an optimal level was estimated with simulated annealing.

In this paper, the conclusions for noise reduction of the intake system are as follows.

(1) SVR can be applied to solve highly correlated and nonlinear problems. Therefore, SVR is suitable for this reduction of the intake noise. SVR gives noticeable results and is a preferable way to analyze the intake system.

(2) The overall level of transmission loss by the optimal designs using SVR with the meta-heuristic method was increased by 4.04 (dB) as compared with the current designs.

References

[1] M. L. Munjal, Acoustics of Ducts and Mufflers, John Wiley & Sons, (1987).

[2] G. Ruspa and G. Schellino, Sound Quality in Cars: New Idea, New Tools, SAE951372, (1995) 123-1129.

[3] W. Eversman and J. A. White, Acoustic Modeling and Optimization of Induction System Components, SAE951261, (1995) 207-215.

[4] G. Francesco and P. Luigi, Optimized Air Intake Systems, SAE951264, (1995) 241-247.

[5] R. J. Astley and W. Eversman, Acoustic Transmission In Non-Uniform Ducts With Mean Flow, Part II: The Finite Element Method, *Journal of sound and vibration*, 74 (1) (1981) 103-121.

[6] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd Edition, Prentice Hall, Upper Saddle River, NJ, (1999).

[7] N. Cristianni and J. Shawe-Taylor, An Introduction to Support Vector Machines and Other Kernel-based Learning Methods, Cambridge University

Press, Cambridge, UK, (2000).
[8] M. A. Hearst, Trends Controversies: Support Vector Machines, *IEEE Intelligent Systems,* 13 (4) (1998) 18-28.
[9] K. Takeuchi and N. Collier, Use of Support Vector Machines in Extended Named Entity, Proceedings of Sixth Conference on Natural Language Learning (CoNLL-2002), D. Roth and A. van den Bosch, eds., Taipei, Taiwan, (2002) 119-125.
[10] S. T. Dumais, J. Platt, D. Heckerman and M. Saharni, Inductive Learning Algorithms and Representations for Text Categorization, Proceedings of the 7th International Conference on Information and Knowledge Management, Bethesda, MD, ACM, (1998) 148-155.
[11] V. Vapnik and A. Lerner, Pattern Recognition using Generalized Portrait Method, *Automation and Remote Control,*24 (6) (1963) 774-780.
[12] V. Vapnik, The Nature of Statistical Learning Theory, Springer, New York, NY, (1995).
[13] A. J. Smola and B. Schölkopf, A Tutorial on Support Vector Regression, NeuroCOLT2 Technical Report Series, NC2-TR-1998-030, Berlin, Germany, (1998).
[14] V. Vapnik, S. Golowich and A. Smola, Support Vector Method for Function Approximation, Regression Estimation, and Signal Processing, Advances in Neural Information Processing Systems, M. Mozer, M. Jordan and T. Petsche, eds., MIT Press, Cambridge, MA, (1997) 281-287.
[15] S. R. Gunn, Support Vector Machines for Classification and Regression, Technical Report, Image Speech and Intelligent Systems Research Group, University of Southampton, UK, (1997).
[16] T. W. Simpson, J. Peplinski, P. N. Koch and J. K. Allen, Metamodels for Computer-Based Engineering Design: Survey and Recommendations, *Engineering with Computers,* 17 (2) (2001) 129-150.
[17] R. H. Myers and D. C. Montgomery, Response Surface Methodology: Process and Product Optimization Using Designed Experiments, John Wiley & Sons, New York, (1995).
[18] N. Dyn, D. Levin and S. Rippa, Numerical Procedures for Surface Fitting of Scattered Data by Radial Basis Functions, *SIAM Journal of Scientific and Statistical Computing,* 7 (2) (1986) 639-659.
[19] M. J. D. Powell, Radial Basis Functions for Multivariable Interpolation: A Review, Algorithms for Approximation, J. C. Mason and M. G. Cox, eds., Oxford University Press, London, (1987) 143-167.
[20] C. Tu and R. R. Barton, Production Yield Estimation by the Metamodel Method with a Boundary-Focused Experiment Design, ASME Design Engineering Technical Conferences - Design Theory and Methodology, Sacramento, CA, ASME, Paper No.DETC97 /DTM-3870, (1997).
[21] M. Meckesheimer, R. R. Barton, Simpson, T. W., Limayem, F. and B. Yannou, Metamodeling of Combined Discrete/Continuous Responses, *AIAA Journal,* 39 (10) (2001) 1955-1959.
[22] J. Sacks, W. J. Welch, T. J. Mitchell and H. P. Wynn, Design and Analysis of Computer Experiments, *Statistical Science,* 4 (4) (1989) 409-435.
[23] J. R. Koehler and A. B. Owen, Computer Experiments, Handbook of Statistics, S. Ghosh and C. R. Rao, eds., Elsevier Science, New York, (1996) 261-308.
[24] T. W. Simpson, T. M. Mauery, J. J. Korte and F. Mistree, Kriging Metamodels for Global Approximation in Simulation-Based Multidisciplinary Design Optimization, *AIAA Journal,* 39 (12) (2001) 2233-2241.
[25] J. H. Friedman, Multivariate Adaptive Regression Splines, *The Annals of Statistics,* 19 (1) (1991) 1-67.
[26] A. J. Smola, B. Schölkopf and K. R. Müller, The Connection between Regularization Operators and Support Vector Kernels, *Neural Networks,* 11 (4) (1998) 637-649.
[27] B. Schölkopf and A. J. S., *Learning* with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, MIT Press, Cambridge, MA, (2002).
[28] F. Markowetz, Support Vector Machines in Bioinformatics, Diploma Thesis in Mathematics, University of Heidelberg, Germany, (2001).
[29] L. A. Schmit, Structural Synthesis. Its Genesis and Development, *AIAA Journal,* 19 (10) (1981) 1249-1263.
[30] J. S. Arora, Introduction to Optimum Design, McGraw-Hill, New York, (1989).
[31] E. Sandgren, Nonlinear Integer and Discrete Programming in Mechanical Design Optimization, *ASME Journal of Mechanical Design,* 112 (2) (1990) 223-229.
[32] K. J. Cha, C. U. Chin, J. S. Ryu and J. E. Oh, The optimal design for low noise intake system using Kriging method with robust design, JSME Inte*rnational Journal*, 47 (3) (2004) 873-881.
[33] J. E. Oh, K. T. Lee and J. C. Lee, Development of the Software for Analysis and Improvement of a Passenger Car's Muffler, *International Journal of Automotive Engineering*, 4 (6) (1996) 133-143.