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Development of Intelligent Gear-Shifting Map Based on Radial Basis Function Neural Networks

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Abstract

Currently, most automobiles have automatic transmission systems. The gear-shifting strategy used to generate shift patterns in transmission systems plays an important role in improving the performance of vehicles. However, conventional transmission systems have a fixed type of shift map, so it may not be enough to provide an efficient gear-shifting pattern to satisfy the demands of driver. In this study, we developed an intelligent strategy to handle these problems. This approach is based on a normalized radial basis function neural network, which can generate a flexible gear-shift pattern to satisfy the demands of drivers, including comfortable travel and fuel consumption. The method was verified through simulations.

Keywords: Automatic transmission, Driver's willingness, Gear-shifting, Normalized radial basis function neural network

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1. Introduction

The demand for automatic transmission (AT) systems has increased greatly since the invention of the electronic transmission control unit (TCU) developed in the early 1980s by Renault and BMW [1]. The representative AT system is stepped transmission (ST) [2] where a fixed gear-shift map is provided to reduce the engine torque during gear-shifting, which correctly matches the oil pressure to the friction elements such as the clutch and band brakes.

However, the fixed gear-shifting map of the ST system has several problems, one of which is that the fixed map can't provide adaptive, flexible shift patterns that are suitable for different driving conditions, so an unnecessary "kick down" phenomenon may occur often. This "kick down" may cause the driver to feel uncomfortable and result in poor fuel efficiency. Another problem is that the ST system cannot adapt the gear-shifting time to the habits and inclinations of the driver, which causes drivers discomfort.

One way to alleviate these problems and provide efficient gear-shifting is to develop more advanced shift maps that can generate adaptive gear-shift patterns and determine the intelligent gear-shifting time without changing the transmission hardware and TCU. Methods such as fuzzy logic [3-6] and neural networks [7, 8] can be used to develop such an advanced system, but the neural network technique was preferred in this study.

In general, neural networks are recognized as an intelligent method because of their advantages such as self-organization by learning, robustness against uncertainty, and fault tolerance. However, the efficiency of neural networks can be reduced in some applications because of the large numbers of neurons and layers, which incur a long learning period. In

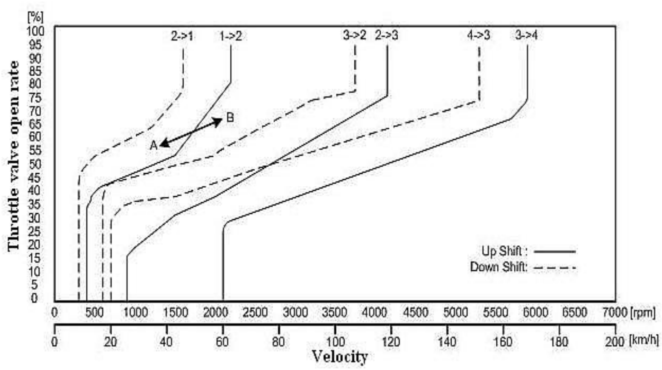

Figure 1. Standard gear-shifting map of a four-speed automatic transmission system.

particular, the problem can be very challenging when many mechanical and environmental factors have to be considered. Given these considerations, the normalized radial basis function neural network (NRBFNN) [9] was preferred in this study instead of the conventional multi-neural network.

The paper is organized as follows. In Section 2, we explain the conventional gear-shifting method of the AT system. In Section 3, the proposed intelligent gear-shifting method is described that utilizes the NRBFNN. Section 4 presents the overall structure. In Section 5, simulation results are provided that verify the effectiveness of this method. Concluding remarks are given in the final section.

2. Gear-Shifting Control

Gear-shifting control means that a shifting point on a given fixed gear-shifting map of the TCU is moved to another, as shown in Figure 1, in terms of the driving velocity (x-axis) and the throttle valve open rate (y-axis) acquired from the engine control unit (ECU).

The procedure of gear-shifting can be understood easily using an example. Assume that the point indicating the current status of the velocity and throttle valve open rate of the vehicle is point A. If a driver steps on the accelerator pedal to increase the current velocity and throttle valve open rate, point A is moved to point B across the up-shift line (drawn in solid line) and the shift position of a vehicle changes from the 1st shift position to the 2nd shift position. If a driver steps off the accelerator pedal to decrease the velocity and the throttle valve open rate at point B, point B is moved to point A across the down-shift line (shown by the dashed line).

The up-shift line is a boundary between the lower position and the higher position, whereas the down-shift line is a boundary between the higher position and the lower position. These boundaries are fixed and impossible to change once the shifting map has been installed on the TCU.

As already mentioned, the fixed type map limits the flexibility of the gear-shifting strategy to adapt to the driving conditions and the driver's inclinations. A viable option for avoiding these problems is to change the up-shift and down-shift boundary lines of a shift map automatically to adapt to different driving conditions and driver inclinations within an admissible range, which is specified by the maximum or minimum limits predetermined by the maximum torque and rotation speed of an engine.

3. Intelligent Gear-Shifting Strategy Based on NRBFNN

In this section, we describe the intelligent gear-shifting method based on NRBFNN, which was developed to address the weakness of the fixed gear-shifting method. First, a brief description of NRBFNN is provided, as follows.

3.1 Normalized Radial Basis Function Neural Network

Neural networks are used widely because of their learning capability, their parallel distributed structure, high fault tolerance, etc. Although there are many types of structures in neural networks, the RBFNN adopted by this approach has distinct advantages: a simple structure with a single hidden layer and a local mapping capacity for fast learning.

In general, the standard RBFNN comprises three layers, and a Gaussian radial function is typically used as the activation function of the hidden neuron. In this study, a normalized Gaussian radial function, which may be superior to the standard one [9, 10], is preferred as the activation function of the hidden neuron. The normalized radial basis function of the hidden neuron shown in Figure 2 is expressed mathematically as

$$\mathrm{Z_q(x)} = \exp\left(-\frac{\|\mathrm{x}-\mathrm{c_q}\|^2}{\sigma_\mathrm{q}^2}\right) \Big/ \sum_{\mathrm{k=1}}^{\mathrm{l}} \exp\left(-\frac{\|\mathrm{x}-\mathrm{c_k}\|^2}{\sigma_\mathrm{k}^2}\right), \tag{1}$$

where x is the input vector of length m, and $\mathrm{c_q}$ and σ_q are the center vectors of length m and the standard deviation of the qth neuron in the hidden layer, respectively.

The ith neuron in the output layer is evaluated as

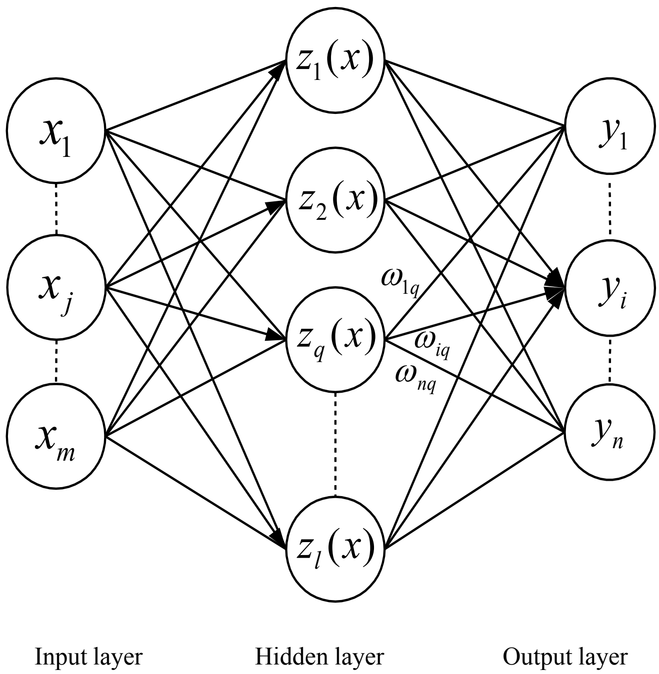

Figure 2. Normalized radial basis function neural network.

$$y_i = \sum_{q=1}^{l} (\omega_{iq} z_q + \theta_i) \tag{2}$$

where ω_{iq} denotes the weight between the qth neuron of the hidden layer and the ith neuron of the output layer and θ_i is the threshold value of the ith output neuron.

In the NRBFNN, three types of parameters need to be adjusted to adapt the network to the desired purpose:center vectors c_q, standard deviation σ_q, and output weights ω_{iq}. The gradient descent method, which is one of the most popular approaches for updating c_q and ω_{iq}, is used, where the fixed value of σ_q is defined as

$$\sigma_q = \sigma = \frac{d}{\sqrt{2l}} \tag{3}$$

where d is the maximum distance between the chosen centers and l is the number of centers.

The update rules for learning the centers and weights can be summarized as follows [9-11]:

$$c_{qj}(t+1) = c_{qj}(t) + \eta_1 (y_i^d - y_i)\omega_{iq} \frac{z_q(x)}{\sigma^2}(x_j - c_{qj}) \tag{4}$$

$$\omega_{iq}(t+1) = \omega_{iq}(t) + \eta_2 \left(y_i^d - y_i\right) z_q(x) \tag{5}$$

where c_{qj} is the ith element of center vector c_q with length m, y_i^d is the desired output of the ith output neuron, and ω_{iq} and

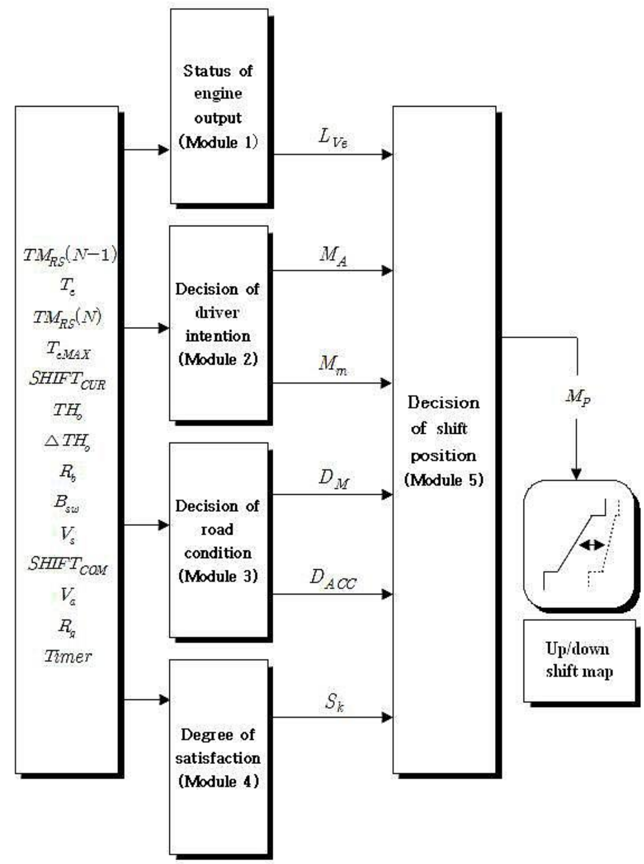

Figure 3. Overall structure of the intelligent gear-shifting system.

ω_{iq} are the connection weights between the qth hidden neuron and the ith output neuron, respectively. η_1 and η_2 are the learning rates, the values of which may vary between 0 and 1.

3.2 Intelligent Gear-Shifting Map Using NRBFNN

The intelligent gear-shifting strategy uses a flexible shift map to adapt to various driving conditions, i.e., the habits or inclination of a driver, road conditions such as uphill or downhill driving, etc. However, it is difficult to develop a neural network that solves all these problems so it is more efficient to classify them into several sub-functions and to construct the corresponding systems using a hierarchical structure.

As shown in Figure 3, the intelligent gear-shifting system comprises five modules, where each module has its own function as follows.

- Module to decide the status of the engine output (Module 1): to evaluate the proximity between the vehicle's load and the allowable maximum engine output.

- Module for the driver's intention (Module 2): to determine the driver's intention when driving.
- Module for the road condition (Module 3): to determine whether the road is uphill or downhill and whether the engine brakes may be required.
- Module for the degree of satisfaction (Module 4): to determine the degree of driver satisfaction with the current shift map.
- Module for the shift position (Module 5): to decide the final shift position.

More detailed descriptions of each module are given below.

3.2.1 Deciding the status of the engine output (Module 1)

This module decides the load of a vehicle based on information provided by the ECU. These are represented as follows:

- $TM_{RS}(n)$: Current transmission output rotation speed
- $TM_{RS}(n-1)$: Previous transmission output rotation speed
- TE: Engine torque
- TE_{MAX}: Maximum engine torque
- TE_{ACC}: Engine torque for acceleration
- L_{ve}: Load of a vehicle

In the mathematical approach, the load of a vehicle ($0 < L_{ve} < 1$) is defined as the ratio of the acceleration torque to the maximum torque, which can be modeled as (according to the manufacturer: Hyundai Motor Company)

$$Lve = \frac{TE_{ACC}}{TE_{MAX} - TE + TE_{ACC}} \tag{6}$$

$$TE_{ACC} = RA \cdot r/(i_T \cdot i_F \cdot \eta \cdot t), \tag{7}$$

$$RA = \frac{W + W'}{g} \times \alpha, \tag{8}$$

$$\alpha = TM_{RS}(n) - TM_{RS}(n-1), \tag{9}$$

where RA is the acceleration resistance; $r$is the radius of the tire; $i_T$is the current transmission ratio, which varies according to the current shift position; $i_F$is the ratio of the velocity at the endpoint; $\eta$is the coefficient of the transmission efficiency at each shift position; $t$is the torque elasticity; W is the total weight of a vehicle; W' is the partial weight of the rotating part

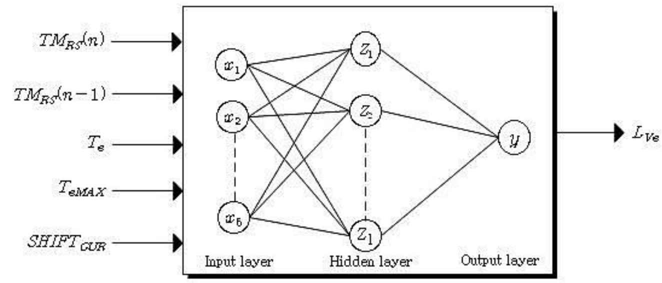

Figure 4. Module 1 to decide the status of engine output.

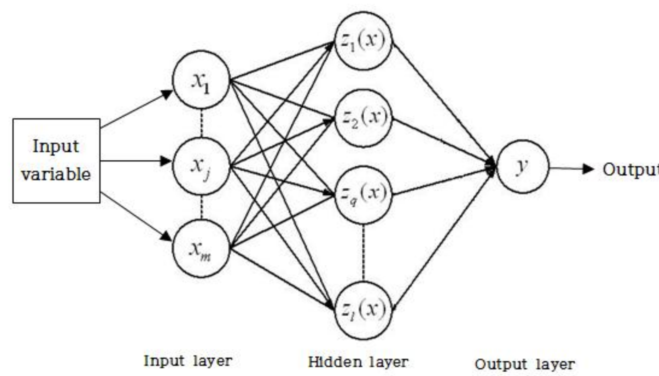

Figure 5. Normalized radial basis function neural network for sub-module M2-A and M2-B of Module 2.

of a vehicle, and g is the acceleration due to gravity. However, these mathematical models are based on approximations and the parameters may be altered by the driving conditions, so it is difficult to determine the optimal value of the load for a vehicle. Neural networks solve this type of problem via adaptive learning from experimental data. Figure 4 shows the corresponding NRBNN used to determine the load of the vehicle. As mentioned earlier, the gradient descent method is used to learn the neural network.

3.2.2 Deciding the driver's intention (Module 2)

This module is designed to decide the driver's intention (M_A), which can be classified into a dynamic mode and a safety mode, which evaluate the driver's willingness to accelerate (M_m) simultaneously. This module comprises two sub-modules: sub-module M2-A to decide the driver's dynamic inclination and sub-module M2-B to evaluate the degree of the driver's willingness to accelerate, as shown in Figure 5 and Table 1.

Sub-module M2-A evaluates the driver's inclination M_A based on four inputs: the throttle valve open rate (TH_0), the

Table 1. Input/output variables of sub-modules of Module 2

Sub-module \ Variables	Input	Output
M2-A	$TH_o, \Delta TH_o, R_t, B_{sw}$	M_A
M2-B	$\Delta TH_o, SHIFT_{COM}, V_s$	M_m

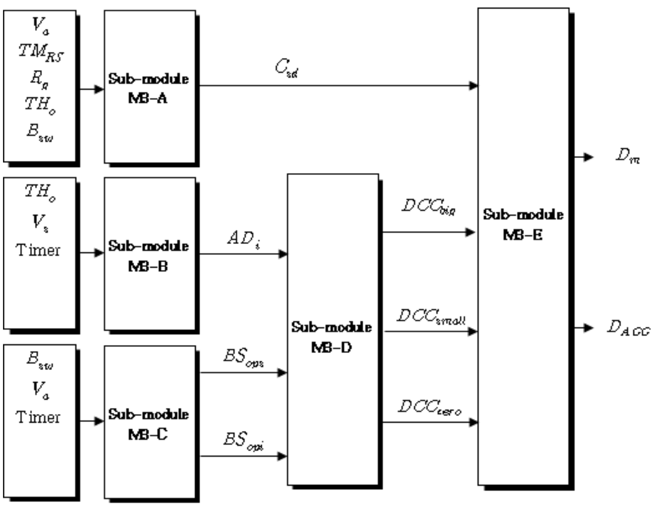

Figure 6. Structure of Module 3, which decides the road condition.

variation in the throttle valve open rate (ΔTH_0), the brake's deceleration resistance (R_b), and the brake switch (B_{sw}). The relationship between the specified inputs and the output M_A can be determine by learning the neural network using the experimental data. If output M_A is close to 1, the system decides that the driver strongly favors a dynamic mode.

Sub-module M2-B is designed to judge whether the driver desires acceleration or deceleration. This module evaluates the degree of the driver's willingness to accelerate based on three inputs: the throttle valve opening rate (TH_0), the current shift position ($SHIFT_{COM}$), and the vehicle's velocity (V_S). The nonlinear relationship between the corresponding inputs and the output M_m can be obtained by learning the neural network using the experimental data. The proximity of output M_m to 1 indicates that the driver wants to accelerate the vehicle.

3.2.3 Deciding the road condition (Module 3)

The role of this module is to decide the road condition and it comprises five sub-modules, as shown in Figure 6. The function of each sub-module, as shown in Figure 7 and Table 2, can be described briefly as follows.

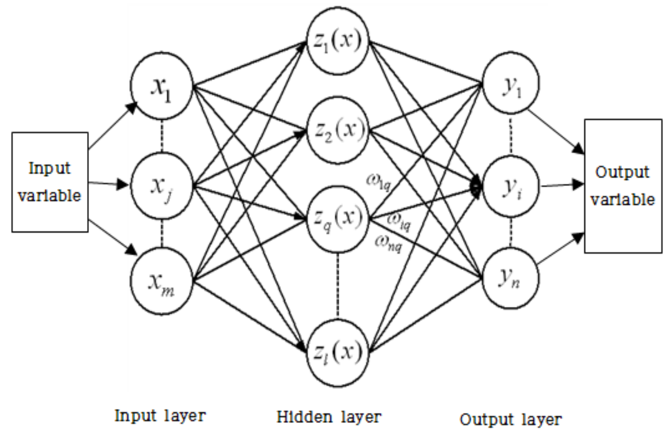

Figure 7. NRBNN for all sub-modules of Module 3.

Table 2. Input/output variables of sub-modules of Module 3

Sub-module \ Variables	Input	Output
M3-A	$V_a, TM_{RS}, R_o, TH_o, B_{sw}$	C_{sd}
M3-B	$TH_o, V_s, timer$	AD_i
M3-C	$B_{sw}, V_a, timer$	BS_{ops}, BS_{opt}
M3-D	AD_i, BS_{ops}, BS_{opt}	$DCC_{small}, DCC_{zero}, DCC_{big}$
M3-E	$C_{sd}, DCC_{big}, DCC_{small}, DCC_{zero}$	D_m, D_{ACC}

- Sub-module M3-A: to decide the slope of the road
- Sub-module M3-B: to decide the driver's willingness to accelerate downhill
- Sub-module M3-C: to decide the driver's willingness to decelerate downhill
- Sub-module M3-D: to decide the driver's intention to use the engine brake
- Sub-module M3-E: to make the final decision to operate the engine brake

Next, each sub-module is explained in detail, and it should be noted that all of the sub-modules are trained using the gradient descent method.

1) Sub-module M3-A

In this module, the slope of the road (C_{sd}) is computed from four inputs: the acceleration of the vehicle (V$_a$), the output velocity of the AT(TM$_{RS}$), the throttle valve opening rate (TH$_0$), and the slope resistance(R$_g$). The relationship between the specified inputs and the output C$_{sd}$ can be obtained by learning the corresponding neural network using experimental data, which are derived from experiments under various road conditions.

2) Sub-modules M3-B and M3-C

In sub-module M3-B, the driver's willingness to accelerate downhill can be determined from the timer, the throttle valve opening rate (TH$_0$), and the velocity of the vehicle (V$_S$). The driver's willingness to decelerate downhill in sub-module M3-C can also be decided from the timer, the brake switch (B$_{sw}$), and the acceleration of the vehicle (V$_a$). The relationship between the specified inputs and the corresponding outputs can be obtained by learning the relevant neural networks using experimental data.

3) Sub-module M3-D

This module evaluates the degree of the driver's willingness (i.e., engine brake selection) to decelerate based on three inputs: AD$_i$, BS$_{ops}$, and BS$_{opi}$. The willingness to decelerate depends on the number of driver brake operations, so the outputs of the previous sub-modules M3-B and M3-C become the inputs of this module. The degree can be classified into three levels: high deceleration (DCC$_{big}$), low deceleration (DCC$_{small}$), and zero deceleration (DCC$_{zero}$).

4) Sub-module M3-E

In this module, the degree of down-shift when operating the engine brake (D$_{ACC}$) and the road condition (D$_m$) are determined from the slope of road C$_{sd}$and the outputs of Module M3-D. D$_m$ = 1 and D$_m$ = 0 denote a downhill road and a flat road, respectively. The output D$_{ACC}$ is determined as follows:

·When $\mathrm{D}_m = 0$, $\mathrm{D_{ACC}} = \mathrm{K}_0$

·When $\mathrm{D}_m = 1$,

$$\mathrm{D_{ACC}} = \begin{cases} K_0 & \text{when the output of } M3-D \text{ is } DCC_{zero} \\ K_1 & \text{when the output of } M3-D \text{ is } DCC_{small} \\ K_2 & \text{when the output of } M3-D \text{ is } DCC_{big} \end{cases}$$

where K$_0$, K$_1$, and K$_2$ indicate no shift, one down-shift, and two down-shifts by operating the engine brake, respectively. The relationships between the inputs stated above and the corresponding outputs can be obtained by learning the neural networks using experimental data.

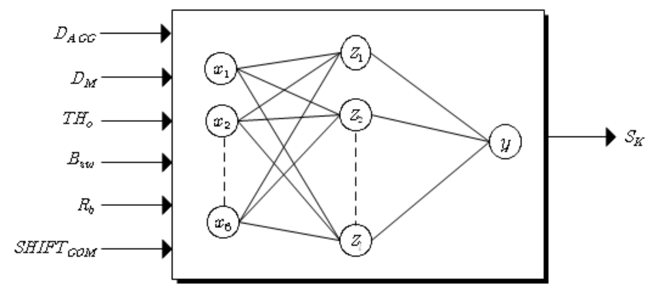

Figure 8. Module 4 to decide the degree of satisfaction.

3.2.4 Deciding the degree of satisfaction (Module 4)

This module (Figure 8) determines the degree (S$_k$) of driver satisfaction with the current shift map. The outputs (D$_M$, D$_{ACC}$) of Module 3 and other variables, such as the throttle valve opening rate (TH$_0$), brake deceleration resistance (R$_b$), brake switch (B$_{sw}$), and current shift position (SHIFT$_{COM}$), are used to decide the S$_k$. This module plays a role in analyzing the driver's inclination, and the results are used to make the next adjustment of the shift map. When S$_k$ is relatively high, the current shift map remains unchanged. Otherwise, some adjustment will be made.

3.2.5 Decision module for the shift position (Module 5)

This module (Figure 3) determines the final gear-shifting rate M_p based on all of the outputs from Modules 1–4. The rate M_p has a value between 0 and 1, which is computed as follows:

$$M_p = (D_{ACC}+\delta)D_M+D_f(1-D_M) \tag{10}$$

$$D_f = M_A(1-M_m)+ M_m(1-L_{ve}) \tag{11}$$

where δ ($\triangleq$ S$_d$ - S$_k$) is the difference between the highest degree (S$_d$) and the current degree (S$_k$) of the driver's satisfaction.

Using the rate M_p, the final shift map position is decided as follows:

$$SM_{final}=SM_{current}+M_p\ \ (SM_{max}-SM_{current}) \tag{12}$$

where $SM_{current}$ is the current shift map position and SM_{max} is the maximum shift map position within the admissible range.

4. Simulation Results

A dynamic model of the Hyundai Sonata with a Ricardo engine was used in the simulation to verify the effectiveness of the

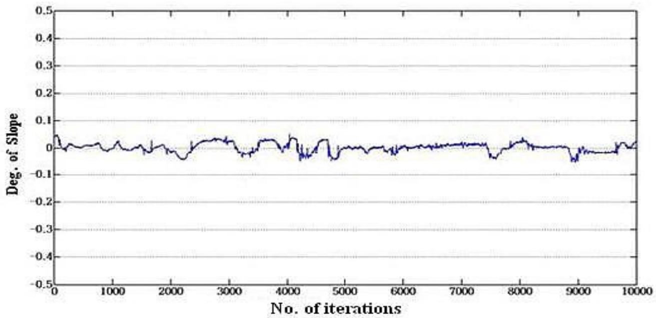

Figure 9. Slope of road.

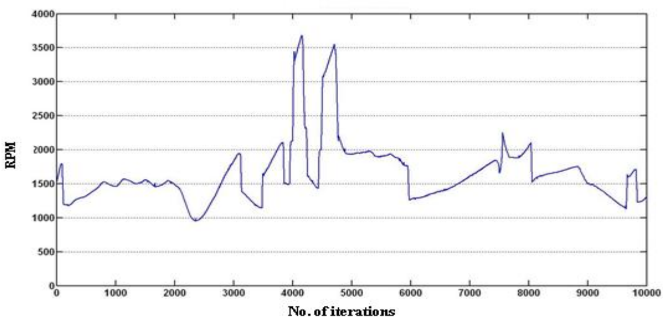

Figure 10. Wheel revolutions per minute (RPM).

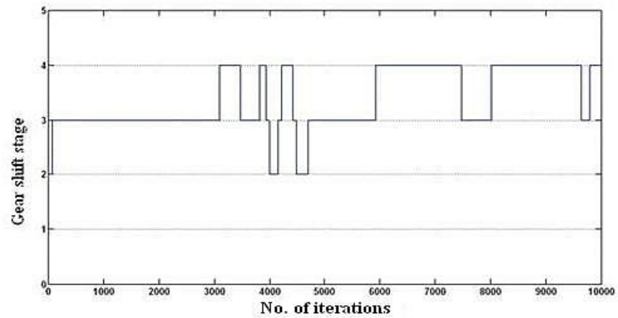

Figure 11. Standard shift map.

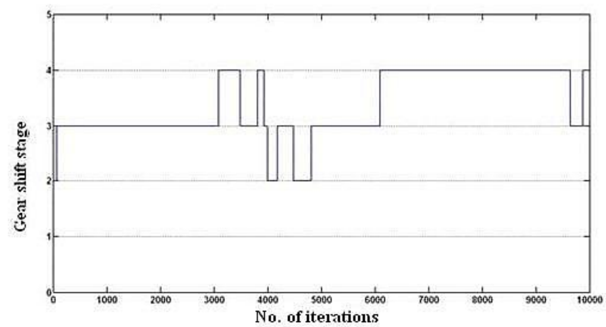

Figure 12. Intelligent shift map.

proposed approach. The simulation results are examined from several important aspects, particularly the number of times that gear-shifting occurred during the test. In general, it is very important to reduce the number of times that unnecessary gear-shifts occur because the “jerk” phenomenon caused by gear-shifting makes a driver uncomfortable. The second aspect is how long a vehicle remains at a high-speed in the high gear-stage. It is well-known that remaining in the high-gear stage during high-speed driving leads to greater fuel economy. The last aspect considers how long the vehicle can keep accelerating in the lower-gear stage. Acceleration in the low-gear stage increases the torque of the engine to change the velocity of the vehicle smoothly.

Figure 9 shows the slope of the road where the simulation was performed, and Figure 10 shows the wheel revolutions per minute (RPM) for the vehicle. In these figures, the x-axis denotes the number of clocks (or iterations) generated in the TCU. It should be noted that each clock is equivalent to 0.016 sec and the number of clocks can be considered as a proxy of time.

Figure 10 shows that the driver required an abrupt acceleration between the 4,000th and 5,000th iterations, before maintaining an almost constant speed after 6,000 iterations. Thus, to increase the degree of satisfaction, the lower gear-stage must be maintained between the 4,000th and 5,000th iterations, whereas the higher gear-stage is required after 6,000 iterations to reduce the fuel consumption.

Figures 11 and 12 show the gear-shifting results derived from the standard shift map and the intelligent shift map produced in this study, respectively. Figure 11 shows that the total number of gear-shifts was 16 and that the gear-4 stage with two gear shifts was maintained after 6000 iterations. Figure 12 also shows that the number of gear-shifts was reduced to 12 and that the gear-4 stage was maintained longer than the previous one. These results indicate that the proposed approach is more effective than the conventional method in several respects.

5. Conclusions

In this study, we developed an intelligent gear-shifting strategy, which may have a major role in AT systems. To improve the capacity to adapt to different driving conditions and driver inclinations, the proposed method was developed using a NRBFNN, which has distinct advantages, including a simple structure, fast learning, local mapping, and fault tolerance. Compared with the standard method, the intelligent shift map can reduce the total number of gear-shifts, which makes a driver more comfortable and provides sufficient driving power. The effectiveness of the proposed method was verified through simulations.

In the future, we will study how to reduce the number of hidden neurons. In general, the radial basis function has no orthogonal properties and does not require unnecessary neurons. The optimal structure of NRBF will make the intelligent shift map more advanced, and it has wide applications.

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