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To cite this article: Ruey-Jing Lian, Bai-Fu Lin & Wun-Tong Sie (2005) Self-organizing fuzzy control of active suspension systems, International Journal of Systems Science, 36:3, 119-135, DOI: 10.1080/00207720512331338102

To link to this article: http://dx.doi.org/10.1080/00207720512331338102

Published online: 18 Aug 2006.
Self-organizing fuzzy control of active suspension systems

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(Received 20 May 2004; in final form 25 November 2004)

A self-organizing fuzzy controller (SOFC) is proposed to control an active suspension system and evaluate its control performance. In complicated nonlinear system control, the SOFC continually updates the learning strategy in the form of fuzzy rules during the control process. The learning rate and the weighting distribution value of the controller are hard to regulate, so its fuzzy control rules may be excessively modified such that the system response generally causes an oscillatory phenomenon. Two fuzzy-logic controllers were designed according to the system output error and the error change, and introduced to the SOFC to determine the appropriate parameters of the learning rate and the weighting distribution, to eliminate this oscillation. This new modifying self-organizing fuzzy-control approach can effectively improve the control performance of the system, reduce the time consumed to establish a suitable fuzzy rule table, and support practically convenient fuzzy-controller applications in an active suspension control system, as verified experimentally.

1. Introduction

The main purpose of suspension systems is to improve the road-holding ability and the quality of the ride in a car. Suppressing the vibration using a suspension system is a feasible method of control for this. Most vibration-suppressing systems in the past have used passive elements, such as springs, plate springs, and hydraulic absorbers, among others. Increasing the stiffness of the spring or increasing the damping of the system can help to improve the effectiveness of the suppression of vibrations in passive suspension systems, but the vibration suppression capability of such passive suspension systems is limited to a certain range of frequencies, which is a function of the spring’s stiffness, damping constant, and mass ratio. A passive control strategy implemented using a suspension system suppresses vibrations when the vehicle is travelling on variable road profiles but in a manner that lacks operative flexibility. It clearly cannot satisfy the requirements of passengers for a better ride, and passive elements are usually heavy, thereby increasing the burden of the vehicle mechanism. Hence, active suspension systems that include an actuator in a dynamic absorber system for controlling the vibration of the vehicle are currently of interest.

Many active vibration-control methods have been proposed to study the ability of vibration suppression by a vehicle suspension system to improve the road-holding and ride quality of cars (Yagiz et al. 1997, Chantranuwathana and Peng 1999, Huang et al. 2000). Optimal control theory has recently been employed to design a controller for an active suspension system. However, an accurate system model must be provided before the controller can be developed. Hac (1990) presented an optimal preview control for active suspension; this control strategy was applied to a vehicle model with two degrees of freedom (DOF). The results showed that the strategy could improve road holding. Preview control was also demonstrated to drastically reduce the power requirements and overcome the trade-off between performance and power. Louam et al. (1993) considered the problem of deriving control laws that minimize the specified performance indices for a vehicle moving on a rough surface, with preview control of the surface evaluation. This approach was based on linear optimal tracking control theory. Hence, the elements
of the system were taken to be linear, and the performance index was constrained to be quadratic. Huisman et al. (1993) developed a continuous time optimal control strategy for an active suspension with preview control. Langlois et al. (1991) proposed a microcomputer to control a hydraulically actuated, active suspension for a one-quarter ton, four-wheel-drive vehicle system with a preview control strategy. Abdel-Hady (1994) developed a continuous look-ahead preview control scheme and applied it to the well-known quarter-car model. The results showed that the active suspension system with preview control can effectively reduce the body acceleration and the dynamic tyre load. Tobata et al. (1993) proposed a new method for controlling active suspension, which employed the preview control rule to improve the comfort and stability of the ride. Yoshimura et al. (1993) proposed an active suspension model for a rail/vehicle system, based on preview and stochastic optimal control.

Fuzzy logic control methods have been applied extensively in recent years, and no model is needed for the development of the controller. Therefore, these methods have been employed in an active suspension system with a complicated dynamic model. Ro et al. (1993) developed a fuzzy-logic algorithm of active ride comfort for a quarter-car model. Yester and McFall (1992) implemented a fuzzy-logic strategy for controlling an automotive suspension system incorporating active elements. Yeh and Tsao (1994) proposed a fuzzy preview control scheme to generate a reference curve by sensing information about the road ahead of the vehicle, so that the actuator can operate within the stroke limit, even on a rough road. Rao and Prahlad (1997) employed a tunable fuzzy-logic controller with an active suspension system model to reduce the acceleration and displacement of the body of the vehicle. Even though fuzzy-logic control has been successfully employed in many industrial applications, fuzzy-logic control still requires considerable effort in finding the appropriate membership functions and fuzzy rules, especially when the system is complicated or rapidly changing. The active suspension system obviously exhibits nonlinear characteristics associated with gravitational force, the bucking of springs, clearance of the transmission mechanism, the saturation of the actuator, and so on. These factors substantially increase the difficulty in designing a fuzzy-logic controller for an active suspension system.

Various design methods for fuzzy controllers have been proposed to solve control problems of nonlinear with uncertain dynamic systems. The fuzzy-model-based control method is one of the most prominent methods for fuzzy-controller design. Johansen (1994) developed a fuzzy-model-based control system to evaluate its stability, robustness, and performance. This fuzzy model is based on a set of ARX models (Ljung 1987) that are combined using a fuzzy inference mechanism. According to the fuzzy model of MIMO dynamic systems, Johansen (1994) designed a discrete-time nonlinear controller that controlled the system and evaluated the performance of the system. Lee et al. (2001) proposed a fuzzy-model-based control methodology for controlling Takagi-Sugeno fuzzy systems with time-varying input delay. The controller design technique is based on the Lyapunov–Razumikhin stability theorem. The proposed controller design technique is effective, as verified from numerical simulation results. Chang et al. (2001) developed an intelligent digital redesign method of a fuzzy-model-based controller to analyse effectively the stability problem of continuous-time complex uncertain systems.

As previous literature has shown, the design of a fuzzy-model-based control method is very complex, so that employing this control strategy for the practical control applications is difficult. Therefore, a fuzzy-logic controller design from the experience of human experts is the most popular control strategy from the viewpoint of realistic engineering applications. However, the main problem in the design of a fuzzy-logic controller is that both the inference table and the knowledge base are fixed after they are chosen, and they depend fully on an expert’s knowledge or the experience of a skilled operator. Procyk and Mamdani (1979) first proposed a self-organizing fuzzy controller (SOFC) to solve this problem. This control strategy involves online learning, rather than human thinking, to establish control rules by online learning, simplifying the procedures for designing a fuzzy-logic controller. Afterward, Shao (1988) and Zhang and Edmunds (1992) developed modified learning methods to simplify the SOFC further. The learning scheme was based on a performance decision table, the determination of which is as difficult as designing a fuzzy-rule table. The output error and the error change in the system were applied directly to adjust the linguistic fuzzy-rule table (Yang 1992) rather than the performance-decision table. The fuzzy-rule table of this SOFC can be begun without any initial fuzzy rules. It avoids the difficulty of designing a fuzzy-logic controller in finding an appropriate membership function and fuzzy rules. Sun et al. (2003) proposed a least-mean-square (LMS) adaptive fuzzy-control algorithm for a vehicle’s active suspension system to evaluate the control performance of the system; this control algorithm can adjust the rectification factor of the fuzzy controller with the LMS, so it not only reflects the advantage of fuzzy-logic in the nonlinearity system but also improves the disadvantage of common fuzzy methods, depending strongly on the experience. Huang and Lin (2003) employed an SOFC to control the position and acceleration oscillatory amplitudes of the sprung mass in the
suspension system owing to the rough road variation for evaluating the control performance of the system. This SOFC adopted parameters of the fixed learning rate and the constant weighting distribution value according to experimental tests obtained to regulate fuzzy control rules online. The SOFC can self-adjust fuzzy rules from initially no fuzzy rules according to the dynamic characteristics of the system. This learning ability eliminates the requirement for understanding the dynamic behaviour of the system and will overcome the difficulty of designing fuzzy control rules. These effects also reduce the computational time to regulate the rules table. Although the SOFC (Yang 1992, Huang and Lin 2003) has a superior learning capability for controlling complicated with uncertain systems, appropriate parameters of the learning rate and the weighting distribution in the SOFC are carefully chosen, and these parameters are fixed after they have been decided. Unfortunately, inappropriately selecting the weighting distribution value or the learning rate or both in the SOFC will substantially affect the system output response so that the system becomes unstable. Hence, this study develops a new modifying self-organizing fuzzy controller (NMSOFC) to solve the above problem, employing two traditional fuzzy controllers to individually regulate parameters of the learning rate and the weighting distribution in the NMSOFC according to the system current error and the error change, to determine a suitable learning rate and an appropriate weighting distribution value rather than from experimental tests obtained (Huang and Lin 2003), to achieve a fast transient response and enhance the system stability. Most work in this field involves computer simulations of simple vehicle suspension models. This investigation studies an NMSOFC for an active suspension control system.

2. System description and mathematical model

Figure 1 presents a photograph of a quarter-car active suspension system designed and constructed in our laboratory to evaluate the performance of the proposed controller based upon the system response. The main
mechanism of the active suspension system consists of the sprung and unsprung masses, the tyre, and two hydraulic cylinders. The system comprises two springs with guiding pillars, two dampers, and one hydraulic cylinder all between the sprung mass and the support frame; the sprung mass was attached to an optical linear scale to obtain position information. An accelerometer was also installed on the sprung mass to measure the acceleration and evaluate the accelerative dynamic effect of the body of the vehicle. A 15-hp power unit was employed to drive two hydraulic cylinders simultaneously and thus achieve the desired control action.

One of these hydraulic cylinders had its extremity of the one fixed on the bottom of the base in the system, and the other end thereof was connected to the frame of the roller, enabling the roller to be in continuous contact with the tyre, and was also attached to another optical linear scale to yield position information. This set-up was used to simulate the disturbance of road profiles when the control signal was excited using a hydraulic servo-valve control. Another hydraulic cylinder was installed between the sprung mass and the support frame, and a hydraulic servo-valve was also employed to control this cylinder and generate an active control force to suppress the vibration of the suspension system when the disturbance generated by the road profiles was input to the system. Additionally, an encoder with 2000 pulses per revolution was mounted on the revolutionary shaft of the tyre to generate feedback regarding the angular position of the tire. A 10-hp power unit was used to support a hydraulic motor to make the tire rotate through a hydraulic proportional valve control to achieve the desired rate of rotation.

This active suspension system was controlled using an IBM Pentium II 400 Mhz PC, which served as the central processing unit to process all the input–output data of the whole system as well as the control parameters. The requisite interface was a PCI-8136 card, comprising a digital-to-analog part with six channels, an analog-to-digital part with six channels, and six decoding channels. The card was from ADLINK Company. Figure 2 shows the experimental set-up of

![Figure 2. Experimental set-up of the active suspension control system.](image-url)
the active suspension control system. A mathematical model was established to investigate further the dynamics of the active suspension system.

The tyre is assumed to contact the surface of the road when the vehicle is travelling; and is regarded as a spring with a mass. Hence, figure 3 presents a simplified diagram of the dynamics of the active suspension system. \( Z_{\text{body}} \) and \( Z_{\text{wheel}} \) are the displacements of the sprung and the unsprung masses, respectively. \( x_1 = Z_{\text{body}} - Z_{\text{wheel}} \) is the relative displacement between the sprung and the unsprung masses; \( x_3 = Z_{\text{wheel}} \) is the displacement of the unsprung mass; \( x_2 \) and \( x_4 \) are the velocities of the sprung and the unsprung masses, respectively; \( C_1 \) is the average damping coefficient of the dampers; \( K_1 \) is the average stiffness coefficient of the springs, and \( K_2 \) is the stiffness coefficient of the tyre.

This active suspension system exhibits nonlinear time-varying characteristics because of the spring’s buckling, the nonlinear dynamics of the hydraulic cylinders with the hydraulic servo valves, the elastic-plastic behaviour of the tyre, the actuator saturation, and other factors. Traditional control theory is difficult to implement on this complex active suspension system. However, the excellent model-free characteristics of an SOFC can be exploited to control a time-varying complex system, especially one with uncertainty or nonlinearity.

3. Self-organizing fuzzy learning algorithm

The control input of a fuzzy-logic control system is determined from a fuzzy inference; no mathematical model is required. This absence of the need for a model overcomes the difficulty of modelling in the designing of controllers for complex dynamic systems. Fuzzy logic control has various industrial applications. However, a traditional fuzzy controller design depends on an expert’s knowledge or the experience of a skilled operator to establish fuzzy rules to perform system control. Therefore, fuzzy-logic control takes much time consumption to derive an appropriate membership function and robust fuzzy rules for complicated dynamic control systems. Moreover, the fuzzy rules cannot be easily changed after they have been established. Clearly, this control strategy lacks operative flexibility. An intelligent fuzzy controller with learning capability is thus presented to simplify the implementation of the fuzzy-logic controller design with suitable control performance, solving the foregoing problems.

The main differences between an SOFC and a traditional fuzzy controller are the characteristics of their databases and their fuzzy rules. The database and fuzzy rules of a traditional fuzzy controller are fixed after the design step. However, the database and fuzzy rules of an SOFC are continually accumulated or modified according to a learning strategy during the control process, to improve the precision of the system output. Procynk and Mamdani (1979) first developed a self-organizing controller, whose learning structure was modified by Shao (1988) and Zhang and Edmunds (1992). Their learning algorithms use a

\[
\begin{bmatrix}
\dot{x}_1 \\
\dot{x}_2 \\
\dot{x}_3 \\
\dot{x}_4
\end{bmatrix} =
\begin{bmatrix}
0 & 1 & 0 & -1 \\
-\frac{K_1}{M_s} & -\frac{C_1}{M_s} & 0 & \frac{C_1}{M_s} \\
0 & 0 & 0 & 1 \\
\frac{K_1}{M_{us}} & \frac{C_1}{M_{us}} & -\frac{K_2}{M_{us}} & -\frac{C_1}{M_{us}}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4
\end{bmatrix}
+ \begin{bmatrix}
0 \\
\frac{1}{M_s} \\
0 \\
-\frac{1}{M_{us}}
\end{bmatrix} F_a + \begin{bmatrix}
0 \\
0 \\
0 \\
\frac{K_2}{M_{us}}
\end{bmatrix} Z_{\text{road}}
\]

where \( F_a \) represents the hydraulic actuation force; \( M_s \) and \( M_{us} \) are the masses of the sprung and the unsprung, respectively.
performance-decision table as the basis of a learning scheme. However, designing a performance decision table is almost as difficult as determining the fuzzy-inference table of a traditional fuzzy controller; the designer must use trial and error to establish a suitable performance-decision table for the special system. Additionally, the robustness of the SOFC is substantially decreased for controlling uncertain dynamic systems. Given the above defects, a new learning algorithm was developed by Yang (1992); it does not use a performance-decision table but directly applies the system output error and the error change to modify the linguistic fuzzy-rule table. The fuzzy-rule table of this SOFC can be begun with zero initial fuzzy rules.

The self-organizing part is introduced into a traditional fuzzy controller to constitute an SOFC, as depicted in figure 4. Self-organizing has three steps: performance measure, model estimation, and rule modification. The system performance measure is important in successful learning algorithms. Two physical features such as system output error and error change are measured as performance indices in a performance-decision table. The measurement of such indices is similar to establishing a fuzzy-rules table. A model is estimated to determine the relationship between the output response of the system and the control input. The performance measure is applied to determine the correction value of each fuzzy rule by applying the estimation model. Nevertheless, the suitable performance-decision table is difficult to organize for each control system. A real-time linguistic SOFC control scheme is developed here, in which two parameters are applied to establish the performance-measure function, instead of the performance-decision table.

The rule table includes only modification of the original fuzzy rules; the correction value of each fuzzy rule is introduced into each original fuzzy rule to generate a new control rule. This approach overcomes the expansive defect of the database in the Procyk and Mamdani (1979) scheme and decreases the time consumption. Furthermore, the dynamic system output may be specified by precise design parameters. The dynamic feature of the system can be represented using an autoregressive moving average (ARMA) model (Ljung 1987):

$$y(k) = A(q)y(k-1) + M u(k-d) + B(q) u(k-d-1),$$

$$A(q) = 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_n q^{-n},$$

$$B(q) = 1 + b_1 q^{-1} + b_2 q^{-2} + \ldots + b_m q^{-(m-d)},$$

where $y(k)$ and $y(k-1)$ are the output responses of the system on $k$-step and $k-1$-step sampling intervals, respectively; $u(k-d)$ and $u(k-d-1)$ are the control input voltages of the system on $k-d$-step and $k-d-1$-step sampling intervals, respectively; $q$ represents a forward-shift operator; $d$ is the system delay; and $M$ is the direct forward system gain in this position control system. The values of $n$ and $m$ depend on the dynamic characteristics of the machining table. The nonlinearity and uncertainty in the system are such that these parameters are difficult to estimate for a complicated suspension system. Fortunately, fuzzy control requires no model; neither does it depend on a precise mathematical model or system parameters. Hence, the following controller design includes none of

![Figure 4. Self-organizing fuzzy control strategy for the suspension system.](image-url)
the error change—excite two fuzzy subsets of the \( E \) and \( EC \) universe of discourse, respectively. The control input \( u(k) \) is derived from the fuzzy rule inference, so the four fuzzy rules will be modified in each control step. The correction value of each fuzzy rule is proportional to its excitation strength \( w \). The excitation strength is represented as a triangular membership function, calculated using a linear interpolation algorithm. Then, the control input of the \( i \)th rule is

\[
u_i(k + 1) = u_i(k) + \Delta u_i(k) = u_i(k) + w_{i, w_{ec}} \frac{\gamma}{M} \times [(1 - \zeta)e(k) + \zeta ec(k)].\]

The term \( \gamma/M \) in the above equation can be regarded as the correction weighting. In this work, \( M \) is set to \( 1 \) to eliminate the identification procedure and reduce the computational time during implementation. The correction weighting is determined only by the learning rate \( \gamma \). A large value of \( \gamma \) will introduce a large rule correction and system output oscillation. This parameter in the system control influences only the transient response and does not affect the steady-state performance.

Although an SOFC exhibits online learning capability, it still cannot solve these problems of selecting appropriate parameters to specify a learning rate and a weighting distribution value. The SOFC can continually modify an inappropriate fuzzy rules table into a satisfactory fuzzy rules table, according to the previously designed learning algorithm for improving control performance; however, for a complicated time-varying system, the weighting distribution value \( \zeta \) between \( \Delta u_i(k) \) and \( \Delta u_{ec}(k) \), and the learning rate \( \gamma \) influence the dynamic behaviour of the system response for SOFC design. The weighting distribution value is chosen to be \( 0.5 \) to avoid any bias toward \( \Delta u_i(k) \) or \( \Delta u_{ec}(k) \). This choice does not guarantee that the selected parameter is appropriate in SOFC design for improving control performance. Additionally, choosing a suitable learning rate \( \gamma \) for the SOFC is difficult, because if the learning rate \( \gamma \) is large in the regulation of the self-organizing fuzzy learning algorithm, then the rules table will be excessively modified, and the system control command will vary over such a large range that the system output response causes oscillatory phenomenon. Then the system is likely to become unstable. Contrarily, if the learning rate \( \gamma \) is small, the system output response will be slow; despite increasing the learning time, the system control performance will not necessarily be improved. Although an appropriate learning rate \( \gamma \) of the SOFC can be obtained experimentally or from the experience of a skilled operator, it is problematic fixed after it is selected. This method considerably limits the dynamic behaviour of the system output.
response. It cannot specify an appropriate parameter online to improve the control performance according to the system output response during the control process.

Consequently, two traditional fuzzy controllers are employed in finding appropriate values of parameters \( \gamma \) and \( \zeta \) which regulate the structure shown in figure 5, and thus easily and effectively regulate both the learning rate \( \gamma \) and the weighting distribution value \( \zeta \) in the self-organizing fuzzy learning algorithm. Both the learning rate \( \gamma \) and the weighting distribution value \( \zeta \) are determined by the system current error and the error change through each traditional fuzzy controller operation. The control law associated with determining appropriate parameters of the learning rate and the weighting distribution is that the system output compares the desired reference input with a large error when both the system output error and error change are large. Then, both the learning rate and the weighting distribution value must be increased to accelerate the output response of the system. However, in order to avoid generating an overly large correction quantity when the system output approaches the reference input, both the learning rate and the weighting distribution value must be decreased, so that the output response of the system can smoothly approximate the reference input and prevent the system output response from causing overshoot. In order to conform to the above control law for fuzzy controllers associated with design parameters \( \gamma \) and \( \zeta \), for example, tables 1 and 2 (Huang and Lian 1996, AI-Holou et al. 2002) list separately control rules of two fuzzy controllers for determining appropriate parameters of the learning rate and the weighting distribution. This new modifying self-organizing fuzzy controller (NMSOFC) not only eliminates the difficulty in finding appropriate parameters \( \gamma \) and \( \zeta \) in the self-organizing learning algorithm, but also improves the transient response of the system and the robustness of the controller during the control process. It can also improve the stability of the system and reduce the computational time required for the controller to learn for a complicated control system.

Figure 5. New modifying self-organizing fuzzy control scheme for the suspension system.

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4. Designing self-organizing fuzzy controller

The SOFC is composed of a self-organizing part and a traditional fuzzy controller, as shown in figure 4. The preceding section presented a self-organizing learning algorithm of the SOFC. The traditional fuzzy-controller design procedure will be described here. The control performance of a traditional model-base controller depends completely on the accuracy of the known dynamic model of the system. However, the dynamics of complex systems with several variables are difficult to model, so a model-free intelligent controller is introduced here to solve such a problem using fuzzy set theory. The primary feature of a fuzzy-logic controller is its usefulness in selecting appropriate linguistic fuzzy rules from a rule table established from human experience of control and a database, using a decision-making process. These fuzzy rules are then transformed into a control type of human thinking according to fuzzy-logic and using fuzzy-set operations. Zadeh (1965) introduced fuzzy-set theory, which has subsequently seen many control applications (Maiers and Sherif 1985, Lee 1990), in most of which the main design objective is to establish a fuzzy system that approximates the desired control action. Fuzzy-set theory is also employed as an alternative to traditional modelling and control design in suitably representing the system (Driankov et al. 1993).

The structure of a traditional fuzzy-controller design consists of the definition of input/output fuzzy variables, decision-making related to fuzzy-control rules, fuzzy-inference logic and defuzzification. Figure 4 presents a generally traditional fuzzy control structure for the suspension system. The control system variables are defined as

\[
e(k) = r(k) - y(k),
\]

\[
e_{\text{c}}(k) = e(k) - e(k - 1),
\]

where \(e(k)\) and \(e_{\text{c}}(k)\) are the position error of the system and the error change of the system on a \(k\)-step sampling interval, respectively; and \(r(k)\) and \(y(k)\) represent the reference input of the system and the output response of the system on a \(k\)-step sampling interval, respectively.

A triangular membership function, depicted in figure 6, is employed to convert these input and output variables into linguistic control variables, where \(S_i\) is a scaling factor. The subscript \(i = y, \xi\) is employed to represent parameters of the traditional fuzzy controllers in NMSOFC for regulating the learning rate (\(\gamma\)) and the weighting distribution (\(\xi\)), respectively. The superscript \(j = 1, 2, 3\) is used to express the system output error, the error change, and the control output.

This study applies the state evaluation fuzzy-control rules (Lee 1990) for controlling complicated nonlinear suspension systems. If the fuzzy-inference logic applied the Max–Min (Mamdani 1974) product composition to operate the fuzzy rules, the change of suitability would not be smooth when \(\wedge\) is applied. In order to improve the problem, the \(\wedge\) operation is replaced by an algebraic product herein (Huang and Lian 1996). Finally, the height method (Lee 1990) was employed to defuzzify the output variables in this study to attain the accurate objectives for controlling this system. The above design process yields the following actual control input voltage of the actuator for this traditional fuzzy control system,

\[
u(k) = u(k - 1) + \Delta u(k),
\]

where \(\Delta u(k)\) indicates the voltage increment of the system on a \(k\)-step sampling interval. \(u(k)\) and \(u(k - 1)\) represent the system control input voltages on \(k\)-step and \(k - 1\)-step sampling intervals, respectively.

5. Experimental results

The active hydraulic suspension system has nonlinear dynamic characteristics and uncertainty, so designing a model-based traditional controller for controlling this system is difficult. An SOFC without a mathematical model required was designed and employed to control this complicated nonlinear suspension system. The SOFC has a superior learning capability and can continually modify the database and control rules online for controlling the suspension system so as to achieve the desired system output response, but the appropriate parameters of the weighting distribution and the learning rate in the SOFC are difficult to select. Therefore, this study develops a NMSOFC control scheme to overcome the problem. The NMSOFC control strategy is that parameters (\(\xi\) and \(\gamma\)) in the
NMSOFC are individually introduced into the operation of two traditional fuzzy controllers according to the system’s current error status and the error change, to determine a suitable learning rate and an appropriate weighting distribution value to achieve a fast transient response, and to enhance the system stability.

The proposed NMSOFC was employed to control the active hydraulic suspension system for evaluating its control performance that compared to using a SOFC. To achieve this purpose, the following experiments were performed to explore the effectiveness of the proposed control strategy. In this study, the learning rate and the weighting distribution value in the SOFC are chosen as $\gamma = 0.05$ and $\zeta = 0.5$, respectively. The scaling factors for the system output error, the error change, and the control output membership functions of the two traditional fuzzy controllers for determining appropriate parameters ($\gamma$, $\zeta$) in the NMSOFC were separately chosen as

$$
\begin{cases}
SL_1 = 0.05 \\
SL_2 = 0.01 \\
SL_3 = 0.01
\end{cases}
\quad
\begin{cases}
SL_1 = 0.15 \\
SL_2 = 0.05 \\
SL_3 = 0.05
\end{cases}
$$

Tables 1 and 2 list traditional fuzzy control rules associated with determining appropriate parameters of $\gamma$ and $\zeta$, respectively. The sampling frequency in the experiment was 200 Hz during all control processes.

5.1. Position control of the square wave of the sprung mass in the suspension system

Figure 7 shows both the system responses of the position control of the square wave with a 30-mm amplitude, to compare the control performance of SOFC with that of NMSOFC. The learning process of the SOFC clearly requires at least three learning cycles to improve control performance, but the NMSOFC needs only one learning cycle with good control performance. The next system output response velocity is increased quickly after the second learning cycle, in spite of the oscillation of the system output response due to the deflection of the tyre that occurs when the position control of the square wave is performed. The NMSOFC can effectively and quickly overcome this oscillatory effect and reduce the tracking error, thus confirming that the NMSOFC is more robust than SOFC in terms of control performance associated with the position control of square wave.

5.2. Suppressing the vibration amplitude of the vehicle’s body under disturbance from sinusoidal road profile

The hydraulic cylinder of the suspension system was driven using a proportional–integral–differential (PID) controller through a servo-valve control, to generate the sinusoidal road profile with an amplitude of 40 mm, to simulate the disturbance of a roadway. Figure 8(a) and (b) show the experimental results of the learning process for suppressing vibration using the SOFC and the NMSOFC, respectively. The dotted line with circular marks is the system output response with no control, as in the case of passive control. Although both the SOFC and the NMSOFC effectively suppress the vibration due to disturbance of the sinusoidal road profile to approximately one-fifth, the SOFC in the learning control process needs at least five learning cycles to improve the control performance in suppressing vibration; moreover, its control performance is difficult to improve, even when the number of learning is increased, according to experimental results. However, the NMSOFC needs only a single learning cycle to achieve the acceptable control performance in suppressing the vibration. The control performance is gradually improved to an appropriate level depending on the number of learning cycles. Figure 9 compares the suppressed vibration responses output by the active suspension system using the SOFC and the NMSOFC. The solid line represents the output vibration suppression response using NMSOFC with two learning cycles. The dashed curve plots the output vibration suppression response using SOFC with five learning cycles. Clearly, the NMSOFC exhibits a better control performance in terms of the suppression of vibration and requires less computational time for suspension system control than does the SOFC. The root-mean-square (rms) errors of the system output responses using the passive control strategy, the SOFC, and the NMSOFC are 28.3 mm, 3.61 mm and 1.90 mm, respectively. These results confirm that the proposed NMSOFC has a better control performance of the vibration suppression in the suspension control system implementation than the SOFC in terms of vibration suppression. Clearly, employing two traditional fuzzy controllers—one each for the learning rate and the weighting distribution value—to yield appropriate parameters for the new modifying self-organizing fuzzy algorithm has a better control performance and less computational time in performing suspension system control, than using a fixed learning rate with a constant weighting distribution value to modify a self-organizing fuzzy strategy.

5.3. Suppressing the vibration and the acceleration of the vehicle’s body given a sinusoidal road profiles and rotating tyres

The hydraulic cylinder of the suspension system was driven using a PID controller through a serve-valve control, to simulate a sinusoidal road profile with an amplitude of 40 mm. The tyre was also driven using another
PID controller, but through a proportional-valve control to obtain the desired rotation speed. This setup represented the disturbance input of a roadway for vibration control, given a tyre speed of 40 km h\(^{-1}\).

Figure 7. Dynamic responses of learning processes associated with the position control with a square wave for the vehicle’s body: (a) using SOFC and (b) using NMSOFC.

Figure 10(a) shows experimental results concerning the suppression of the vibration using the SOFC and the NMSOFC. The dotted line with circular marks is the system response without control action; the dashed
curve is the system response with the SOFC; the solid line is the system response with the NMSOFC. Both the SOFC and the NMSOFC for the active suspension system effectively suppress the amplitude of vibration to about one-fifth of the original amplitude without control. Figure 10(b) presents both the system output responses to evaluate further the control performance of the vibration amplitude suppression in the suspension
systems using SOFC and NMSOFC. The solid line represents the system response using the NMSOFC with two learning cycles. The dashed curve plots the system response using the SOFC with five learning cycles. The NMSOFC exhibits a better control performance than SOFC in terms of the suppression of vibration. Furthermore, the number of learning cycles of the NMSOFC is two, even though the disturbance of the tyre rotation was also introduced. However, the number of learning cycles of SOFC must increase to five to yield a satisfactory control performance, when the disturbance due to the rotation of tyre is input. This result verifies that the NMSOFC not only exhibits a better control performance than the SOFC but requires less computational time during experimental implementation. The rms errors of the system response without control action, using SOFC and using NMSOFC, were 28.25 mm, 4.64 mm, and 2.17 mm, respectively. Clearly, the NMSOFC has a better control performance in suppressing the vibration amplitude of the sprung mass under a random sinusoidal road profile, which is a road profile with different frequencies and different amplitudes.

Under the above same operating conditions, the robustness and learning capacity of the proposed control strategies in terms of suppression of the acceleration of the car’s body can be used to evaluate further the passengers’ comfort. The following experiments were performed to verify the effectiveness of these strategies. Figure 12(a) compares the responses of the system in terms of the suppression of acceleration using SOFC and NMSOFC. The solid line plots the acceleration response of the car’s body using NMSOFC with two learning cycles; the dashed curve represents the acceleration response of the car’s body using SOFC with five learning cycles. The rms errors of the acceleration amplitude of SOFC and NMSOFC are 0.632 m s$^{-2}$ and 0.295 m s$^{-2}$, respectively. The NMSOFC outperforms SOFC in terms of the suppression of the acceleration amplitude and learning capability in suppressing vibration than other controllers in an active suspension control system. Figure 11 shows the system output responses to evaluate further control performance of the vibration suppression in the suspension system, under a random sinusoidal road profile using NMSOFC. The solid line represents the system response using the NMSOFC with two learning cycles. The dotted line with circular marks is the system response without control. The rms errors of the system response without control and using NMSOFC were 20.76 mm and 1.67 mm, respectively. Clearly, the NMSOFC has a good control performance in suppressing the vibration amplitude of the sprung mass under a random sinusoidal road profile, which is a road profile with different frequencies and different amplitudes.

Figure 9. Comparison of vibration suppression responses of the sprung mass under disturbance input of the sinusoidal road profile with a 40 mm amplitude. -----: SOFC; ——: NMSOFC.
Figure 10. Output suppression of amplitude of vibration of the vehicle’s body under disturbance input of a sinusoidal road profile with a 40-mm amplitude and a tyre speed of $40 \text{ km h}^{-1}$: (a) comparison among situations without control, using SOFC, and using NMSOFC, and (b) comparison between results obtained using SOFC and NMSOFC. $\cdot \cdot \cdot \cdot \cdot \cdot$: passive control strategy; $\cdot \cdot \cdot \cdot \cdot \cdot$: SOFC; $\cdot \cdot \cdot \cdot \cdot \cdot$: NMSOFC.
of the car’s body under a disturbance input of a 40-mm amplitude sinusoidal road profile at a tyre speed of 40 km h\(^{-1}\). Figure 12(b) compares the system responses in terms of the suppression of the acceleration of the car’s body using SOFC and NMSOFC, under the input disturbance of a sinusoidal road profile with a random amplitude, given a tyre speed of 40 km/hr. The dashed curve and the solid line represent the system acceleration using SOFC with five learning cycles and using NMSOFC with two learning cycles, respectively. NMSOFC with two learning cycles effectively suppressed the acceleration of the system, SOFC with five cycles yielded divergence after 13 s, so the tyre bounced violently during the experimental control process. As the number of learning cycles increased, the tyre-bouncing situation gradually became worse because the rules table of the SOFC was excessively modified by inappropriate parameters \((\gamma, \zeta)\) being selected. This result verified that the control performance and robustness of the SOFC did not improve in proportion to the number of learning cycles. The SOFC may have the weakness in the excessive modification of rules table if an inappropriate learning rate is designed, or the weighting distribution is unsuitably regulated so the tyre-bouncing situation gradually becomes worse. However, the NMSOFC requires only two learning cycles to achieve an appropriate control performance; then, even though the number of learning cycles is increased during the control process, a good control performance is still maintained. Clearly, employing NMSOFC to control the active suspension system and thus evaluate the comfort of the ride during suppression of the acceleration can eliminate the difficulty in choosing an appropriate learning rate and weighing distribution, as well as reducing the computational time because the learning algorithm requires only two cycles. The rms errors in the acceleration amplitude obtained using SOFC and NMSOFC are 2.350 m s\(^{-2}\) and 0.282 m s\(^{-2}\), respectively. Clearly, the NMSOFC in an active suspension control system is more robust and adaptable than the SOFC in the suppression of acceleration of the car’s body.

6. Conclusion

A SOFC has been successfully applied to control a quarter-car suspension system. Although the associated learning scheme can be begun with no initial fuzzy rules and be converted quickly, and the control strategy is established using the appropriate rules table by continual online learning instead of by trial and error to simplify the implementation of the fuzzy controller, the system response oscillates at the beginning with zero initial fuzzy rules, and the learning rate and
weighting distribution are difficult to select in this controller design. This work proposed an NMSOF to eliminate the difficulty of selecting suitable parameters associated with the learning rate and weighting distribution in the SOFC. The main motivation for this control strategy is to apply two traditional fuzzy controllers to finding two parameters—a learning rate and a weighting distribution value, instead of the

Figure 12. Comparison of output acceleration suppression for the vehicle’s body under disturbance input of the sinusoidal road profile (a) with an amplitude of 40 mm and (b) a random amplitude, at a tyre speed of 40 km h$^{-1}$. - - - - -: SOFC; ——: NMSOF.
original SOFC parameters—which must be determined experimentally or from the experience of skilled operators. Experimental results indicate that the NMSOFC outperforms the SOFC in reducing the tracking error and quickening the transient response for the position control with square wave. Additionally, both SOFC and NMSOFC outstandingly suppress the oscillation of the sprung mass and the acceleration of the body of the vehicle, improving the comfort of the ride during the control process, with or without tyre rotation, as indicated by the experimental results. However, the NMSOFC exhibits a better control performance than does the SOFC. Clearly, NMSOFC is a good choice for implementation in vehicle active suspension systems for improving ride comfort. The use of NMSOFC to control a suspension system can effectively reduce the computational time, because it requires only two learning cycles to achieve good control performance, but the learning algorithm of the SOFC requires five cycles to perform equally well, and its performance does not increase in proportion to the number of learning cycles. This result also verifies not only that the NMSOFC exhibits a better control performance than that presented previously but that this control scheme also has an effectively lower computational time than the SOFC during the control process.

Acknowledgement

The authors would like to thank the National Science Council of the Republic of China for financially supporting this research under Contract No. NSC 90-2212-E-027-004.

References

C.Z. Yang, ‘Design of real-time linguistic self-organizing fuzzy controller’, MSc thesis, Department of Mechanical Engineering, National Taiwan University, Taiwan (1992).