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# Composite adaptive fuzzy output feedback dynamic surface control design for stochastic large-scale nonlinear systems with unknown dead zone ☆

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ABSTRACT

In this paper, a composite adaptive fuzzy output feedback decentralized control problem is investigated for a class of nonlinear stochastic large-scale systems. The nonlinear large-scale systems under study have unknown nonlinear functions, unknown dead-zone and immeasurable states. Fuzzy logic systems are used to approximate the unknown nonlinear functions, a fuzzy adaptive state observer is designed to estimate the unmeasured states. By utilizing the designed fuzzy state observer, a serial-parallel estimation model is established. Based on adaptive backstepping dynamic surface control technique and the prediction error between the system states observer model and the serial-parallel estimation model, an adaptive output feedback controller is constructed. The designed fuzzy controller with the composite parameters adaptive laws ensures that all the variables of closed-loop system are bounded in probability, and tracking error converges to a small neighborhood of zero. A numerical example is provided to verify the effectiveness of the proposed approach.



## 1. Introduction

In the past decade, stability analysis and control design on stochastic nonlinear systems have received considerable attention, since stochastic modeling has come to play an important role in many real systems. Based on the Itô stochastic differential equation, many stochastic nonlinear system control results and the methods, such as sliding mode control [1,2], Lyapunov function approach [3–7] have been reported in the literature. In recent years, the well-known backstepping technique has been applied to solve the problem of stochastic nonlinear systems (see [8]). For example, the authors in [9] first investigated adaptive backstepping control design problem for a class of strict-feedback stochastic systems by using the approach of risk-sensitive cost criterion. Deng and Krstic [10] proposed an output-feedback backstepping controller for a class of s stochastic nonlinear systems and proved the stability of the closed-loop system based on quadratic Lyapunov function. In [11,12], the backstepping control design approaches were developed for nonlinear stochastic large-scale systems with unmodelled dynamics, respectively. However, it should be pointed out that the aforementioned results in [9–12] are only suitable for nonlinear systems in which the nonlinearities are known or with the unknown parameters appearing linearly with respect to known nonlinear functions. Therefore, the approaches in [9–12] cannot be applied to those stochastic systems with completed unknown structured uncertainties. To solve the above problem, in recent years, many adaptive fuzzy and neural network (NN) backstepping control design methods have been developed for stochastic nonlinear systems with completed unknown nonlinear functions, for example, see [13–19]. Adaptive output feedback controllers have been investigated in [15–17] for SISO stochastic nonlinear systems, and adaptive fuzzy and NN decentralized output control design approaches have been developed in [18,19] for stochastic large-scale nonlinear systems.

It should be mentioned that because of the employment of the backstepping design technique, the previous control design methods in [13–15,19–23] inevitably suffer from the problem of "explosion of complexity," which is caused by repeating differentiations of some nonlinear functions, i.e., the virtual controllers designed at each step with the conventional backstepping technique. As a result, the complexity of a controller drastically grows as the order of the system increases. To solve the problem of the "explosion of complexity" inherent in adaptive fuzzy or NN backstepping design method, some adaptive fuzzy or NN dynamic surface control approaches have been extensively studied in [16,24,25] for several classes of uncertain stochastic nonlinear systems. However, the control approaches in [16,24,25] all cannot

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solve the output feedback control problem for uncertain nonlinear stochastic large-scale systems with unknown dead-zone by using DSC design technique. It should be mentioned that many control systems have constraints on their inputs or states in the form of the physical stoppage, performance and safety specifications, for example, see [26–28]. Dead-zone is one of the most important nonsmooth nonlinearities in many industrial processes. Its presence severely limits system with unknown dead-zone, many adaptive control approaches have been developed [29–32].

Though the adaptive fuzzy or NN control design gained much progress, the original intention employing fuzzy system/NN for approximating the system uncertainty is missing. Intuitively, the more precise approximation of the nonlinear function is achieved, the better performance is expected. However, most efforts have been directed towards achieving the stability and tracking performance. Little attention has been paid to the accuracy of the identified intelligent models and to the transparency and interpretability. By designing a serial-parallel estimation model and by using the modeling error, the hybrid adaptive fuzzy identification and control was proposed in [33]. The method achieves faster and improved tracking performance. However, the nth derivative of the plant output is required to be known in [33], which is quite impractical. Thus, some similar control design methods with prediction error with a slightly different serial-parallel estimation model [34] can be found in [35–36]. It should be pointed out that the systems studied in [33–36] are restricted to the canonical form (satisfying the matching conditions). The great feature of this model is that the derivative information can be directly derived from the states. Recently, the authors in [37] proposed a novel composite neural dynamic surface control of a class of uncertain nonlinear strict-feedback systems without satisfying the matching conditions. The proposed control method used the prediction error between system states and serial-parallel estimation model to construct the composite laws for NN weights updating, and achieved better tracking performance than the previous methods [39]. However, the result in [37] requires that the states of the controlled system are measured directly. The authors in [38] proposed a composite adaptive fuzzy dynamic surface control approach for a class of uncertain nonlinear strict-feedback systems with input saturation and unmeasured states. To the author's best knowledge, by far, no composite control results are available for uncertain nonlinear stochastic large-scale systems with unknown dead-zone based on DSC technique, without satisfying the matching conditions, and without the direct measurement of the states. Compared to the aforementioned control approaches, in this paper, an observer-based composite adaptive fuzzy approach is proposed for a class of uncertain nonlinear stochastic large-scale systems with unmeasured states and unknown dead-zone. However, aforementioned control approaches all limited to SISO or MIMO nonlinear systems, no composite control results are available for uncertain nonlinear stochastic large-scale systems.

Motivated by the above observations an observer-based composite adaptive fuzzy backstepping output feedback DSC approach is proposed for a class of uncertain stochastic large-scale nonlinear systems contain unmeasured states and unknown dead-zone. In the control design, fuzzy logic systems are used to approximate the unknown nonlinear functions, a fuzzy adaptive observer is designed for state estimation as well as system identification. By utilizing the designed fuzzy state observer, a serial-parallel estimation model is established and the prediction errors are obtained. Based on adaptive backstepping dynamic surface control technique and utilizing the prediction error between the system states observer model and the serial-parallel estimation model, an adaptive output feedback controller is constructed. The designed fuzzy controller with the composite parameters adaptive laws ensures that all the variables of closed-loop system are bounded in probability, and tracking error converges to a small neighborhood of zero. Compared with existing results, the main contributions of this paper can be summarized as follows.

1. This paper first proposed a composite adaptive fuzzy output-feedback control method for a class of nonlinear stochastic large-scale systems. Although the previous literature [35–38] also addressed the composite adaptive fuzzy output-feedback control method for nonlinear systems. However, they are limited to a class of SISO or MIMO nonlinear systems. Thus they cannot be applied to the nonlinear stochastic large-scale systems.
2. By designing a serial-parallel estimation model, the prediction error between system states observer model and serial-parallel estimation model is incorporated into the control design scheme, and the good control and tracking performances can be achieved.
3. By using the DSC technique, the proposed fuzzy adaptive control approach can overcome the problem of "explosion of complexity" inherent in the previous literature, thus the computational burden of the control algorithm can be reduced greatly. However, the control approaches in [20–25] all cannot solve the composite adaptive fuzzy output-feedback control problem for uncertain nonlinear stochastic large-scale systems with unmeasured states and unknown dead-zone.

## 2. Problem formulations and preliminaries

### 2.1. System descriptions

Consider a large-scale nonlinear system which is composed of $N$subsystems interconnected by their outputs. The $i$th subsystem $\Sigma_i (i=1,2,\cdots,N)$ is given as

$$\Sigma_i : \begin{cases} dx_{i,1} = (x_{i,2} + f_{i,1}(\underline{x}_{i,1}) + \Delta_{i,1}(\overline{y}))dt + g_{i,1}(\overline{y})dw_i \\ dx_{i,2} = (x_{i,3} + f_{i,2}(\underline{x}_{i,2}) + \Delta_{i,2}(\overline{y}))dt + g_{i,2}(\overline{y})dw_i \\ \vdots \\ dx_{i,n_i-1} = (x_{i,n_i} + f_{i,n_i-1}(\underline{x}_{i,n_i-1}) + \Delta_{i,n_i-1}(\overline{y}))dt + g_{i,n_i-1}(\overline{y})dw_i \\ dx_{i,n_i} = (u_i + f_{i,n_i}(\underline{x}_{i,n_i}) + \Delta_{i,n_i}(\overline{y}))dt + g_{i,n_i}(\overline{y})dw_i \\ y_i = x_{i,1} \end{cases} \tag{1}$$

where $x_{i,j} = [x_{i,1},\cdots,x_{i,j}]^T \in R^i$, $i=1,\cdots,N$, $j=1,\cdots,n_i$ are the system state vectors; $u_i \in R$ and $y_i \in R$ are the subsystem control input and output, respectively. $f_{i,j}(\cdot)$ are unknown smooth nonlinear functions, $\Delta_{i,j}(\overline{y})$ and $g_{i,j}(\overline{y})$ $(\overline{y} = [y_1, y_2, \cdots, y_N]^T)$ are unknown smooth functions representing the interconnection effects between the $i$th subsystem and the other subsystems. $w_i \in R$ is an independent Wiener process defined on a complete probability space, with the incremental covariance $E\{dw_i \cdot dw_i^T\} = \sigma_i(t)\sigma_i(t)^T dt$.

Throughout this paper, it is assumed that the only output $y_i$ is available for measurement. $u_i$ is the output of the dead-zone, which can be expressed as

$$u_i = D_i(v_i) \triangleq \begin{cases} m_{i,r}(v_i - b_{i,r}) & \text{if } v_i \ge b_{i,r} \\ 0 & \text{if } -b_{i,l} < v_i < b_{i,r} \\ m_{i,l}(v_i + b_{i,l}) & \text{if } v_i \le -b_{i,l} \end{cases} \tag{2}$$

$v_i \in \mathfrak{R}$ is the input to the $i$th dead zone. $m_{i,r}$ and $m_{i,l}$ stand for the right and the left slopes of the dead-zone characteristic. $b_{i,r}$ and $b_{i,l}$ represent the breakpoints of the input nonlinearity. The coefficients $m_{i,r}$,$m_{i,l}$,$b_{i,r}$and $b_{i,l}$ are assumed to be unknown strictly positive constants.

To facilitate the control system design, we need the following assumptions.