A New Smith Predictor and Fuzzy RBF Neural Network Control for Wireless Networked Control Systems

Du Feng, Du Wencai, Lei Zhi

***Abstract*—To aim at time-variant or random network delay in the wireless networked control systems (WNCS), as well as controlled plant might be uncertain, a novel approach is proposed that new Smith predictor combined with fuzzy radial basis function neural network (FRBFNN). Because new Smith dynamic predictor hides predictor model of the network delay into real transmission process of the network data, further the network delay no longer need to be measured, identified or estimated on-line. Therefore it is applicable to some occasions that network delay is the random, time-variant or uncertain, possibly large compared to one, even tens sampling periods, meanwhile, there are some data dropouts in closed loop. Based on IEEE 802.11b/g (WLAN), the results of simulation show validity of the control scheme, and indicate that system has better dynamic performance and robustness.**

***Index Terms*—Wireless networked control systems (WNCS), fuzzy radial basis function neural network (FRBFNN), network delay, Smith predictor.**

I. INTRODUCTION

As wireless network technology becomes more widespread, industrialists and academics alike are looking at the potential of wireless networked control systems (WNCS) [1]-[4]. In the WNCS, dynamical system is controlled by feedback over a wireless communication network. The defining feature is that control system components (sensor, controller and actuator) are all connected to the wireless network as nodes, and information (reference input, plant output, control input, etc.) is exchanged among control system components through the wireless network. The examples of the WNCS include sensor networks [5][6], networked autonomous mobile agents [7] etc. The primary advantages are reduced system wiring, ease of diagnosis and maintenance, increased system agility and reconfigurability [8].

Unfortunately, such networks are susceptible to even minor disturbances in the environment and often experience periods of deep fading in transmission strength, which leads to a higher chance of frames being transmitted in error [9]. Because of the limitation of network resources, there exists network delay that occurs when data are exchanged among the systems components connected to the shared medium. The delay, either constant or time varying can degrade the control performance even make the system destabilized [10][11].

Many control techniques have been developed for systems with constant time delays [12], but variable time delays can be much more difficult to compensate for. Some methodologies have been formulated based on several types of network behaviors and configurations in conjunction with different ways to treat the delay problem [13]. For example, Halevi and Ray [14] proposed a methodology as the augmented deterministic discrete-time model to control a linear plant over a periodic network delay. Nilsson [15] proposed the optimal stochastic control method to control networked control systems (NCS) on random delay network. Walsh *et al*. [16] considered a linear continuous plant and a continuous controller, and introduced the notation of maximum allowable transfer interval (MATI). Gokas [17] used a modified Pade approximation and considered the network delay as an uncertainty. Zhang *et al*. [18] used a hybrid system technique to study the stability of the NCS under the network delay. However, most of the aforementioned papers fall into the case of constant time delay. Existing constant time-delay control methodologies [19] and [20] may not be directly suitable for controlling a system over the network, since network delays are usually time-varying and/or uncertain, especially on the wireless. Although time delay is an important factor to consider for control systems implemented over industrial networks, it has not been well defined or studied by standards organizations defining network protocols [21].

The radial basis function neural networks (RBFNN) are recently adopted widely for fuzzy rules drawing and fuzzy inference system modeling because they possess simple structure, good local approximating performance [22], a fuzzy radial basis function neural network (FRBFNN) system was developed [23].

In this paper, we use self-learning ability of the FRBFNN to automatically tune and modify the robust PID parameters on-line, and a new Smith predictor for compensation network delays is proposed in the WNCS. Based on new Smith predictor, all delays of the network and controlled plant in the forward path can be removed, while the network delay in the return paths can be eliminated totally. Furthermore, the traffics on the return path do not need to be scheduled, and allow utilizing the capacity of the communication channel more effectively than static or dynamic scheduling could.

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Based on IEEE 802.11b/g (WLAN), the results of simulation show validity of the control scheme, and indicate that system has better dynamic performance and robustness.

This paper is organized for the four sections as follows: section II analyzes the Smith predictor and proposes a new Smith predictor, introduces adaptive PID control based on the FRBFNN. The simulation is described in section III, and conclusions in section IV.

II. Problem Description

A. Structure of the WNCS

In the WNCS, the network delay is primary factor which influences on the system performance. The typical structure of the WNCS is shown as fig.1.

We assume that sensor is time-driven, and controller and actuator are event-driven, at the same time, the actuator and sensor are co-located on the same node. Where $G_p(s)$ is controlled plant without delay, the $C(s)$ is controller, the r and y are input and output of system respectively, the τ_{sc} and τ_{ca} are network delays, the τ_{sc} is from sensor to controller, and the τ_{ca} is from controller to actuator. The total network delay ($\tau = \tau_{sc} + \tau_{ca}$) is larger than one, even tens sampling periods.

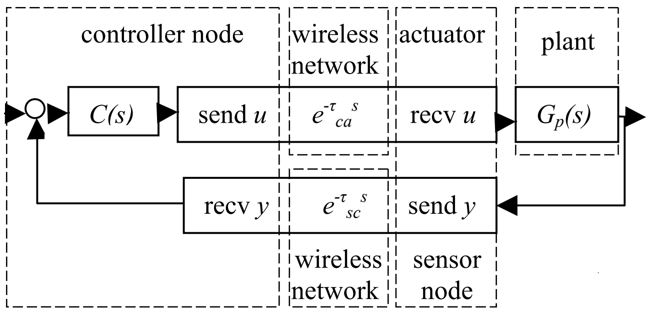

Fig. 1 Structure of the WNCS

The closed loop transfer function is given by

$$y(s)/r(s) = C(s)e^{-\tau_{ca}s}G_p(s)\big/(1 + C(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_{sc}s}) \quad (1)$$

From the (1), we can be seen that $e^{-\tau_{ca}s}$ and $e^{-\tau_{sc}s}$ have been contained in the denominator of the closed loop transfer function. They can degrade the performances of the WNCS and even cause system instability.

B. Smith Predictor for the WNCS

The internal compensation loop is closed around controller side of wireless network, the Smith predictor can be described as Fig.2.

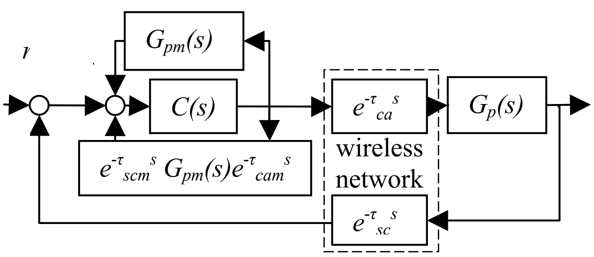

Fig. 2 WNCS with Smith predictor

Where $G_{pm}(s)$ is prediction model of the $G_p(s)$, the τ_{scm} and τ_{cam} are prediction values of the τ_{sc} and τ_{ca} respectively. The closed loop transfer function of the system is given as follows

$$\begin{aligned} y(s)/r(s) = C(s)e^{-\tau_{ca}s}G_p(s)/(1 + C(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_{sc}s} \\ - C(s)e^{-\tau_{cam}s}G_{pm}(s)e^{-\tau_{scm}s} + C(s)G_{pm}(s)) \end{aligned} \quad (2)$$

When $\tau_{cam} = \tau_{ca}$, $\tau_{scm} = \tau_{sc}$, $G_{pm}(s) = G_p(s)$, the prediction models can approximate the true models, the above (2) is reduced to

$$y(s)/r(s) = C(s)e^{-\tau_{ca}s}G_p(s)\big/(1 + C(s)G_p(s)) \quad (3)$$

According to the (3), the fig.2 can be treated as fig.3.

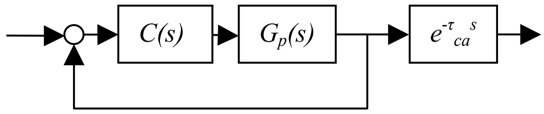

Fig. 3 Equivalent control system

Though Smith predictor can totally eliminate the delay τ_{sc} in the return path, remove the delay τ_{ca} in the forward path from the closed loop, when the prediction models can accurately approximate the true models, and the delays can be totally compensated. However, the above-mentioned Smith predictor has some problems:

1) It is difficult to satisfy complete compensation conditions. First, because of uncertainty of wireless network delay, it is hard to get the precise prediction models of the τ_{sc} and τ_{ca}. Secondly, on account of the clock of network nodes might be asynchronous [24], it is difficult to get the exact values of delays by measurement on-line, identification or estimation. Thirdly, owing to network delays result in vacancy sampling and/or multi-sampling, the Smith predictor will bring errors of compensation model.
2) Because network delay τ_{ca} occurs in a process that is controller transmission data to actuator, therefore it is impossible that data are truly predicted in the controller node beforehand, no matte method is adopted, and the prediction error of delay τ_{ca} is always existent.
3) When network delay large compared to one, even tens sampling periods, a lot of memory units are required for storing old data, consume memory resources and increase calculation delays, shorten life of the wireless nodes.
4) When the controlled plant includes delay τ_p, the denominator of transfer function in the (3) will contain exponent $e^{-\tau_p s}$. Therefore, the stability of the WNCS should be affected.

C. New Smith Predictor for the WNCS

We aim at existent problems of the fig.2, if the controlled plant with delay τ_p is know, a new Smith dynamic predictor is shown in Fig. 4.

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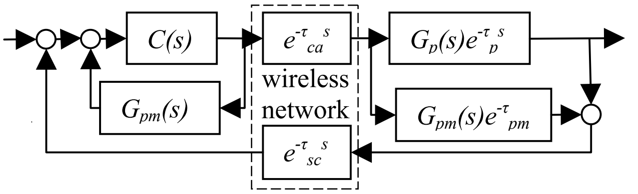

Fig. 4 WNCS with new Smith predictor

Where τ_{pm} is prediction value of the τ_p, thus the closed loop transfer function of the WNCS is given as follows

$$\begin{aligned} y(s)/r(s) = C(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_p s} / (1 + C(s)G_{pm}(s) + \\ C(s)e^{-\tau_{ca}s}(G_p(s)e^{-\tau_p s} - G_{pm}(s)e^{-\tau_{pm}s})e^{-\tau_{sc}s}) \end{aligned} \quad (4)$$

When $\tau_{pm} = \tau_p$, $G_{pm}(s) = G_p(s)$, the prediction models can accurately approximate true models, above (4) is reduced to

$$y(s)/r(s) = C(s)e^{-\tau_{ca}s}G_p(s)e^{-\tau_p s} \big/ (1 + C(s)G_p(s)) \quad (5)$$

As can be seen from the (5), the effects of the delays have been completely eliminated from the denominator of the transfer function.

According to the (5), the fig.4 can be treated as fig.5.

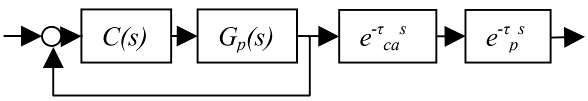

Fig. 5 Equivalent control system

From the fig.4 to fig. 5 and the (5), we can see

1) New Smith predictor realizes the double Smith dynamic prediction compensation on structure for the delays of the wireless network and controlled plant.
2) The delays of the forward network path and controlled plant can be removed from the closed loop and appear as gain blocks before the output, and the time-variant uncertain network delay in the return path is totally eliminated from the system. Further, it can cancel effects of the delays of the network and controlled plant for the system stability in the closed loop. Therefore, it enhances the control performance quality of the WNCS.
3) Because the network delay on the return path can totally be eliminated, therefore the traffic on the return path does not need to be scheduled, and the output signal of the sensor, whenever possible, can be transmitted back to remote controller node on line. On the one hand, this allows utilizing the capacity of the communication channel more effectively than static or dynamic scheduling could. On the other hand, increases system robustness when there are data packet dropouts on the return path of the WNCS.
4) The new Smith predictor is the real-time, on-line and dynamic predictor, and it doesn't include the predictor models of all network delays on actualization. Because the information flow passed through the network delays which are true network delays in the data transmission process, therefore network delays no longer need to be measured, identified or estimated on line. Therefore it reduces the requirement of the clock synchronization of the nodes. Furthermore, it avoids estimate errors which are brought due to inaccurate model, and avoids nodes memory resource to be wasted when the network delays are identified or estimated. At the same time, it avoids compensation errors, which are brought by network delays owing to vacancy-sampling and multi-sampling.
5) Based on intelligent nodes, it is easy to be realized in controller, actuator and sensor nodes.
6) The controller *C(s)* can adopt the traditional PID control, also adopt the intelligent control strategy when the controlled plant is time-variant or nonlinear, and the tuned parameters of the *C(s)* could take no account of the existent of the Smith predictor.

D. FRBFNN Control for the WNCS

We adopt 2-5-5-3 network structure (n = 2, N = 5), a structure of four-layer FRBFNN is shown in the Fig. 6.

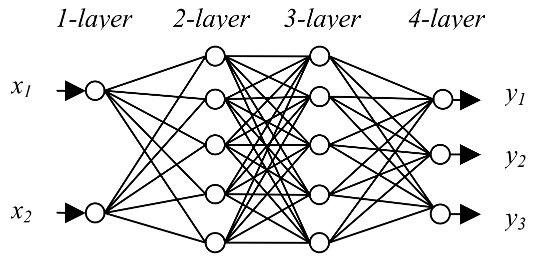

Fig. 6 Structure of the FRBFNN

It comprises the input (*1-layer*), membership (*2-layer*), rule (*3-layer*) and output (*4-layer*) layers. The nodes in the input layer represent the input linguistic variables, and nodes in the membership layer act as the membership functions. Moreover, all the nodes in the rule layer form a fuzzy rule base. The signal propagation and the basic function of each layer are introduced in the following [25].

Layer 1(input layer): For every node i in this layer, the net input and the net output are represented as:

$$f_1(i) = X = [x_1, x_2] \quad (6)$$

Where x_i represents the i^{th} input to the node of layer 1.

Layer 2(membership layer): In this layer, each node performs a membership function. The Gaussian function is adopted as the membership function. For the j^{th} node:

$$f_2(i,j) = \exp\left\{ -\frac{(f_1(i) - c_{ij})^2}{(b_{ij})^2} \right\} \quad (7)$$

Where c_{ij} and b_{ij} are, respectively, the mean and the standard deviation of the Gaussian function in the j^{th} term of the i^{th} input linguistic variable x_i to the node of layer 2.

Layer 3 (rule layer): The match of fuzzy rule is finished by connection of fuzzy rule layer and membership layer. The output of each node j in this layer is product from all incoming signal, namely:

$$f_3(j) = \prod_{j=1}^{N} f_2(i,j) \quad (8)$$

Where N is represented: $N = \prod_{i=1}^{N} N_i$.

Layer 4(output layer): This layer is formed by three nodes, and its output f_4 is the result from adjusting the k_p, k_i and k_d, the f_4 is represented as:

$$f_4(j) = wf_3 = \sum_{j=1}^{N} w(i,j) f_3(j) \tag{9}$$

Where the link weight w_{ij} is the output action strength of the 4^{th} layer output associated with the 3^{th} layer, and i = 1, 2, 3. The controller is adopted by increment PID algorithm:

$$\begin{aligned} u(k) &= u(k-1) + \Delta u(k) \\ \Delta u(k) &= f_4 \cdot xc = k_p xc(1) + k_i xc(2) + k_d xc(3) \end{aligned} \tag{10}$$

Where the k_p, k_i, k_d express proportional, integral and derivative gains of the controller respectively.

$$\begin{aligned} & k_p = f_4(1), k_i = f_4(2), k_d = f_4(3) \\ & xc(1) = e(k) \\ & xc(2) = e(k) - e(k-1) \\ & xc(3) = e(k) - 2e(k-1) + e(k-2) \end{aligned} \tag{11}$$

We use delta adaptation law of on-line learning algorithm in order update adjusted parameters, first the energy function E is defined as:

$$E = \frac{1}{2}(r-y)^2 \tag{12}$$

Where the r and y are the output and reference signals respectively, therefore the network weight is defined as:

$$\begin{aligned} \Delta w_j(k) &= -\eta \cdot \frac{\partial E}{\partial w_j} \\ &= \eta \cdot (r(k) - y(k)) \cdot \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial f_4} \frac{\partial f_4}{\partial w_j} \\ &= \eta \cdot (r(k) - y(k)) \cdot \frac{\partial y}{\partial \Delta u} xc(j) f_3(j) \end{aligned} \tag{13}$$

Where w_j is link weight between network output and 3^{th} layer nodes, j = 1, 2, N, η is the learning rate parameter of the weight. If momentum factor α is considered, thus the weight of output layer is defined as

$$w_j(k) = w_j(k-1) + \Delta w_j(k) + \alpha(w_j(k-1) - w_j(k-2)) \tag{14}$$

III. Simulation Experiment

A. Simulation Design

However, in the actual control process, it is usually difficult that the model and parameter of the true controlled plant are exactly known, and the most of the model and parameter might be still in unceasing change process, to establish the exact mathematical model will be very difficult. At the same time, it is also unrealistic to meet the conditions that the Smith prediction model and the true controlled plant are complete matching. Therefore, when the model and parameter are not complete matching, the robustness issues of the WNCS with new Smith predictor will be emphases of the simulation research.

We select the simulation software TrueTime 1.5 [26]. The WNCS is composed by the wireless network, actuator/sensor, controller, interference nodes and the controlled plants. Wireless network is the IEEE 802.11b/g (WLAN), the data rate is 800,000 bits/s, minimum frame size is 272 bits, transmit power is 20 dbm, receiver signal threshold is -48.00 dbm, path loss exponent is 3.5, act timeouts is 0.00004 s, retry limit is one, error coding threshold is 0.03, the distance between nodes is 20.0 m, maximum signal reach is 86.67 m, and sampling period of the sensor is 0.01s. Reference signal r adopts square wave and its amplitude is from −1 to 1.There are some data dropouts in the closed loop, and the network delays are allowed to be random, time-variant and uncertain, possibly large compared to one, even tens sampling periods.

The FRBFNN adapts 2-5-5-3 network structure (n = 2, N = 5), moment factor α = 0.3650, learning rate η = 0.0515.

In order to compare control effects under the same network conditions, we select controlled plant1, plant2 and plant3, and their outputs are the $y1$, $y2$ and $y3$, respectively. The transfer functions of the plant1 and plant2 are given as follows

$$G_p(s)e^{-\tau_p s} = \frac{100}{s+100} e^{-0.01s} \tag{15}$$

In order to research robustness of the system with new Smith predictor, the controlled plant3 is given as follows

$$G_p(s)e^{-\tau_p s} = \frac{1050}{s^2 + 55s + 1570} e^{-0.02s} \tag{16}$$

However, the Smith predictor models of the plant1 and plant3 are given by

$$G_{pm}(s)e^{-\tau_{pm} s} = \frac{100}{s+100} e^{-0.01s} \tag{17}$$

As can be seen from the (16) and (17), the true model of the plant3 and its Smith predictor model are mismatching.

The plant1 and plant3 are controlled by the new Smith predictor plus the FRBFNN, and the plant2 is controlled by the FRBFNN. But, the all tuned parameters of the FRBFNN controller completely depend on the (15).

In the simulation process, the data of the sampling and control are encapsulated in the same data package for network transmission, and a step disturbance signal, which amplitude is 0.3, is inserted in output sides of controlled plants at 1.0s.

B. Result Analysis

The simulation results are shown in fig.7 to fig.11.

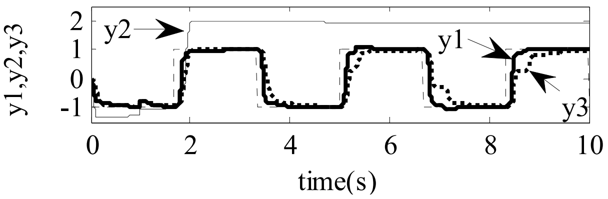

Fig. 7 The *y1* is new Smith predictor plus FRBFNN control, the *y2* is FRBFNN control. The *y3* is new Smith predictor plus FRBFNN control (model parameters of the Smith predictor and true plant3 are mismatching)

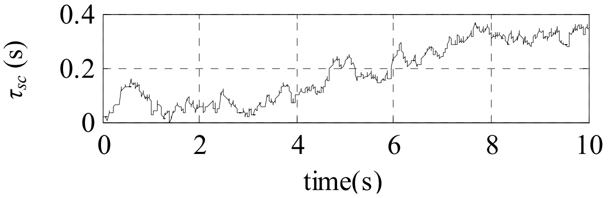

Fig.8 Network delay τ_{sc} is from sensor to controller

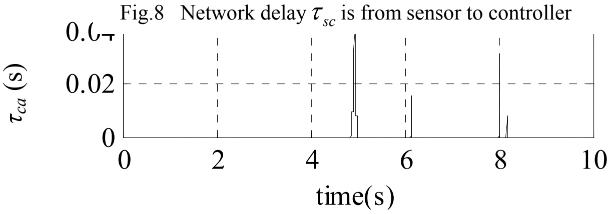

Fig.9 Network delay τ_{ca} is from controller to actuator

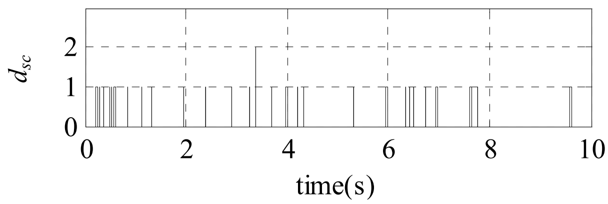

Fig. 10 Data dropout d_{sc} is from sensor to controller

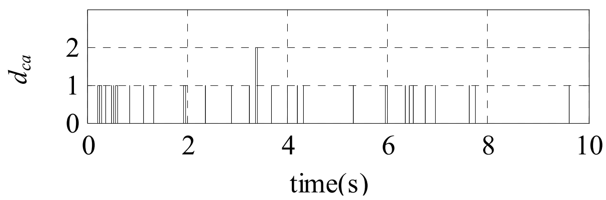

Fig. 11 Data dropout d_{ca} is from controller to actuator

From the fig.7 to fig.11, we can see

1) The τ_{sc} and τ_{ca} are the random, time variant and uncertain. The τ_{ca} maximum is 0.041s, it exceeds four sampling periods (one sampling period is 0.010s).
2) The data dropout d_{sc} maximum is 2, and the d_{ca} is also 2. However lost messages consume the network bandwidth, but never arrive at the destination.
3) In the fig.7, the *y1* (thick real line) and *y3* (thick dot line) are timely in tracking square wave, and their overshoots are less. Therefore, they completely satisfy performance requirements of the WNCS. At the same time, it also indicates that systems with new Smith predictor have stronger robustness although the true model of the plant3 and its Smith predictor model are mismatching.
4) Along with increasing and fluctuating of the network delays and data dropouts, the *y2* gives bigger tracking error after 2.012s, immediately it become uncontrolled. Therefore, the *y2* doesn't satisfy performance requirements of the WNCS.
5) After a step disturbance signal, which amplitude is 0.3, is inserted in the output sides of the controlled plants at 1.0s. The *y1* and *y3* can reinstate and track up reference signal quickly. Therefore, it indicates that systems with new Smith predictor have stronger anti-jamming ability.

Simulation results show that new Smith predictor combined with FRBFNN control is effective for the WNCS.

IV. Conclusion

In order to overcome influences of network delays, this paper proposes a novel approach that new Smith predictor combined with FRBFNN control for the WNCS. It actualizes to hide predictor models of the network delays into real network data transmission processes, further the network delay no longer need to be measured, identified or estimated on-line. The structure of new Smith predictor is simple, and has stronger robustness, therefore it is easy to be implemented, and will have wide engineering application prospect.

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