Letter

Neural Network-Based State Estimation for Nonlinear Systems With Denial-of-Service Attack Under Try-Once-Discard Protocol

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Dear Editor,

This letter deals with state estimation issues of discrete-time nonlinear systems subject to denial-of-service (DoS) attacks under the try-once-discard (TOD) protocol. More specifically, to reduce the communication burden, a TOD protocol with novel update rules on protocol weights is designed for scheduling measurement outputs. In addition, unknown nonlinear functions vulnerable to DoS attacks are considered due to the openness and vulnerability of the network. For such systems, the neural networks (NNs) are exploited to estimate the unknown nonlinear system dynamics in the designed Luenberger-like observer. With the help of Lyapunov theory, some sufficient conditions are derived under which the estimation error and the approximation errors of NNs weights are uniformly ultimately bounded (UUB). Finally, the validity of designed observers is demonstrated by a power system example.

State estimation refers to the process of determining the internal state variables of a system based on the available measurements [1]. It plays an important role in engineering applications such as aircraft, robotics and power grids and therefore has received a great deal of research attention. However, the behavior of addressed systems is much more complex and the nonlinear features are unknown compared to ones in existing results, which lead to its state not being estimated accurately. Fortunately, the ability of NNs to approximate highly complex and nonlinear functions, and adapt to changes in the system makes them a powerful tool for approximating nonlinear systems. In the past few years, various types of NNs have been utilized for state estimation, including polynomial NNs [2], Markov jump NNs [3], memristive NNs [4], and recurrent NNs [5].

With the rapid development of communication technology, networks have been introduced into practical engineering. This implies that the exchange of data between devices is achieved via a shared network medium. On the one hand, the measurement output is scheduled using a dynamic scheduling protocol, the TOD protocol, to relief the channel burden [6]. Under this protocol, usage rights are assigned to the communicating nodes by comparison. However, the traditional scheduling matrix of the TOD protocol is fixed, and not suitable for the current situation where information about each node is often required in practical applications. Therefore, there is an urgent need to design a new weight update rule to overcome this shortage.

On the other hand, it cannot be avoided that malicious attacks, including deception attacks and DoS attacks, may occur in the sensor-to-observer channels due to the openness and vulnerability of the network [7], [8]. Thus, we consider the case of DoS attacks that block the information transmission channel. It is obvious that the scheduling employed to save communication resources and the possible attacks considered may lead to degraded system performance and affect the observation results. Therefore, the research interest in this letter focuses on designing an NN-based observer to estimate the system state when the system is scheduled by the TOD protocol with DoS attacks. The innovations are concluded as

1) A new weight update rule is proposed to increase the transmission opportunity of the node with the second highest demand in the next instance with the hope to improve the estimation performance without increasing the communication burden;

2) The UUB sufficient conditions are obtained for the estimation errors of the observer and the NN's weights when considering the unknown nonlinear system is affected by the TOD protocol and DoS attacks.

Problem statement: Consider the unknown discrete-time nonlinear system

$$\begin{cases} x_{k+1} = f(x_k) + g(x_k)\omega_k \\ y_k = Cx_k \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^{n_x}$ is the system state, $\omega_k \in \mathbb{R}^{n_\omega}$ is the external bounded disturbance, i.e., $|\omega_k| \le \omega_m$ where ω_m is a positive constant. $f(x_k) \in \mathbb{R}^{n_x}$ and $g(x_k) \in \mathbb{R}^{n_x \times n_\omega}$ are the unknown nonlinear function with $f(0) = 0$ and $g(0) = 0$, respectively. $y_k \in \mathbb{R}^{n_y}$ is the measurement output, and $C \in \mathbb{R}^{n_y \times n_x}$ is the known constant matrix.

For system (1), based on the spatial distribution of sensors, it is divided into n ($n > 1$) nodes. Therefore, the measurement output can be written as follows:

$$y_k = [y_{1,k}^T,\ y_{2,k}^T,\ \dots\ y_{i,k}^T,\ \dots,\ y_{n,k}^T]^T \tag{2}$$

where $y_{i,k}$ ($i \in \{1,2,\dots,n\}$) is the measurement of the ith node.

The TOD protocol is performed to transmit the signal at first. Let $\xi_k \in \{1,2,\dots,l\}$ be the sensor node with network access at instant k. Then, the selection of ξ_k can be characterized by

$$\xi_k = \arg\max_{i\in\{1,2,\dots,n\}} (y_k - \bar{y}_{k-1})^T \bar{Q}_k \Phi_i (y_k - \bar{y}_{k-1}) \tag{3}$$

where $\bar{y}_{k-1} = [\bar{y}_{1,k-1}^T\ \bar{y}_{2,k-1}^T\ \cdots\ \bar{y}_{n,k-1}^T]^T$ and $\bar{Q}_k = \text{diag}\{Q_{1,k}, Q_{2,k}, \dots, Q_{n,k}\}$ with $\bar{y}_{i,k-1}$ is the last output of ith node before k (excluding k) and $Q_{i,k}$ ($i \in \{1,2,\dots,n\}$) is a known positive definite matrix denoting the weight matrix of the ith sensor node. Here, $\Phi_i = \text{diag}\{\sigma_i^1 I, \sigma_i^2 I, \dots, \sigma_i^n I\}$ and $\sigma_i^n \triangleq \sigma(i-n) \in \{0,1\}$ ($i = 1,2,\dots,n$) is a Kronecker delta function.

In this letter, a new weight update method is given in order to allow the node with the second largest demand to have a higher opportunity to obtain transmission at the next instance. The second most demanded node is introduced as

$$\acute{\xi}_k = \arg\max_{i\in\{1,2,\dots,n\}, i\neq\xi_k} (y_k - \bar{y}_{k-1})^T \bar{Q}_k \Phi_i (y_k - \bar{y}_{k-1}). \tag{4}$$

Here, the novel update rule on protocol weights is proposed by

$$Q_{j,k} = \begin{cases} Q_M, & \text{if } j = \acute{\xi}_k \\ Q_m, & \text{otherwise} \end{cases} \tag{5}$$

where Q_M is a known positive definite upper-bounded weight, and Q_m is the known positive definite weight satisfying $0 \le Q_m < Q_M$. Moving forward, the attacked measurement is denoted by $\vec{y}_k = [\vec{y}_{1,k}^T\ \vec{y}_{2,k}^T\ \cdots\ \vec{y}_{n,k}^T]^T$, where $\vec{y}_{i,k}$ represents the measurement of the ith

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sensor node being received by observers. The attacked output could be expressed as follows:

$$\vec{y}_k = \alpha_k y_k \tag{6}$$

where α_k is an index function that indicates whether an attack has occurred at time instance k, and has the form

$$\alpha_k = \begin{cases} 0, & \text{DoS attack} \\ 1, & \text{otherwise.} \end{cases} \tag{7}$$

At the time instant k, the occurring probability of an attack follows a Bernoulli distribution with probability p.

According to the definition of $\bar{y}_{k-1}$, it is easy to see that

$$\bar{y}_k = \begin{cases} \vec{y}_k, & \text{if } i = \xi_k \\ \bar{y}_{k-1}, & \text{otherwise} \end{cases} \tag{8}$$

where the zero-order-holder is utilized in the viewpoint of practical engineering. By means of the above variable, the actually received measurement is further denoted as

$$\bar{y}_k = \alpha_k \Phi_{\xi_k} y_k + (I - \Phi_{\xi_k})\bar{y}_{k-1}. \tag{9}$$

Let $F(x_k) = f(x_k) - Ax_k$, in which A is a known positive matrix. Then, the system is

$$\begin{cases} \eta_{k+1} = \mathcal{A}_k \eta_k + \mathcal{F}(\eta_k) + \mathcal{G}(\eta_k)\omega_k \\ \bar{y}_k = C_k \eta_k \end{cases} \tag{10}$$

where

$$\eta_k = [\ x_k^T \quad \bar{y}_{k-1}^T\ ]^T,\ C_k = [\ \alpha_k \Phi_{\xi_k} C \quad I - \Phi_{\xi_k}\ ]^T$$

$$\mathcal{G}(\eta_k) = [\ g^T(D\eta_k) \quad 0\ ]^T,\ \mathcal{F}(\eta_k) = [\ F^T(D\eta_k) \quad 0\ ]^T$$

$$D = [\ I \quad 0\ ]^T,\ \mathcal{A}_k = \begin{bmatrix} A & 0 \\ \alpha_k \Phi_{\xi_k} C & I - \Phi_{\xi_k} \end{bmatrix}.$$

Main results:

Based on the approximation properties of NNs for nonlinearities [9], the system dynamics (10) can be rewritten as

$$\eta_{k+1} = \mathcal{A}_k \eta_k + W_I^T \phi(\eta_k)\check{\omega}_k + \check{\theta}(\eta_k) \tag{11}$$

where

$$W_I = \begin{bmatrix} W_f \\ W_g \end{bmatrix} \in \mathbb{R}^{l \times n_\eta},\ \check{\omega}_k = \begin{bmatrix} 1 \\ \omega_k \end{bmatrix} \in \mathbb{R}^{(1+n_u)}$$

$$\phi_I(\eta_k) = \begin{bmatrix} \phi_f(\eta_k) & 0 \\ 0 & \phi_g(\eta_k) \end{bmatrix} \in \mathbb{R}^{l \times (1+n_u)}$$

$$\check{\theta}(\eta_k) = \begin{bmatrix} \theta_f(\eta_k) & \theta_g(\eta_k) \end{bmatrix} \check{\omega}_k \in \mathbb{R}^{n_\eta}.$$

Here, l is the number of hidden neurons, W_I is the ideal weight of NNs and satisfies $\|W_I\| \le w_{IM}$; $\theta(\eta_k)$ is the bounded approximation error, i.e., $\|\check{\theta}(\eta_k)\| \le \theta_M$; and $\phi(\eta_k)$ is the activation function satisfying $\|\phi(\eta_k)\| \le \phi_M$. In addition, w_{IM}, θ_M, and ϕ_M are all positive scalars.

Since the true system dynamic is unavailable and the variable α_k is random, the Luenberger-like observer using an NN is proposed by

$$\begin{cases} \hat{\eta}_{k+1} = \bar{\mathcal{A}}_k \hat{\eta}_k + \hat{W}_{I,k}^T \phi_I(\hat{\eta}_k, \check{\omega}_k) + L(\bar{y}_k - C_k \hat{\eta}_k) \\ \hat{\bar{y}}_k = \bar{C}_k \hat{\eta}_k \end{cases} \tag{12}$$

where $\hat{W}_{I,k}$, $\hat{\eta}_k$, and $\hat{\bar{y}}_k$ are the estimated values of W_I, η_k, and $\bar{y}_k$, respectively. $L \in \mathbb{R}^{n_\eta \times n_y}$ is the observer gain that can be obtained using the pole assignment method. Here, $\bar{\mathcal{A}}_k = [A, 0;\ p\Phi_{\xi_k} C, I - \Phi_{\xi_k}]$, $\bar{C}_k = [p\Phi_{\xi_k} C,\ I - \Phi_{\xi_k}]^T$, and $\phi_I(\hat{\eta}_k, \check{\omega}_k) = \phi_I(\hat{\eta}_k)\check{\omega}_k$ with $\|\phi_I(\hat{\eta}_k, \check{\omega}_k)\| \le \phi_{IM}$.

Denote $\mathcal{A}_{ck} = \mathcal{A}_k - LC_k$, $\bar{\mathcal{A}}_{ck} = \bar{\mathcal{A}}_k - LC_k$, $\tilde{\mathcal{A}}_{ck} = \mathcal{A}_{ck} - \bar{\mathcal{A}}_{ck}$, and then the state estimation error is

$$\tilde{\eta}_{k+1} = \bar{\mathcal{A}}_{ck} \tilde{\eta}_k + \tilde{\mathcal{A}}_{ck} \eta_k + \tilde{W}_{I,k}^T \phi_I(\hat{\eta}_k, \check{\omega}_k) + \check{\theta}_W(\eta_k) \tag{13}$$

where $\tilde{W} = W - \hat{W}_k$ is the NN weights estimation error; $\tilde{\phi}_I(\eta_k, \hat{\eta}_k) = \phi_I(\eta_k, \check{\omega}_k) - \phi_I(\hat{\eta}_k, \check{\omega}_k)$ and $\check{\theta}_W(\eta_k) = \check{\theta}(\eta_k) - \mathcal{W}_I \tilde{\phi}_I(\eta_k, \hat{\eta}_k)$ are bounded terms, and $\mathcal{W}_I \tilde{\phi}_I(\eta_k, \hat{\eta}_k) = [W_I \tilde{\phi}_I(\eta_k, \hat{\eta}_k)\ \ 0^{(1+n_\omega)\times 1}]$.

Define the estimated output error to be $\tilde{\bar{y}}_k = \bar{y}_k - \hat{\bar{y}}_k$. To minimize $1/2 \tilde{\bar{y}}_k^T \tilde{\bar{y}}_k$, based on the gradient descent algorithm, the tuning law of $\hat{W}_{I,k}$ is given as follows:

$$\hat{W}_{I,k+1} = (1 - \beta_1)\hat{W}_{I,k} + \beta_2 \phi_I(\eta_k, \check{\omega}_k)\tilde{\bar{y}}_{k+1}^T C_k \tag{14}$$

where β_1 and β_2 are positive adjustable parameters. Hence, the estimation error dynamics of NN weights is

$$\begin{aligned} \tilde{W}_{I,k+1} = {} & (1 - \beta_1)\tilde{W}_{I,k} + \beta_1 W_I - \beta_2 \phi(\eta_k, \check{\omega}_k) \\ & \times \tilde{\eta}_k^T \mathcal{A}_{ck}^T C_k^T C_k - \beta_2 \phi(\eta_k, \check{\omega}_k)\phi^T(\eta_k, \check{\omega}_k) \\ & \times \tilde{W}_{I,k} C_k^T C_k - \beta_2 \phi(\eta_k, \check{\omega}_k)\check{\theta}_W^T(\eta_k) C_k^T C_k. \end{aligned} \tag{15}$$

Before proceeding, the useful definitions are introduced as follows.

Definition 1 [10]: A system with any initial state $\eta_0 \in \Omega$ is said to be UUB if there exist a compact set $\Omega \in \mathbb{R}^{n_\eta}$, a bound d and a step time $t(d, \eta_0)$ such that $\|\eta_k - \eta_0\| \le B$ for all $k \ge t$.

Definition 2: For all $k_0 \ge 0$, if the positive constants b satisfies $\sum_{i=k_0}^{k_0+i-1} \eta_k \eta_k^T > bI_n$, then the function $\eta_k \in \mathbb{R}^n$ is persistently exciting.

Next, we will give the relative parameters to ensure the boundedness of estimation errors.

Theorem 1: Consider the proposed observer (12) with NN weight tuning law (14). Let the initial value $\hat{W}_{I,0}$ be selected within the Ω_W. If the matrix L satisfies $\|\bar{\mathcal{A}}_{ck}\| = \|\bar{\mathcal{A}}_k - LC\| \le (1/(1 + 4C_M^2(1 + \phi_{\min}^2)))^{1/2}$ $(k \in \{1, 2, \ldots, l\})$ and positive constants β_1 and β_2 satisfy $(2 - \sqrt{2})/2 < \beta_1 < 1$ and $0 < \beta_2 < 2(1 - \beta_1)C_M/(1 + \phi_{\min}^2)$ with $0 < \|C_k\| < C_M$, then the observer error $\tilde{\eta}_k$ and the NN weights estimation errors $\tilde{W}_{I,k}$ are all UUB.

Proof: The Lyapunov function, which includes the estimation errors of the observer and the NN's weights, is designed as

$$V_k = V_{1,k} + V_{2,k} = \tilde{\eta}_k^T \tilde{\eta}_k + \text{tr}\{\tilde{W}_{I,k}^T P \tilde{W}_{I,k}\} \tag{16}$$

where $P = (2(1 + \phi_{I\min}^2)/\beta_2) \times I$ with I being the identity matrix and $0 < \phi_{I\min}^2 < \|\phi_I(\hat{\eta}_k)\|^2 < \|\phi_I(\hat{\eta}_k, \check{\omega}_k)\|^2$ is ensured due to the persistently exciting conditions.

First, it can be calculated that $\mathbb{E}\{\tilde{\mathcal{A}}_k^T \tilde{\mathcal{A}}_k\} = \sigma^2$, where σ is defined as the standard deviation of $\mathcal{A}$. Taking the first-order difference of $V_{1,k}$ along with the state estimation error, yields

$$\begin{aligned} \mathbb{E}\{\Delta V_{1,k} | \alpha_k\} \le {} & -(1 - 3\|\bar{\mathcal{A}}_k\|^2)\|\tilde{\eta}_k\|^2 \\ & + 3(\|\tilde{W}_{I,k}\|^2 \phi_{IM}^2 + \check{\theta}_{WM}^2) + \sigma^2 \eta_M^2. \end{aligned} \tag{17}$$

For the first-order difference of $V_{2,k}$, noting $C_k^T C_k P C_k^T C_k \le a\|C_k^T C_k\|^2 P$, one has

$$\begin{aligned} \mathbb{E}\{\Delta V_{2,k} | \alpha_k\} \le {} & \Theta_{WM} - (1 - 2(1 - \beta_1)^2)\|P\|\|\tilde{W}_{I,k}\|^2 \\ & - 6\beta_2^2 \|P\|\phi_{IM}^2 \|\bar{\mathcal{A}}_{ck}\|^2 \|C_k^T C_k\|^2 \|\tilde{\eta}_k\|^2 \\ & - 2\beta_2((1 - \beta_1)\|C_k^T C_k\| - \beta_2 \phi_{I\min}^2)\|P\|\phi_{IM}^2 \|\tilde{W}_{I,k}\|^2 \end{aligned} \tag{18}$$

where $\Theta_{WM} = 6\beta_1^2 \|P\| w_{IM}^2 + 6\beta_2^2 \|P\| \phi_{IM}^2 C_M^2 \check{\theta}_{WM}^2 + \beta_2^2 \|P\| \phi_{IM}^2 \|C_k^T C_k\|^2 \times \sigma^2 \eta_M^2$ with $0 \le \|\phi_I(\hat{\eta}_k, \check{\omega}_k)\|^2 \le \phi_{IM}^2$ and $\|\check{\theta}_W\|^2 \le \check{\theta}_{WM}^2$.

Combining (17) and (18), one has

$$\begin{aligned} \mathbb{E}\{\Delta V_k | \alpha_k\} \le {} & -(1 - (1 + 4C_M^2(1 + \phi_{I\min}^2))3\|\bar{\mathcal{A}}_k\|^2)\|\tilde{\eta}_k\|^2 + \check{\Theta}_{WM} \\ & - \phi_{IM}^2 \|\tilde{W}_{I,k}\|^2 - (1 - 2(1 - \beta_1)^2)\|P\|\|\tilde{W}_{I,k}\|^2 \end{aligned} \tag{19}$$

where $\check{\Theta}_{WM} = 3\check{\theta}_{WM}^2 + \Theta_{WM}$. Using Lyapunov stability, $\mathbb{E}\{\Delta V_k | \alpha_k\}$ is less than zero outside a compact set when $(2 - \sqrt{2})/2 < \beta_1 < 1$, $0 < \beta_2 < 2(1 - \beta_1)C_M/(1 + \phi_{I\min}^2)$ and the following conditions hold:

$$\|\tilde{\eta}_k\| > \sqrt{\frac{\check{\Theta}_{WM}}{1 - (1 + 4C_M^2(1 + \phi_{I\min}^2))3\|\bar{\mathcal{A}}_k\|^2}} = a_{\tilde{\eta}} \tag{20}$$

or

$$\|\tilde{W}_{I,k}\| > \sqrt{\frac{\check{\Theta}_{WM}}{\phi_{IM}^2 + (1 - 2(1 - \beta_1)^2)\|P\|}} = a_{\tilde{W}}. \tag{21}$$

To ensure that the denominator of (20) is positive, one has $0 < 3\|\bar{\mathcal{A}}_k\|^2 < 1/(1 + 4C_M^2(1 + \phi_{I\min}^2))$ with $0 < \|C_k\| < C_M$ when the designed parameter L is selected using pole placement such that $\|\bar{\mathcal{A}}_{ck}\| = \|\bar{\mathcal{A}}_k - LC\| \le (1/(1 + 4C_M^2(1 + \phi_{I\min}^2)))^{1/2}$. ■

An illustrative example: Considering the nonlinearity of the system itself and the coupling effects between subsystems, the dynamic equation of a power system can be expressed as

$$\dot{x} = Ax + f(x) + g(x)\omega, \;\; y = Cx$$

where $x = [\Delta f \; \Delta P_m \; \Delta P_v]^T$, $C = I_{3\times 3}$, $A = [-1/T_p, K_g/T_p, 0; 0, -1/T_T, 1/T_t; -1/RT_g, 0, -1/T_g]$, f, P_m and P_v represent the frequency, generator power, and steam valve position of power systems, respectively. Select $f(x) = [10\sin(\Delta f),\, 5\sin(\Delta P_m),\, 0]^T$ and $g(x) = [0,\, 0,\, 5+\sin(\Delta P_v)]$, respectively. Note that the disturbance ω_k satisfies the normal distribution. The sampling period is selected as 0.01 s and simulation step size is 300. The other physical meaning of the parameters are the same as in [11] and the respective values are $T_p = 2$, $K_g = 0.5$, $T_T = 5$, $T_g = 0.2$, $R = 0.5$. In the TOD protocol, the corresponding parameters are selected as $Q = \mathrm{diag}\{3,3,3\}$, $Q_M = 5$, $Q_m = 1$. In the DoS attacks description, the probability p_k is chosen to be 0.9. In the NNs weight training process, the initial weight is chosen as $\hat{W}_{I,0} = [I_{3\times 3} \; 0_{3\times 3}]$, the activation function is chosen as $\phi(\cdot) = 0.05\tanh(\cdot)$ with $\phi_M = 0.05$, and the learning rates are $\beta_1 = 0.2$, $\beta_2 = 0.8$. The observer gain is

$$L = \begin{bmatrix} 1.5 & 0.2 & -0.1 & 1.0 & 0.0 & 0.0 \\ -0.2 & 1.5 & 0.0 & 0.0 & 1.0 & 0.0 \\ 0.0 & 0.0 & 1.2 & 0.0 & 0.0 & 1.0 \end{bmatrix}^T.$$

After checking, the parameters taken all satisfy the conditions in Theorem. The initial values of state and estimation state are $x_0 = [0.5; -0.2; 0.2]$ and $\hat{x}_0 = 0_{3\times 1}$.

The states and their estimated trajectories of the power system, as shown in Fig. 1, indicate that the observer can effectively estimate the original state. Additionally, it can be observed from Fig. 2 that the NNs weight $\hat{W}_{I,k}$ fluctuates within a bounded range, which is mainly attributed to the random disturbance ω_k and the random DoS attack. These results demonstrate the effectiveness of the proposed NN-based observer method for the nonlinear systems with DoS attacks under TOD protocol.

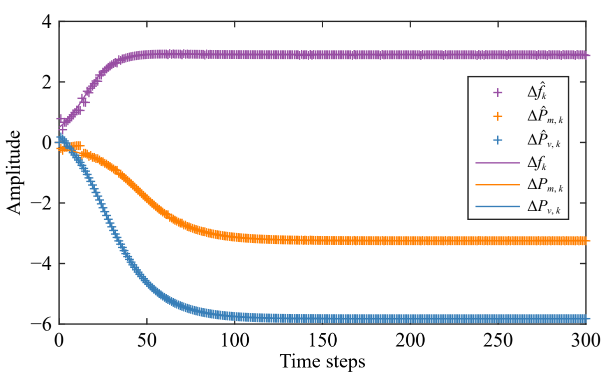

Fig. 1. The original and estimated state trajectories of power system.

Conclusion: This letter has investigated the state estimation problem of nonlinear system with DoS attacks under the TOD protocols. Based on NNs approximation capability and Lyapunov technique, the UUB conditions for the NN-based Luenberger-like observer have been formulated. Finally, an illustrative example of a power system has proved the validity of the state estimation framework in this letter. One of the future research topics would be to extend the main results in this letter to distributed systems [12].

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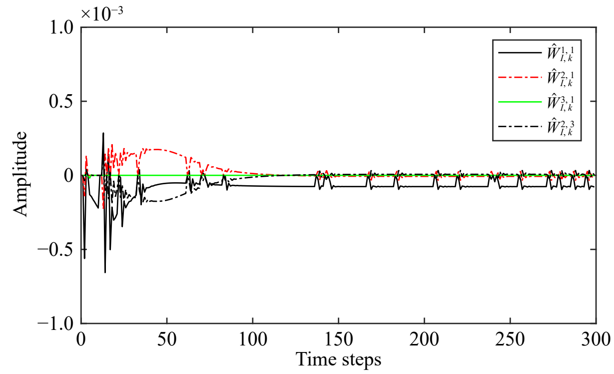

Fig. 2. The updating trajectories of partial NNs' weights.

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