

Convolutional Multi-Spike Neural Network as Intelligent System Prediction for Control Systems

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ABSTRACT

The evolution in the field of Artificial Intelligent (AI) with its training algorithms make AI very important in different aspect of the life. The prediction problem of behavior of dynamical control system is one of the most important issue that the AI can be employed to solve it. In this paper, a Convolutional Multi-Spike Neural Network (CMSNN) is proposed as smart system to predict the response of nonlinear dynamical systems. The proposed structure mixed the advantages of Convolutional Neural Network (CNN) with Multi-Spike Neural Network (MSNN) to generate the smart structure. The CMSNN has the capability of training weights based on a proposed training algorithm. The simulation results demonstrated that the proposed structure has the ability to predict the response of dynamical systems more powerful than with the CNN. The proposed structure is more powerful than the CNN by 28.33% in terms of minimizing the root mean square error.

Keywords: Convolutional Neural Network, Multi-Spike Neural Network, Non-linear dynamical systems.

الشبكة العصبية التلافيفية متعددة الاشواك كنظام ذكي للتنبؤ في أنظمة السيطرة

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الخلاصة

التطور في مجال الذكاء الاصطناعي (AI) بخوارزميات التدريب الخاصة به يجعله مهمًا جدًا في جوانب مختلفة من الحياة. تعد مشكلة التنبؤ بسلوك نظام التحكم الديناميكي من أهم المشكلات التي يمكن استخدام الذكاء الاصطناعي لحلها. في هذا البحث، تم اقتراح الشبكة العصبية متعددة الأشواك (CMSNN) كنظام ذكي للتنبؤ باستجابة الأنظمة الديناميكية غير الخطية. مزج الهيكل المقترح مزايا الشبكة العصبية التلافيفية (CNN) مع الشبكة العصبية متعددة الأشواك (MSNN) لتوليد هيكل ذكي. حيث ان CMSNN لديها القدرة على

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تدريب الأوزان بناءً على خوارزمية تدريب مقترحة. أظهرت نتائج المحاكاة أن الهيكل المقترح لديه القدرة على التنبؤ باستجابة الأنظمة الديناميكية بقوة أكبر من تلك الموجودة في شبكة CNN. الهيكل المقترح أقوى من CNN بنسبة 28.33% من حيث تقليل جذر متوسط الخطأ التربيعي.

الكلمات الرئيسية: الشبكة العصبية التلافيفية، الشبكة العصبية متعددة الاشواك، أنظمة ديناميكية لاقطية.

1. INTRODUCTION

The developments in the field of AI and Machine Learning (ML) is grown dramatically within few years ago. The applications of AI in different areas are increased. The dynamic systems have been applied in different fields such as pattern recognition, communication, control and Internet of Things (IoT). The non-parametric system identification approach is important to construct the control system model, which can be applied to analyze the performance, dynamic and static response characteristics of the system (Han, et. al, 2020). The spike and multi-spike neural networks which are the types of third generation of neural networks, are also improved by many researches with different applications (Shiltagh and Abas, 2014; Miao, et al., 2018; Wu, Lin and Du, 2019; Yellakuor et al., 2020).

A supervised multi-spike learning algorithm proposed by (Miao, et al., 2018) was used to train neurons to output spike train with a target firing rate. By assuming a special condition of the threshold, their algorithm simplified the equation of the membrane potential. This contribution allows the algorithm of a gradient descent to optimize the synaptic weights. Also, their results demonstrated that the proposed algorithm can attain a competitive accuracy in temporal pattern classification and sound recognition.

(Hu et al., 2019) proposed a probability-modulated timing mechanism which was built on the stochastic neurons, where the discontinuous spike patterns were converted to the likelihood of generating the desired output spike trains. (Wu, et.al., 2019) presented an algorithm for multi-layer spiking neural networks based on adaptive structure learning, in which the synaptic weights are updated according to inner product of spiking sequences and depending on the supervised learning algorithm.

In the field of applying AI in system identification and control, (Han, et. al., 2020) proposed a new algorithm based on a combination of a broad learning system (BLS) and particle swarm optimization (PSO) to identify nonlinear dynamical systems.

(Genc, 2017) solved the problem of scalability and robustness issues in complex nonlinear system identification of dynamic system within the framework of deep Convolutional Neural Networks (CNNs). A new deep CNN architecture was proposed by (Genc, 2017) to overcome scalability and robustness issues of system identification and control.

(Chen, et.al., 2018) proposed a novel CNN-based framework, ranking CNN, for age estimation. Ranking-CNN contains a set of basic CNNs, each of which is trained with ordinal age labels.

(Goel, et.al., 2020) developed an approach for deep convolutional neural network-based patch-learning to predict the cutline by learning the network to estimate and learn the pattern around the area of the joint fingerprint.

This paper proposed a Convolutional Multi-Spike Neural Network to predict the dynamical nonlinear system. Also, a training algorithm is modified to update the weights in CMSNN.

The rest of this paper is presented as follows. Section 2 presents the proposed system architecture, section 3 the training algorithm of the proposed CMSNN is explained. In section 4, the prediction model is explained, whilst section 5 simulation results are provided. The conclusion to the paper is presented in section 6.



2. CONVOLUTIONAL MULTI-SPIKE NEURAL NETWORK STRUCTURE

The proposed structure of CMSNN as shown in **Fig. 1** consists of input layer, four MSNN layer, a Rectified Linear Unit (ReLU) layer and output layer. The ReLU function is defined as in Eq. (1), the ReLU function is faster than sigmoid function that is used in gradient descent training algorithm.

$$g(z) = \max\{0, z\} \tag{1}$$

The proposed MSNN shown in **Fig.2** is a modified structure of SNN (**Xu et al., 2013**). The internal state of the neuron is shown in **Fig.3** which explained the connection between the hidden node and output node as it is explained as a dotted line in **Fig. 2**. A Membrane Potential (MP) is the internal state of the neuron, which is defined as the sum of PostSynaptic Potential (PSP) that spikes and affected by the weights for synapses that transmit the input spikes. The internal state of the neuron is explained as in Eq. 2.

$$u(t) = \sum_{i=1}^L \sum_{t_i^l \in N_i} w_i \varepsilon(t - t_i^l) + \mu(t - t^{fr}) \tag{2}$$

Where, L is the input synapses of a neuron. The (t^{fr}) is the time of the latest recent spike output of the neuron prior to the present time at (t) greater than zero. The weight of the (i^{th}) synapse is defined as w_i . The i^{th} synapses transmits N spikes and the arrival times at the neuron are given by Eq. 3.

$$N_i = \{t_i^1, t_i^2, \dots, t_i^{N_i}\} \tag{3}$$

The spike response function $\varepsilon(t)$ is defined as in Eq. 4.

$$\varepsilon(t) = \begin{cases} \frac{t}{\tau} e^{1-\frac{t}{\tau}} & t > 0 \\ 0 & t \leq 0 \end{cases} \tag{4}$$

where τ is the constant of the time decay.

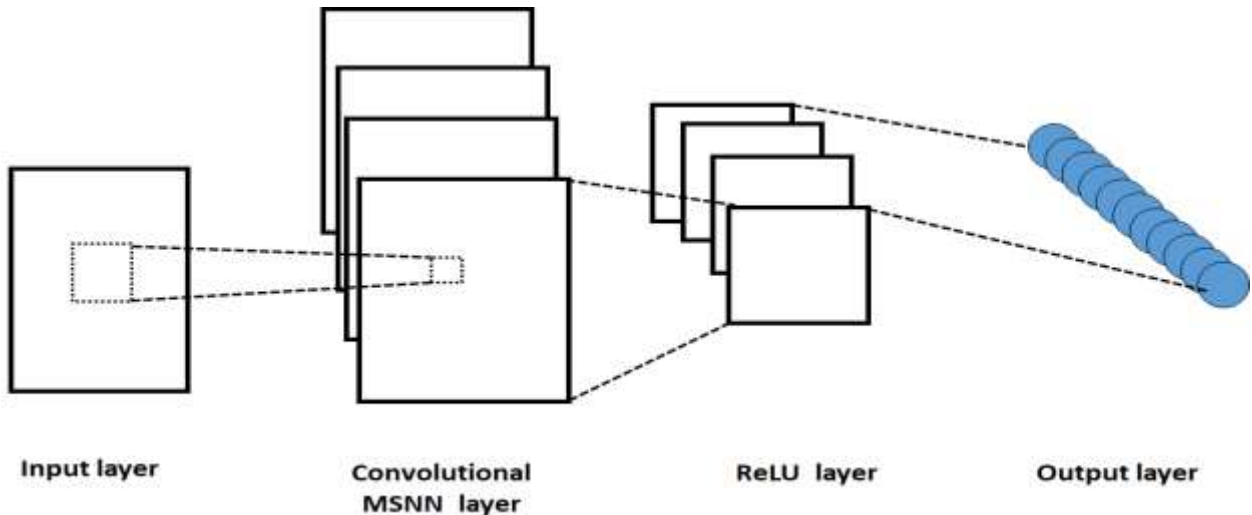


Figure1. The Convolutional Multi-Spike Neural Network (CMSNN) Structure.

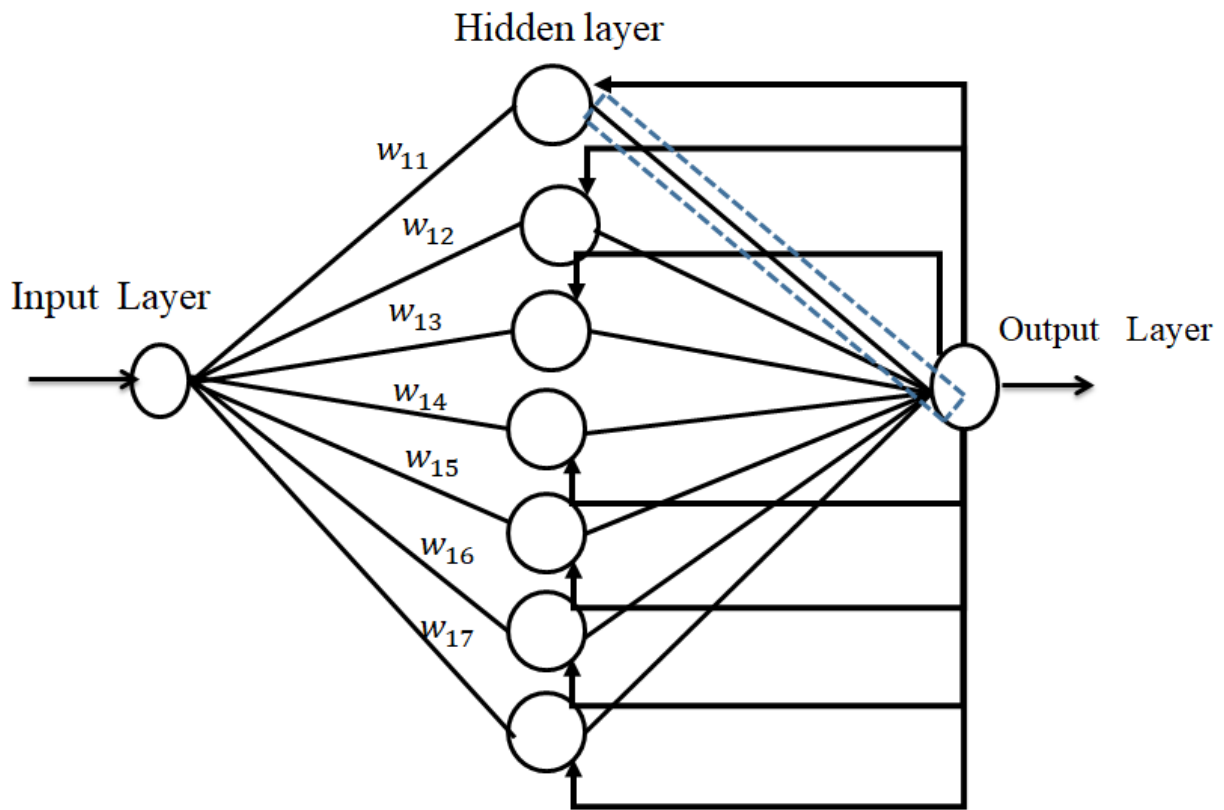


Figure 2. The structure of MSNN.

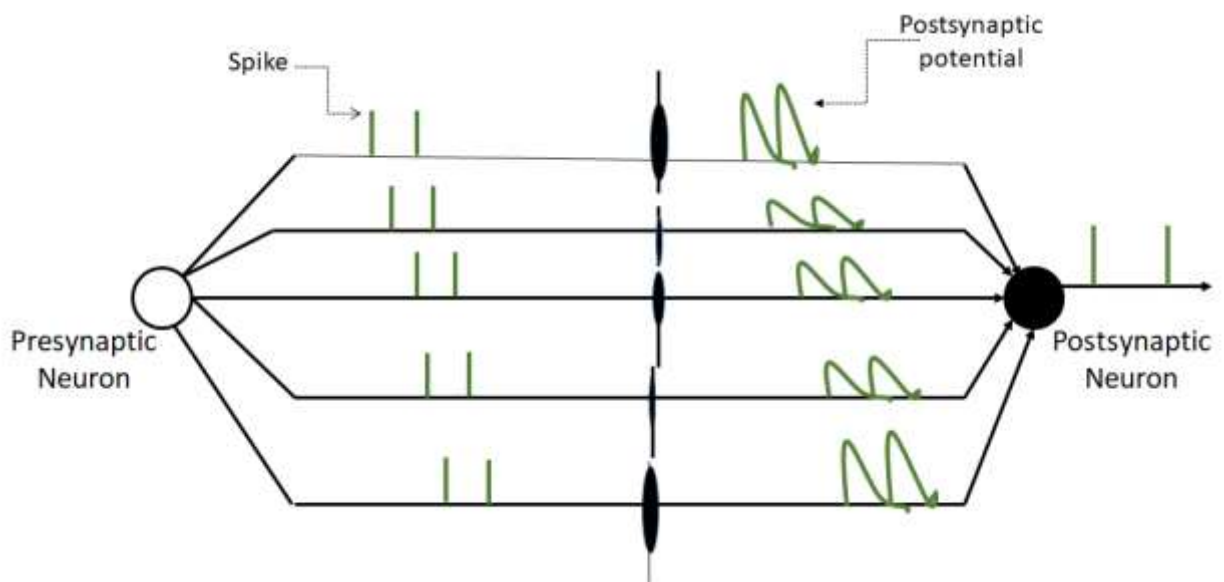


Figure 3. The connection between the hidden node and output node (blue dotted line in Fig.2).



3. TRAINING ALGORITHM FOR CMSNN

The dynamic equations in Multi-Spike Neural Network are given in Eq.5 and Eq. 6.

$$h_{ci} = w_{ci} * X_c \tag{5}$$

$$y_{ij}(k) = w_{ij} * [h_{ci} + y_{ij}(k - 1)] \tag{6}$$

The weights w_{ci} between input layer and hidden layer and the weights w_{ij} between hidden and output layer are updated based on Backpropagation Bigger Adjustments (BBPA) algorithm (Xu *et al.*, 2013). There are two phases in MSNN, these phases are repolarization phase and hyperpolarization phase. These two phases depend on internal state of the neuron and the spike firing time. Recall to Eq. 2, the term $\mu(t - t^{fr})$ represents the multi-spike and it is defined in Eq. 7, where ϑ is the threshold value and it selected by trial and error.

$$\mu(t) = \begin{cases} -2\vartheta e^{-t \setminus \tau R} & \text{if } t > 0 \\ 0 & \text{if } t \leq 0 \end{cases} \tag{7}$$

The constant τR represents the time decay constant.

Eq. 2 can be updated to Eq. 8

$$u_j(t) = \sum_{i=1}^{L_{n+1}} \sum_{k=1}^K \sum_{\substack{t_i^l \in N_i \\ t_i^f + d^k > t_j^{fr} + R_a}} w_{ij}^k \varepsilon(t - t_i^l - d^k) + \mu(t - t_j^{fr}) \tag{8}$$

All the parameters of the equations are defined in **Table1**. The basic idea of MSNN is explained in **Fig.3** when the neuron (L_{n+1}) in layer (n+1) and neuron (i) has emitted a spike train in firing time $FF_i = \{t_i^1, t_i^2, \dots, t_i^{Fi}\}$, the arrival time of the spike t_i^f is arriving to neuron (j) which means that the postsynaptic neuron at time $t_i^f + d^k$. The training algorithm is minimized the difference between the desired and actual time output of postsynaptic neuron. Eq. 9 represents the error function.

$$E = 1 \setminus 2 \sum_{j=1}^{L_n} \sum_{f=1}^{F_j} (t_j^f - \widehat{t}_j^f)^2 \tag{9}$$

Where the weights are updated according to Eq. 10

$$\frac{\partial t^{(1)}}{\partial w_i} = \frac{\partial t^{(1)}}{\partial u_i} \frac{\partial u^{(1)}}{\partial w_i} \tag{10}$$



Table 1. Parameters of MSNN.

Symbols	Definition
h_{ci}	Vector output of the hidden layer
X_c	Input vector
$y_{ij}(k)$	Output layer
R_a	Length of the Multi-Spike period
d^k	Delay of the (k^{th}) synapses
L	Number of neurons in hidden layer

4. PREDICTION MODEL

The prediction model used in this paper is shown in **Fig. 4**. The same input signal is applied to the dynamical system and to the proposed CMSNN. The output of the dynamical system is compared with the output of CMSNN to have the error signal that is used to update the weights. The accuracy of the prediction process is increased with the increased of the powerful of CMSNN. At the begging, the CMSNN trains off line with the random input then after reaches the error goal, the CMSNN works in online stage and can predict the response of the dynamical system efficiently. The structure of CMSNN is different from other types of SNN in that it does not need much more information during the training process. The learning process depends on the firing time to adjust the weights that reach the firing time under supervised gradient descent to train a desired output spike.

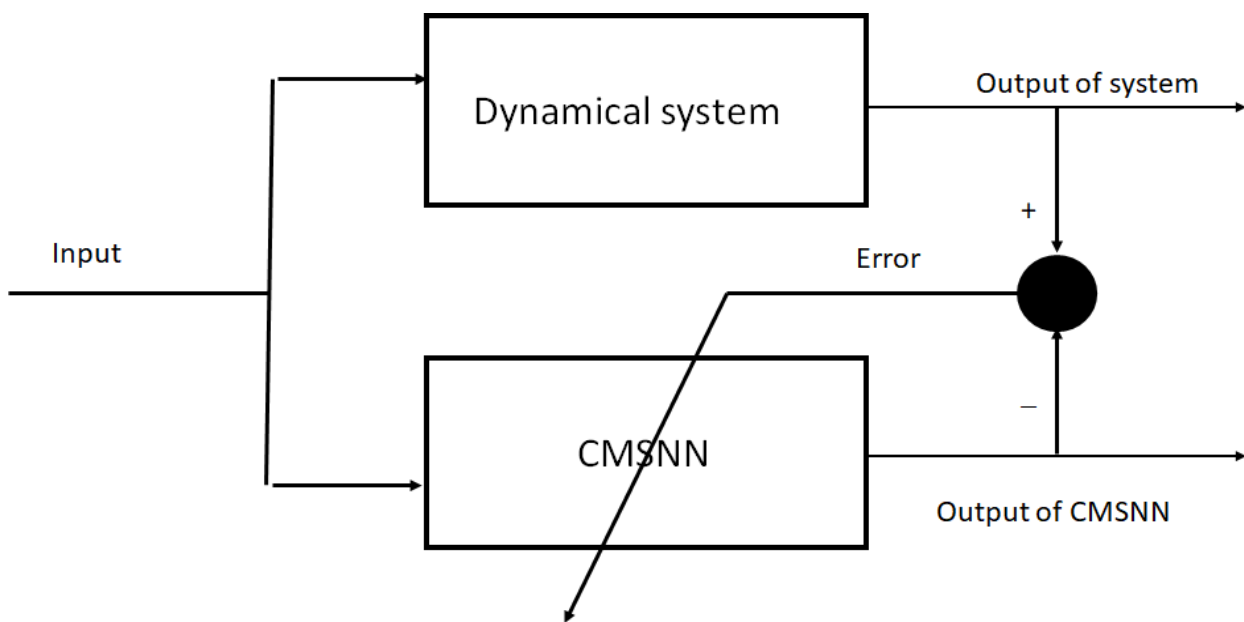


Figure 4. The Identification Model.



5. SIMULATION RESULTS

The proposed model is implemented using MATLAB simulation for two types of dynamical systems. The input to the proposed model is described as in Eq. 11 as a test signal

$$u(k) = \begin{cases} \sin\left(\frac{2\pi k}{250}\right) & \text{for } k \leq 250 \\ 0.8 \sin\left(\frac{2\pi k}{250}\right) + 0.2 \sin\left(\frac{2\pi k}{25}\right) & \text{for } k > 250 \end{cases} \quad (11)$$

The second order systems are described by the Eq. 12 and Eq. 13 (Han, et. al, 2020).

$$\begin{cases} yy(k + 1) = 0.3yy(k) + 0.6yy(k - 1) + g[u(k)] \\ g(.) = 0.6 \sin(\pi u(k)) + 0.3 \sin(3\pi u(k)) + 0.1 \sin(5\pi u(k)) \end{cases} \quad (12)$$

$$\begin{cases} yy(k + 1) = ff(yy(k)) + g(u(k)) \\ ff(yy(k)) = \frac{yy(k)[yy(k)+0.3]}{[1+yy(k)^2]} \\ g(u(k)) = u(k)[u(k) + 0.8][u(k) - 0.5] \end{cases} \quad (13)$$

Fig. 5 shows the Root Mean Square Error (RMSE) as a comparison between the CNN and CMSNN. It is clear from the **Fig.5** that the performance of CMSNN is better than that for CNN in terms of minimizing the RMSE and number of epochs. The combination of CNN with MSNN to constructed the proposed model gives the structure more powerful in training phase during the offline stage. The model is training with the random input to minimize the different between the desired output and the actual output of the CMSNN. The actual response of the dynamical system in Eq. 12 and the output of CMSNN after training phase is shown in Fig.6, also Fig.6 shows the comparison between the output of the proposed model CMSNN and the output of CNN, it is clear from the Fig. 6 that the accuracy of the CMSNN is higher than that with the CNN. The structure of CNN that is used in this paper is the same as CMSNN but instead of MSNN there is single SNN. The Multi-Spike mechanism that modified in this paper is improved the capability of the prediction system to speed up the training process as well as to increase the accuracy of it as compared with CNN. **Fig. 7** shows the performance of dynamical system in Eq. 13 as an example of more complex second order system.

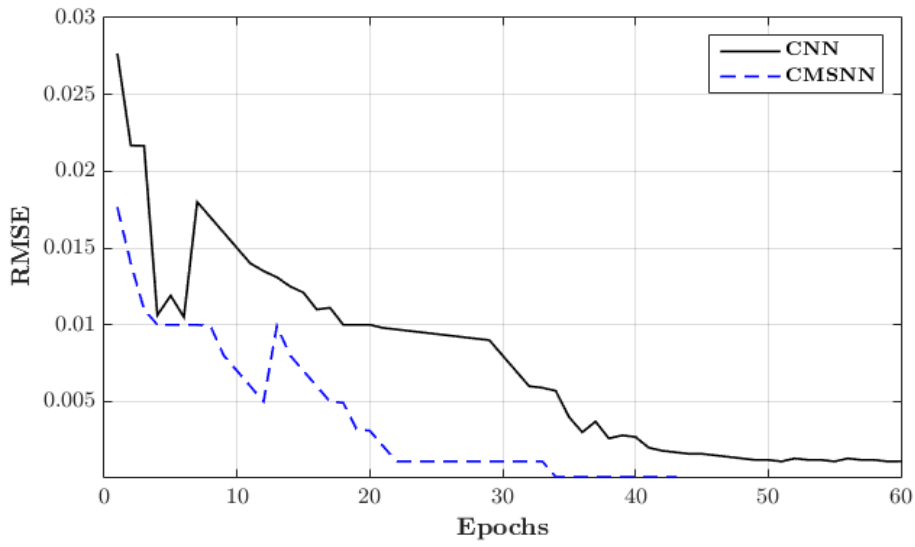


Figure 5. The RMSE for offline training phase.

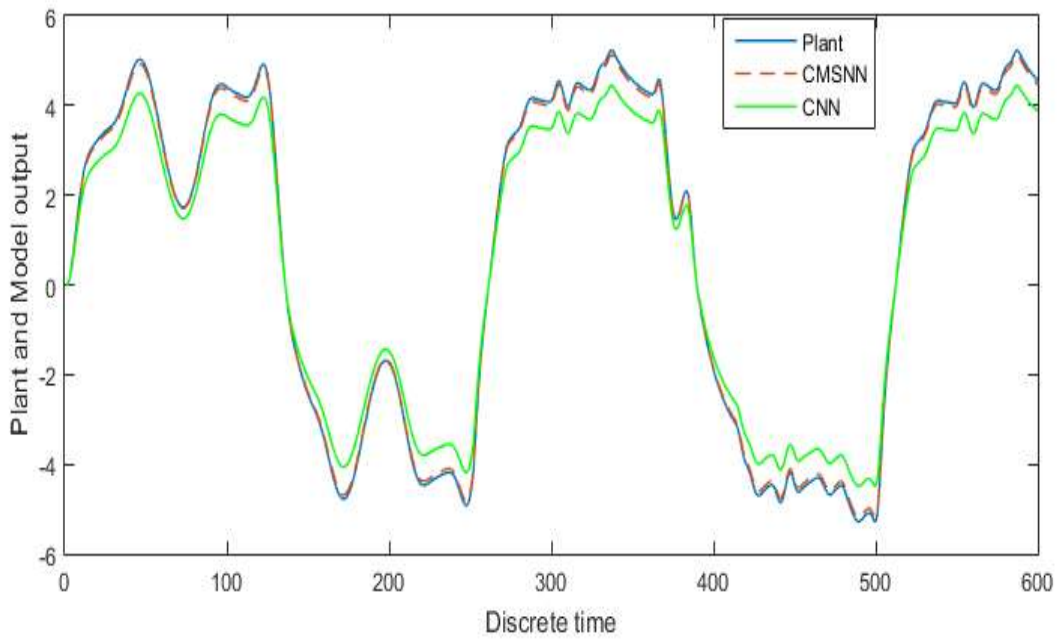


Figure 6. The Response of the dynamical system for Eq. 12

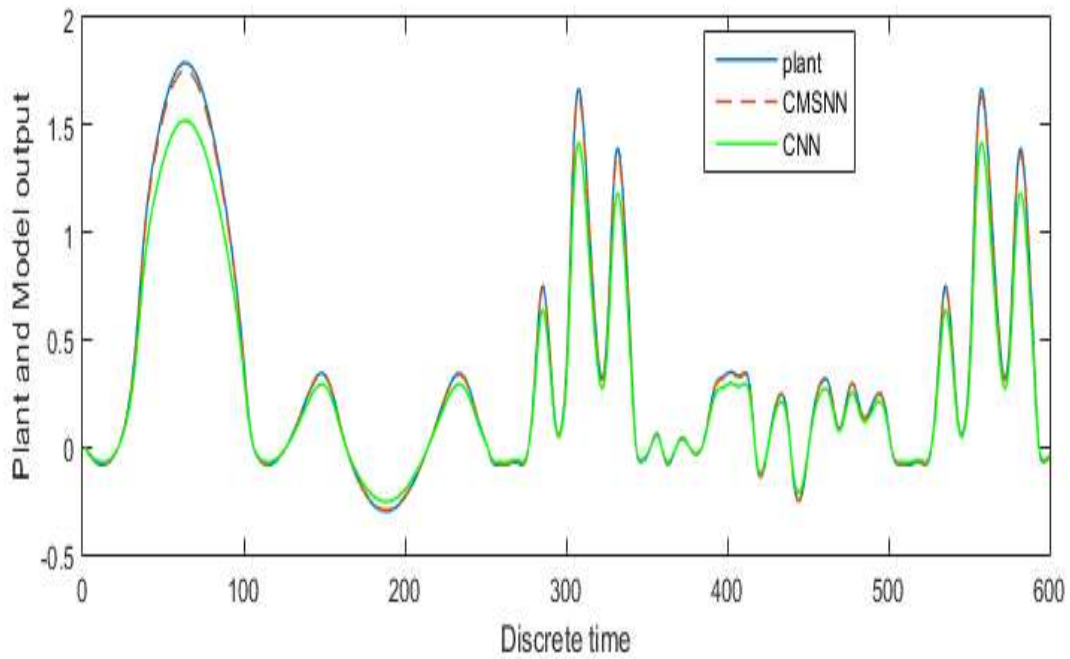


Figure 7. The Response of the dynamical system for Eq. 13.

To show the efficiency of the proposed model the input signal given in Eq. 11 is replaced by the other one as in Eq. 14 and the response system is shown in **Fig. 8** when it is applied to the dynamical system described by Eq. 12.

$$u1(k) = \begin{cases} \sin\left(\frac{3\pi k}{150}\right) & \text{for } k \leq 150 \\ 0.9 \sin\left(\frac{2\pi k}{150}\right) + 0.12 \sin\left(\frac{2\pi k}{20}\right) & \text{for } k > 150 \end{cases} \quad (14)$$

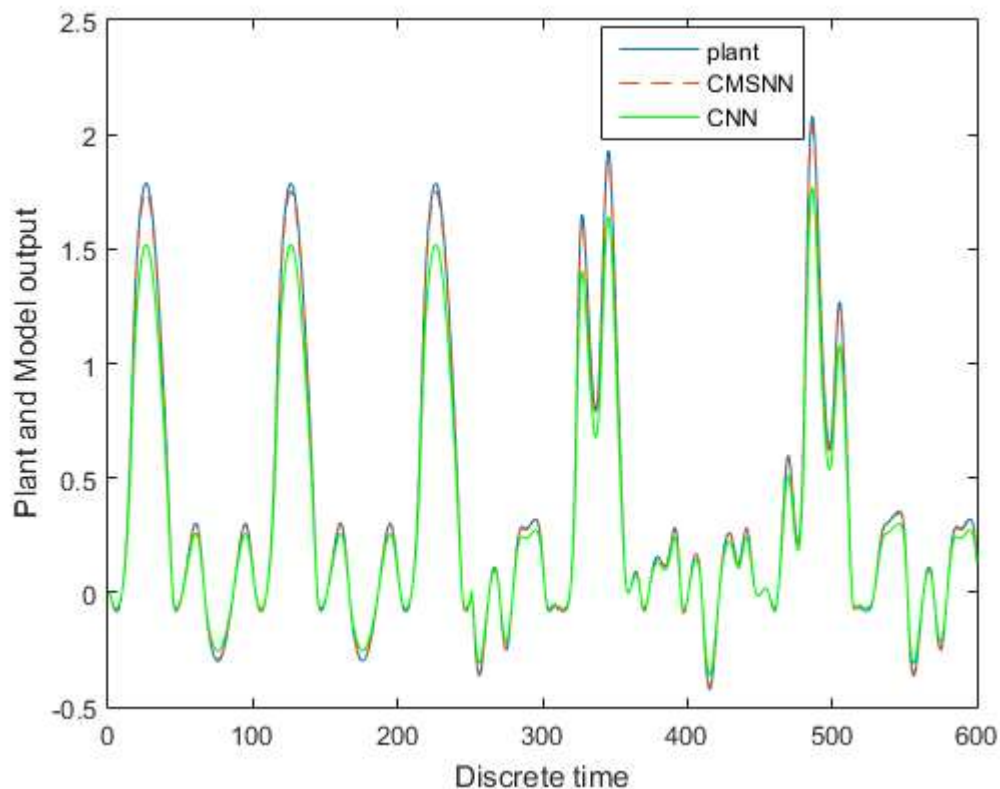


Figure 8. The Response of the dynamical system for Eq. 12 when another test signal is applied.

The performance of the proposed system based on CMSNN is better than that one based on CNN, as it is very clear in **Fig. 8**.

6. CONCLUSION

In this paper, a Convolutional Multi-Spike Neural Network (CMSNN) for prediction a dynamical system is proposed. The CMSNN is more powerful than the CNN with single SNN in its capability to predict the response of dynamical system. The MSNN is a modified version of SNN in which the former has multi-spike features that increased the opportunities of the network to just update the weights that specifically relative to the system to be identify. The training algorithm based on Backpropagation Bigger Adjustments is modified to become more powerful to train the proposed CMSNN. The simulation results demonstrate that the proposed structure in more efficient that the CNN in terms of minimizing the RMES by 28.33% with minimum number of epochs.

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