The Esns-Based Traction Electric Quantity Prediction of High-Speed Train with Adaptive Model Inputs Temporal Scale

Kaixuan Chang1*, Xiaoxiao Shu1, Yichao Zheng1, Jing Tian1 and Wei Li1
1State Grid Jiangxi Electric Power Research Institute, Nanchang 330096, China

*Corresponding author: kxchang@126.com

Abstract. The precise and reliable speed prediction provides a basis for predicting the traction electric quantity of high-speed train (HST). However, various existing mathematical speed control modes of HST may be insufficiently applicable because of the complex nonlinear and uncertain disturbance. To address this issue, in this paper, a speed predictive model of HST is established by taking the advantages of the efficient and robust prediction capability of echo state networks (ESNs) in dealing with nonlinear time-series. In consideration of the uncertainties of the temporal scale of the model inputs, an adaptive temporal scale selection criterion is set up to further enhance the model prediction accuracy. Then, based on the given traction characteristic curve of HST, the ESNs-based traction electric quantity prediction framework is established. Some experimental results illustrate that the proposed predictive framework can achieve a good performance in terms of predicting accuracy and reliability.

1. Introduction

The traction electric quantity consumed by high-speed train (HST) is mainly determined by the traction control strategy, which is closely related to the operation speed of HST. Besides, the precise speed predictive control technique of HST plays an essential role in realizing the energy-efficient railway transportation [1, 2]. Over the years, considerable research effort has been investigated on the model predictive control (MPC) of HST. Based on the Newtonian mechanical analysis, a nonlinear speed control model of HST was given in [3] and a predictive speed control model for HST was presented in [4], while an energy-saving control model of HST was proposed in [5]. Actually, in many cases, it is even impossible to obtain a suitable physically speed control model for HST due to the complex nonlinearity and the lack of knowledge of some critical parameters. On the other hand, as pointed out in [6], the physical phenomena that generate the temporal signals may occur at different speed. In other words, the input temporal scale of the predictive model of HST may be various in different operation states including traction, coasting and braking.

Echo state networks (ESNs) have the salient advantage of that the complex training task of classical RNN is reduced to a simple linear regression over readout weights while well preserving the memory capacities of RNNs. While ESNs showing a good modelling performance on time-series dataset, the temporal scale selection of the model input is out of the previous literature. Fortunately, the minimum description length (MDL) method has shown a great potential in analyzing real-world time-series data [6], and MDL-based criterions were developed for the semi-supervised classification in [7] as well as for model order selection in [8].

Thus, in this paper, ESNs is employed to deal with the input order uncertainties and approximately represent the nonlinear mapping of the speed and control force of HST, comparing with an adaptive
selection method for the model input temporal scale. Subsequently, the MPC of HST is performed by using a PSO-based searching scheme. Finally, based on the predictive speed and control force, traction electric quantity prediction framework is built. The numerical experiments with real-world operation data of HST demonstrated the effectiveness and feasibility of the proposed predictive framework.

2. Preliminary and problem formulation

It is a fact that the properties of time-series appear in different ways depending on the temporal scale of observation, which is essential for modelling an unknown system accurately. In other words, as stated as the principle of automatic scale selection in [6], the selected temporal scale can be regarded as reflecting a characteristic length of the corresponding structure in the data under certain conditions.

Here, we take Mackey-Glass time-series for example, of which prediction model is

\[ x(t + \Delta t) = f(X) \]
\[ X = [x(t), x(t - \Delta t), \ldots, x(t - k\Delta t)], \Delta t \in \mathbb{Z}, k \in \mathbb{Z} \]  

where \( \Delta t = 6 \) and \( k = 3 \) donate the temporal scale and order of the model inputs, respectively. \( X \) donates an data observation point.

Similarly, for the speed prediction of HST, as a typical time-series prediction task, the data observation interval is determined by the temporal scale of model inputs, as shown in follows:

\[ x(t) = f(z(t - 1), u(t)) \]
\[ v(t) = \hat{\xi}(x(t)) \]
\[ z(t) = \{v(t - md), u(t - nd)\} \]  

where \( u(t), z(t - 1), x(t) \) and \( v(t) \) are the current system control input, model predictive input vector, output states and current speed of HST, respectively. \( f(\cdot) \) donates the nonlinear mapping from the control force to the speed of HST. \( d \) is the data observation temporal scale, \( m, n \in \mathbb{Z} \) are the orders of prediction input (v) and output (u), respectively, and here \( m = n \).

Given \( m \) and \( d \), as well as a sufficiently large number of training data, we can obtain the speed control error

\[ J(t) = \frac{1}{M} \sum_{i=1}^{M} \xi(v_{i}(t), v_{i}(t)) \]
\[ v_{i}(t) = f(m, d, \theta, z(t)) \]  

where \( \theta \) donates the parameter vector of ESNs, M is the trial times at each iteration.

Based on the speed prediction model, the MPC of HST is to determine the current optimal control input \( u(t) \) by solving the following optimization problem

\[ \arg \min_{u(t)} \frac{1}{T} \sum_{j=0}^{T-1} J(v(t + j), u(t + j)) \]
\[ \begin{align*}
    \phi(t + 1) &= f(z(t), u(t), \theta) \\
    u(t + j) &= g(cl), cl \in [-1, 0, 1] \\
    U(t) &= \{u(t), u(t + 1), \ldots, u(t + K - 1)\} \\
    0 < v(t) < V(t)
\end{align*} \]  

where \( T \) is the control and prediction horizon, \( g(\cdot) \) represents nonlinear mapping between the control force of HST and the operation states of HST control inputs \( cl \), where “-1, 0, 1” donate the control states of braking, coasting and traction, respectively.

With the obtained optimal control strategy and the corresponding speed, we can predict the traction electric quantity of HST \( Q \) as follows

\[ Q_j(t) = \psi(u(t + j), v(t + j)) \]  

where \( \psi \) donate the traction characteristic relationships of HST.
3. The ESNs-based MPC of HST with adaptive temporal scale selection

In this section, the ESNs-based prediction model of HST is introduced accompanied with the adaptive temporal scale selection criterion. Then, the MPC of HST is performed with the PSO-based optimization strategy.

3.1 ESNs-based speed prediction model of HST

The typical ESNs can be defined by the state update and output equations, and for simplicity, we focus on the basic ESNs without output feedback, of which the architecture is shown in Figure 1 [9].

Based on Figure 1, the state update and output equation are shown as follows:

\[
X(t) = f(W_{in}^T z(t) + W X(t-1) + B) \quad (7)
\]

\[
v(t) = g(W_{out}^T X(t)) \quad (8)
\]

where \(W_{in}^T\), \(W\) and \(W_{out}^T\) are the weight matrices of input connection, internal feedback and output connection, respectively. \(X(t) = [x_1(t), ..., x_l(t)]^T\) is the internal activation states vector of ESNs, \(B = [b_1, ..., b_l]^T\) are biases. \(f\) and \(g\) are the activation functions of the internal states and outputs of ESNs, which generally are chosen as sigmoid function and identity function, respectively.

![Figure 1. The ESNs-based speed prediction model of HST (each node has the connection like the one with b1; dashed arrows donate randomly generated and then fixed connection weights, and solid arrows donate trained connection weights)](image)

3.2 Adaptive temporal scale selection

Motivated by the successful application of MDL in automatically discovering the intrinsic dimensionality of time-series [6], we apply the MDL-based criterion to adaptively choose the appropriate temporal scale of the model inputs. According to the idea that MDL method provides the same information as the minimum eigenvalue of the covariance matrix of observation datasets [8], we have the selected criterion for the temporal parameters defined as follows:

\[
J_{m,d} = \frac{N}{2} \log(\lambda_n) + \frac{m + d}{2} \log N \quad (9)
\]

where \(J_{m,d}\) is the selected criterion, \(N\) is the number of observation data points, \(\lambda_n\) donates the minimal eigenvalue.

Then, as \(\log(\cdot)\) is monotonically increasing, given a sufficiently large \(N\), it can be derived out [9]

\[
J_{m,d} = \sum_{i=1}^{c} \gamma_i \lambda_{n,i} \quad (10)
\]

where \(c\) is the number of approximated linear subsets obtained by fuzzy clustering, and \(\gamma_i\) is
the weighted value of the $i$th subset.

Finally, we obtained the selection criterion for temporal scale and input orders as follows:

$$[m,d] = \arg \min_{m,d} \left( \frac{J(m,d)}{J(m-1,d)} \right)$$

### 3.3 Traction electric quantity prediction of HST with PSO-based optimization

PSO is a parallel and heuristic searching algorithm, which shows a good optimization performance in terms of efficiency and convergence rate. The update mechanism for the speed $v_j(k+1)$ and position $x_j(k+1)$ of particles is [10]:

$$v_j(k+1) = \omega \cdot v_j(k) + \phi_1 \cdot r_1 \cdot (p_{b_j}(k) - x_j(k)) + \phi_2 \cdot r_2 \cdot (g_{b_j}(k) - x_j(k))$$

$$x_j(k+1) = x_j(k) + v_j(k+1)$$

(12)

where $j$ and $k$ represent the particle and iteration times, $p_{b_j}(n)$ and $g_{b_j}(n)$ donate the current optimal position of a particle and the population, $\phi_1$ and $\phi_2$ are the acceleration coefficients of particles, $r_1$ and $r_2$ are random parameters valued in [0, 1], $\omega$ is the dynamic weighting factor.

For the MPC of HST, the root-mean-square error ($e_\mu$) and standard derivation ($s_d$) of the speed tracking accuracy are used as criterion indexes

$$e_\mu = \left( \frac{1}{M} \sum_{t=1}^{M} (v_j(t) - v(t))^2 \right)^{1/2}, \quad s_d = \left( \frac{1}{M} \sum_{t=1}^{M} (v_j(t) - \mu)^2 \right)^{1/2}$$

(13)

where $\mu$ is the average of the predicted speed of M times running for each independent trial.

Then, based on the obtained predictive speed and the traction characteristic of HST[2], (6) can be rewrote as follows:

$$Q_j(t) = \begin{cases} 
\psi_j(u(t+j),v(t+j)), & 0 < v(t+j) < 50 \\
\psi_j(u(t+j),v(t+j)), & 50 \leq v(t+j) < 168 \\
\psi_j(u(t+j),v(t+j)), & 168 \leq v(t+j) \leq 350 
\end{cases}$$

(14)

### 4. Experimental studies

To evaluate the performance of the proposed prediction framework for the traction electric quantity of HST, two groups of simulation experiments ($a$ and $b$) are carried out in this section based on the real-world operation data of HST which are collected from the driving cab of HST serviced on “Beijing-Shanghai high-speed railway” in China. Then, the ESNs-based speed prediction model of HST is trained with the structure of one input node, 60 internal nodes and one output node.

For the experiment $a$, the temporal scale was calculated according to (11) at the initial iteration and then fixed; on the contrary, for the experiment $b$, the temporal scale was updated by (11) at each predictive iteration. By applying the established prediction model and the indexes defined in (13), we performed the MPC of HST for 5 dependent trials, and each trial was running for M=50 times. Then, we obtained the evaluation results as shown in Table 1.

| Trails | 1 | 2 | 3 | 4 | 5 |
|--------|---|---|---|---|---|
| $e_\mu/\mu_{-3}$ | 5.2 | 4.8 | 5.1 | 4.6 | 4.9 | 4.5 | 5.3 | 5.0 | 5.2 | 4.9 |
| $s_d/\mu_{-4}$ | 2.0 | 1.6 | 1.7 | 1.7 | 1.8 | 1.5 | 1.9 | 1.7 | 1.7 | 1.4 |

where $a$ and $b$ represent the experimental results with fixed and adaptive temporal scale selection, respectively.
According to Table 1, we choose the simulation results of the third trial to demonstrate the speed tracking performance, as shown in Figure 2. Then, from Table 1 and Figure 2, we can see that the ESNs-based MPC of HST with both fixed and adaptive temporal scale could achieve a sound speed tracking performance. Furthermore, it can be observed from Table 1 that the MPC of HST with adaptive temporal scale selection (b in Table 1) obtain a better speed tracking performance in terms of accuracy and reliability than that of a in Table 1. Intuitively, as shown in Figure 2, it is found that the tracking speed in Figure 2b can follow the target speed of HST significantly more precisely than that in Figure 2a.

Figure 2. The tracking speed of the ESNs-based MPC of HST

Figure 3. The predictive control orders of the ESNs-based MPC of HST (here (a) and (b) corresponding to that in Figure 2)

Then, according to equation (14), Figure 2 and Figure 3, we have the predicted traction electric quantity as shown in Figure 4.

The total traction electric quantities corresponding to (a) and (b) in Figure 4 are 6455Kwh and 6340Kwh, respectively.
The traction electric quantity prediction of HST is a kind of typical industrial process control problem, accompanying with the characteristics of complex nonlinearity and parameter uncertainties. Owing to the good training efficiency and memory capacities, ESNs show a promising potential to deal with this predictive control issue. Besides, the determination of temporal scale and order of the modeling inputs plays an important role in guaranteeing the predictive control performance. The further work about the proposed predictive control framework can be carried out from the aspects including efficient predictive control algorithms and online temporal scale selection criterions.

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