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A Deep Long Short-Term Memory Neural Network based Autoencoders for Signal Validation

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1. Introduction

In the present fourth industrial revolution, the degree of automation is growing significantly and enormous amount of time-series data are collected from industrial systems for analysis. The demand for robust and resilient performance has led to the use of signal validation and on-line monitoring schemes to monitor sensors and equipment conditions using data-driven-based models built by those time-series data. However, most data-driven models are developed and applied under steady-state or time-invariant conditions since this belongs to most of system's uptime, but it is vital to have condition monitoring during transient operations as well, which has been less concerned. In this study, transient operations are any non-steady state but time-varying within normal operating conditions, such as start-up, shutdown, and load following modes of the system [1,2]. Recently, Ahmed *et al* [3] proposed a novel data-driven method, weighted distance Auto Associative Bilateral Kernel Regression (AABKR), for on-line monitoring during transient operation which has been successfully applied to the start-up transient of a nuclear power plant (NPP). However considering the availability of massive industrial time-series data or big data, in this work, the authors seek to explore the possibility and applicability of the deep learning techniques for signal validation and condition monitoring of safety parameters and sensors in NPPs during transient operations. Deep learning is a branch of machine learning algorithms that uses a cascade of many layers of non-linear processing units for feature extraction and transformation. There are various deep learning architectures, which include Restricted Boltzmann Machine (RBM) based deep belief network (DBN), Convolutional Neural Network (CNN), deep Auto-encoders, and deep Recurrent Neural Network (RNN). Since sensor data is a time-series data, this work chose to use a deep recurrent neural network (RNN) architecture based on deep learning technique, long short-term memory (LSTM) to capture the time-varying dependencies of transient data for the purpose of sensors' signal validation and condition monitoring. The deep LSTM model is developed in form of autoencoder: the encoder-decoder network, such that the multi-dimensional sensors signals can be effectively reconstructed on-line for the purpose of condition monitoring.

2. Methods and Results

In this section the core algorithm of the LSTM and the proposed autoencoder architecture for sensors' signal validation and monitoring in transient operation of NPP are described. At the end of this section, the application of the proposed method to a start-up transient of a NPP for sensors' condition assessment are presented and discussed.

2.1 LSTM Neural Network

RNN is a special type of neural network in which the output of hidden layers will return recurrently as input. This implies that the hidden layers have self-connections to itself across time as shown in Fig. 1. Therefore, unlike conventional artificial neural network that ignore dependencies among time-series data, RNN has a strong ability in processing sequential and time-dependent data. Mathematically, the mechanism of RNN cell at time t is described by the following equations:

$$h_t = tanh(Ux_t + Wh_{t-1} + b_h) \quad (1)$$

$$o_t = Vh_t \quad (2)$$

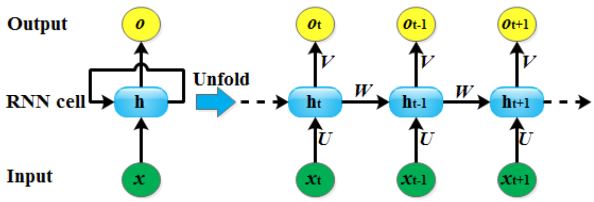

Fig. 1. The architecture of RNN cell

where h_t and h_{t-1} are the states of RNN cells of current time t and previous time $t-1$, x_t is the input at time t, o_t is the output at time t, W is the weight matrix between the hidden states at t and $t-1$, U and V are the weight matrices from input to the hidden state and from the hidden sate to the output, respectively, and b_h is a bias input. Due to vanishing gradient problem during training based on back propagation through time (BPTT), RNN has no ability to capture long-term dependencies in the data. To alleviate this problem, Hochreiter and Schmidhuber [4] proposed LSTM based on the RNN architecture, where the conventional RNN hidden cells are replaced by the LSTM network structure. In every LSTM neuron, there exists three gates function: input gate, forget gate, and output gate, which ensure that the LSTM neuron has the ability to discover and retain long-term dependencies.

The LSTM architecture is depicted in Fig. 2. As shown in the figure, the LSTM neuron provides nonlinear mechanism for controlling information flow into and out of the LSTM cell. The forget gate determines the information that need to be discarded or forgotten from the previous cell states. The input gate determines what information will be allowed to enter into the neuron state. Finally, the output gate decides the information to be passed out of neuron state. Mathematically, the representation of the LSTM neuron is as follows:

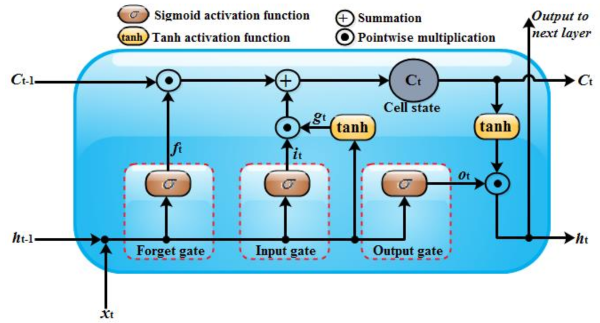

Fig. 2. The architecture of LSTM neuron

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (3)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (4)$$

$$g_t = tanh\left(W_g[h_{t-1}, x_t] + b_g\right) \quad (5)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot g_t \quad (7)$$

$$h_t = o_t \odot tanh(C_t) \quad (8)$$

where W_f, W_i, W_g and W_o are weights of the forget gate, input gate, input node and output gate, respectively, and b_f, b_i, b_g and b_o are their corresponding bias inputs; f_t, i_t, g_t and o_t are the output of forget gate, input gate, input node and output gate; h_{t-1} and h_t are the previous and current out of LSTM neurons at time t and $t-1$; C_{t-1} and C_t are the LSTM cell states at time t and $t-1$; $\odot$ represents the pointwise multiplication; σ and $tanh$ are sigmoid and tanh activation functions.

2.2 Proposed Deep LSTM-based autoencoder model for signal validation

In this paper, a deep LSTM-based autoencoder model is developed to automatically capture the sequential time-series sensor data and effectively reconstruct on-line signals for condition monitoring. Autoencoder is an encoder-decoder model which is basically a kind of neural network composed of a hidden layer that sets the target to repeat the input. The hidden units are often viewed as the higher-dimensional representation of the input, thus, hidden units is always less than input dimension. Therefore a deep autoeconder can be built by stacking layers, in this case, LSTM layers. The architecture of the proposed model is depicted in Fig. 3.

With the selection of the time window length r, the time-series input data to the proposed model is built into a two-dimensional array in which the number of rows and columns of the matrix array are p and r respectively, where p is the number of sensors parameters to be monitored and r is the time window of sampling data. Multiple LSTM layers are stacked to form a deep autoencoder in order to carry out deep exploitation of the sensor data, and the data are output from the lower layer to the LSTM neurons in the next layer, hence, the data flow at each LSTM layer is time-dependent. In every LSTM layer, there are many LSTM neurons to capture long-term dependencies of sensor time-series data. At each LSTM layer, LSTM cells established information exchange with each other in order to understand clearly self-connection across sequential time-series data. The stacked LSTM autoencoder architecture consists of two architectures: the encoder and decoder. The encoder reads the input sequence through several LSTM layers and encodes it into a fixed-length vector. While, the decoder decodes the fixed-length vector and outputs the predicted sequence through several LSTM layers. With this, the on-line signal reconstruction can be achieved. At the end of the kth LSTM layer of the decoder, a fully connected dense layer is built to translate the decoded information that has been sequentially processed by the LSTM layers into a regression for sensor signal prediction. The sensors values at current time t are predicted and the result is compare with the query input at current time t to evaluate the residual. The residual is then analyzed to determine the sensors status.

2.3 Network parameter optimization

Since the deep LSTM is based on learning, the network parameters directly affect the deep LSTM performance in predicting the sensor values. Therefore, to obtain a high degree of signal estimation performance, the optimal parameters of the model are determined based on the following. (1) The network structure is first established through the determination of the number of LSTM layers and the number of LSTM neurons per layer, which are two important hyper parameters in the model, using grid search method. Instead of using the genetic algorithm [5] which is obviously complex and computational intensive considering complexity of the deep LSTM network, this paper used the grid search approach to determine the network hyper parameters in which the candidate number of LSTM layers and the LSTM neurons in each layer form a two-dimensional grid, and each node in the grid is verified to choose the optimal network structure. This approach does not only have low computational requirement but also simple and easy to implement. The hyper parameters with best performance on the validation dataset is then chosen as optimal and used for on-line signal validation. (2) Having determined the LSTM network structure, the minimization of the loss function, which is mean squared error (MSE), to determine the optimal weights of the model is performed by utilizing the Adam optimization algorithm, an adaptive moment estimation algorithm. Unlike traditional stochastic gradient descent

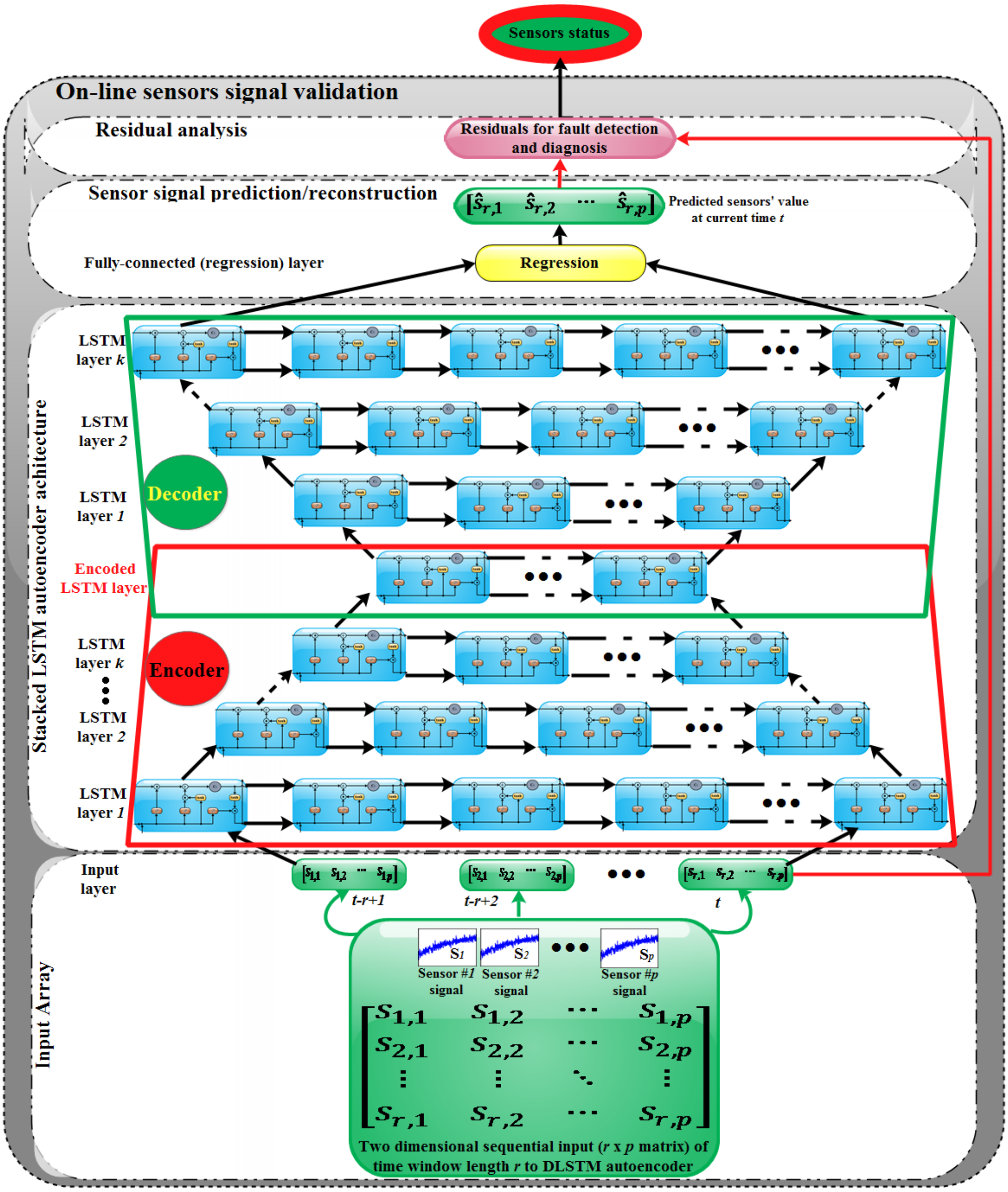

Fig. 3. Architecture of the proposed model for sensor signal validation

(SGD) with fixed learning rate, the Adam optimizer determines adaptive learning rate for different parameters. (3) Finally, the dropout strategy is applied during the training to avoid over fitting. All the algorithms are implemented in R programming language and keras package, an R interface to keras.

2.4 Applications

In this section, the performance of the propose model for sensor signal validation is verified using real-time simulation dataset from a pressurized water reactor (PWR) nuclear power plant (NPP). The dataset is collected from the compact nuclear simulator (CNS) during heating from cool-down mode (start-up operation) and used as a normal start-up transient operation for training the model. Six sensors' process parameters from the reactor coolant system (RCS) were selected for monitoring during this operation: S1 (cold leg temperature), S2 (core exit temperature), S3 (hot leg temperature), S4 (safety injection flow) S5 (residual heat removal flow) and S6 (sub-cooling margin temperature). The data consist of 1000 observations sequentially collected at constant time intervals of 1s. The data is first pre-processed by min-max normalization technique. The sliding window length *r* is then chosen to be 3 with window shifting step of 1, and based on this; the data is divided into training and validation dataset. A plot of errors in the prediction of training and validation sets is shown in Fig. 4. After training, the threshold for fault detection and diagnosis is determined from the residual of the prediction from validation dataset. To verify the fault detection capability of the built deep LSTM model, we simulated abnormal conditions on the dataset by adding fault to a particular sensor data at a time. The faulty signal is sampled from a uniformly distributed signal within the interval [2, 8] (i.e., F~***U***[2, 8]) and added on S6 from *t*=51s to *t*=1000s.

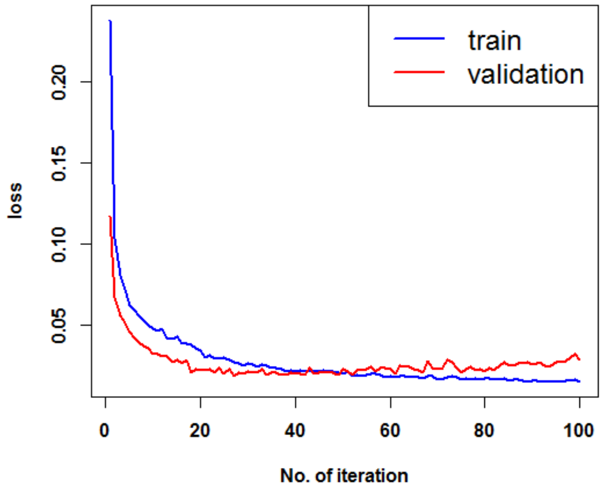

Fig. 4. A plot of error in training and validation datasets

3. Conclusions

In this paper, a deep learning model based on deep LSTM network is developed for signal validation and condition monitoring of sensors parameters in nuclear power plant. The developed architecture is based on the autoencoder, the encoder-decoder network, for signal reconstruction. The proposed network structure is validated using simulation dataset for start-up transients of a PWR NPP. The deep LSTM based autoencoder demonstrated its ability in signal validation of process parameters during transient operations.

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REFERENCES

[1] I. Ahmed and G. Heo, Development of a Transient Signal Validation Technique via a Modified Kernel Regression Model, *10th International Embedded Topical Meeting on Nuclear Plant Instrumentation, Control, & Human-Machine Interface Technologies NPIC&HMIT 2017, San Francisco, CA, USA*, pp.1943-1951, June 11-15, 2017.

[2] G. Heo, I. Ahmed, and G. Ha, “Apparatus and Method for Authenticating Time-Varying Signal in Online via Kernel Regression Model”, Korea Patent, 10-1967524, Korea, 2019.

[3] I. Ahmed, G. Heo, and E. Zio, On-line process monitoring during transient operations using weighted distance Auto Associative Bilateral Kernel Regression, ISA Transactions, In Press, 2019, https://doi.org/10.1016/j.isatra.2019.02.010.

[4] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Computing, Vol. 9, p. 1735-1780, 1997.

[5] A. Almalaq and J. J. Zhang, Evolutionary deep learning-based energy consumption prediction for buildings, IEEE Access, Vol. 7, p. 1520-1531, 2019.