Dependability Prediction with Logical Link Correlation for Industrial Wireless Communication Systems

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***Abstract*—Dependability is critical for industrial wireless communication systems because of the high requirements of industrial applications. As an important phase, dependability prediction can foresee future states of a wireless communication system and can support control and improve the state of the wireless communication system. Recent dependability prediction methods predict the states only based on time series which ignores the logical link correlation. Therefore, this paper proposes a sequence to sequence model based on long short-term memory and an attention mechanism to leverage the logical link correlation to improve prediction accuracy. We conducted comparative experiments on realistic measurement data sets with three cases, where the proposed model always outperforms the benchmark, which proves the novelty.**

***Index Terms*—Dependability assessment, dependability prediction, wireless communication systems, attention mechanism**

I. Introduction

Wireless communication systems (WCSs) are increasingly critical for future networks. However, its applications in scenarios such as industrial automation [1] still have huge challenges. Organizations such as the German Electro and Digital Industry Association (ZVEI) [2], [3], 5G Alliance for Connected Industries and Automation (5G ACIA) [4], and 3rd Generation Partnership Project (3GPP) [5] issued documents to guide and recommend users to manage WCS indicators for different types of industrial applications.

Automation factories are commonly full of machines and stuff which will block the wireless channels, and the protocols such as Wifi, Bluetooth, and Zigbee will also interfere with each other if they communicate at the same time, position, and spectrum [6], [7]. Therefore, dependability is one of the most important indicators for supporting industrial applications. Dependability is a comprehensive indicator that has many parameters and is summarized and generalized by the project report [8]. In general, we can assess or/and control these parameters to improve WCSs, which leads to two phases: dependability assessment [9]–[13] and control [14]–[18]. The two phases can work independently or together. Dependability assessment can have multiple tasks, such as dependability scoring and dependability prediction. These tasks can be addressed by one multi-task learning model [13] or several corresponding models [11], [19]. This paper focuses on the dependability prediction task. In 2019, Sobhgol et al. [19] proposed a Long Short-term Memory (LSTM) model to predict the dependability parameters but cannot address multiple tasks. To address this issue, sun et al. [13] proposed a multi-task learning model which has a better performance than the LSTM model, because it additionally leverages the relationships between different tasks. However, these models still ignore the relationship between logical links which is a useful knowledge to improve the prediction accuracy. Therefore, this paper proposed a model of dependability prediction with logical link correlation for industrial wireless communication systems, where a sequence to sequence model based on the

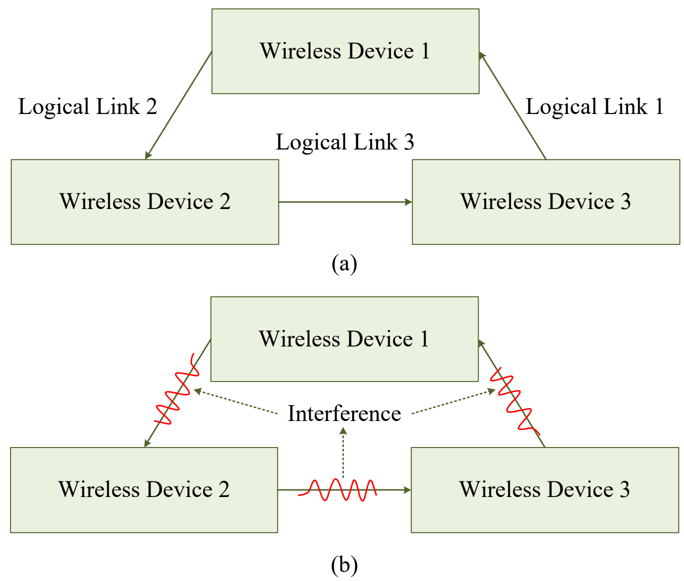

Fig. 1: (a) An example of a sample wireless communication system with three wireless devices where every device accesses one logical link. (b) Interference can come from the environment or/and other logical links.

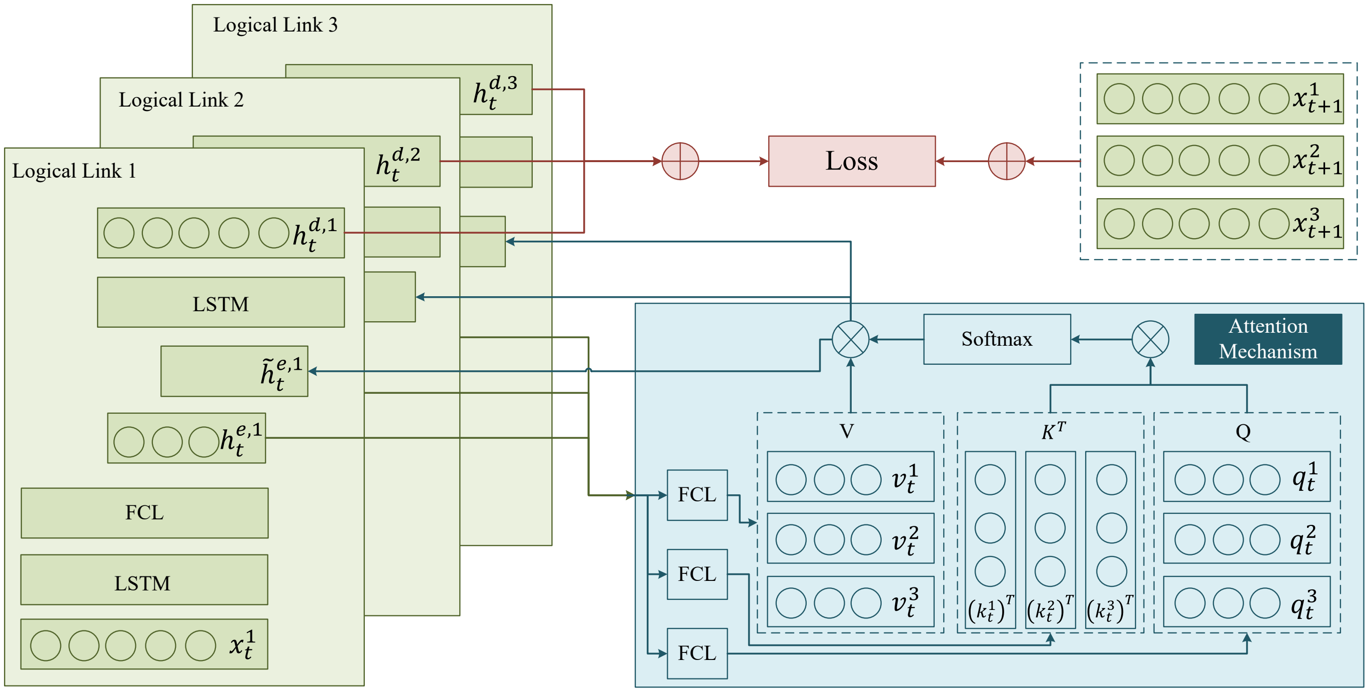

Fig. 2: The proposed model structure where the attention mechanism parts can learn the relationships between logical links to improve the prediction performance with the designed loss.

LSTM and attention mechanism is designed. The sequence to sequence part is responsible for flexible dimension reduction and prediction, and the attention mechanism is used to learn the relationships between logical links.

II. Dependability Prediction

A. Problem Statement

Fig. 1 shows the WCSs with and without interference produced from the environment or other wireless communication channels. We consider the logical link as the base, and the wireless devices are communicated with each other via logical links. The logical link has dependability parameters that can be different in terms of requirements [8]. The dependability parameters adopted in this paper are transmission time, update time, lost message state, consecutive message loss, and lost message ratio. Their definitions and collecting methods are detailed in References [8] and [13], respectively. We assume values of these parameters at time t as a vector of $\boldsymbol{x}_t \in \mathbb{R}^{1\times 5}$ and use its secondary subscript to distinguish different parameters and its superscript to represent the logical link number such as $x_{t,1}^1$ is the transmission time value of logical link 1 at time t. Considering the state continuity of WCSs, a time series of dependability parameters denoted as $\boldsymbol{X} \in \mathbb{R}^{n\times 5}$ can be used for prediction, and n is the length of the time series which is also called time steps. $\boldsymbol{X}$ is a matrix that contains n time steps:

$$\boldsymbol{X} = [\boldsymbol{x}_1; \boldsymbol{x}_2; ...; \boldsymbol{x}_i; ...; \boldsymbol{x}_t], \tag{1}$$

where $[\cdot;\cdot;\cdot]$ denotes the operation that connects vectors in one column. Thus, the dependability prediction task is to find a model when we input X it will predict the next dependability state $\boldsymbol{x}_{t+1}$.

B. The model

To address the problem, we proposed a model of dependability prediction with logical link correlation. Fig. 2 shows the model structure where the attention mechanism parts can learn the relationships between logical links to improve the prediction performance, and the main structure of the model is a sequence to sequence model which is based on LSTM cells [20], [21]. We denote an LSTM cell executing as Eq. 2, where c_t and h_t are the hidden state and output of the LSTM cell; $\delta(\cdot)$ and $\epsilon(\cdot)$ are Sigmoid and tanh activation functions. Note that all $\boldsymbol{W}$ and $\boldsymbol{b}$ in this paper are weight matrices and bias vectors and a subscript letter is used to distinguish them. $\delta(\cdot)$ and $\epsilon(\cdot)$ are calculated as:

$$\delta(z) = \frac{1}{1+e^{-z}}, \tag{2}$$

$$\epsilon(z) = \frac{1-e^{-2z}}{1+e^{-2z}}, \tag{3}$$

To simplify the following description, we take logical link 1 as an example since logical links 2-3 have the same neural network structure, and we omit the superscript for the logical link number. In addition, we use first-level superscript e and d to distinguish LSTM cells in the encoder and decoder parts. Here, the logical link number becomes a second-level superscript. For instance, $c_t^{d,1}$ denotes the hidden state of the LSTM cell in the decoder parts for logical link 1.

$$\begin{cases} \boldsymbol{c}_t = \delta(\boldsymbol{W}_f\boldsymbol{x}_t + \boldsymbol{W}'_f\boldsymbol{h}_{t-1} + \boldsymbol{b}_f) \odot \boldsymbol{c}_{t-1} + \delta(\boldsymbol{W}_i\boldsymbol{x}_t + \boldsymbol{W}'_i\boldsymbol{h}_{t-1} + \boldsymbol{b}_i) \odot \epsilon(\boldsymbol{W}_g\boldsymbol{x}_t + \boldsymbol{W}'_g\boldsymbol{h}_{t-1} + \boldsymbol{b}_g) \\ \boldsymbol{h}_t = \delta(\boldsymbol{W}_o\boldsymbol{x}_t + \boldsymbol{W}'_o\boldsymbol{h}_{t-1} + \boldsymbol{b}_o) \odot \epsilon(c_t) \end{cases} \tag{4}$$

The mathematical derivation of the proposed model is detailed as follows.

Dependability state $\boldsymbol{x}_t$ is fed into the proposed model, and c^e_t and h^e_t are obtained by Eq. 2. Then, we input the h^e_t into the attention mechanism and get the v_t, k_t, and q_t as follows.

$$\begin{cases} \boldsymbol{v}_t = \boldsymbol{W}_v\boldsymbol{h}^e_t + \boldsymbol{b}_v, \\ \boldsymbol{k}_t = \boldsymbol{W}_k\boldsymbol{h}^e_t + \boldsymbol{b}_k, \\ \boldsymbol{q}_t = \boldsymbol{W}_q\boldsymbol{h}^e_t + \boldsymbol{b}_q. \end{cases} \tag{5}$$

Note that v_t, k_t, and q_t are one row of matrices of V, K, and Q, and their dimension is decided by the output of the encoder.

Then the calculation of the attention matrix A as follows:

$$A = Softmax(\boldsymbol{K}^T\boldsymbol{Q}), \tag{6}$$

where $(\cdot)^T$ is transpose operation. Here, $Softmax(\cdot)$ is calculated as:

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{J} e^{z_j}}, \tag{7}$$

where J is the number of z.

We can obtain the tuned $\tilde{\boldsymbol{h}}^e_t$ learning from logical link correlation as follows:

$$\tilde{\boldsymbol{h}}^e_t = \boldsymbol{v}_t A. \tag{8}$$

The $\tilde{\boldsymbol{h}}^e_t$ is input into the decoder part which outputs the prediction result $\boldsymbol{h}^d_t$. We adopt mean squared error as the loss function to minimize the distance between input and output as follows.

$$Loss = \sum \|\boldsymbol{h}^d_t - \boldsymbol{x}_t\|^2. \tag{9}$$

Note that in practice, we can insert fully connected layers (FCLs) before and after the encoder and decoder parts. The number of FCLs mainly depends on the dimension of the input to get the best prediction results. Regarding the encoder part, it also depends on depress rate from the encoder input to the attention input. In this paper, we set one layer after the encoder to reduce the dimension by three. In addition, the example adopted in this paper has three logical links but the proposed model is applicable for cases of any number of logical links if we increase or decrease the number of sub-neural networks of the green parts in Fig. 2.

III. Experiment

Fig. 3 is the setup for measuring data sets. To prove the novelty of our model, we collected three data sets as the way described in Reference [22] by ifak's Multifiace [23]. The difference between the three data sets is the distance between wireless devices, where the setting distances are 10 m, 100 m, and 150 m, respectively. The number of every data set is 10 000, and 90% of it is used for training. For every case, it has

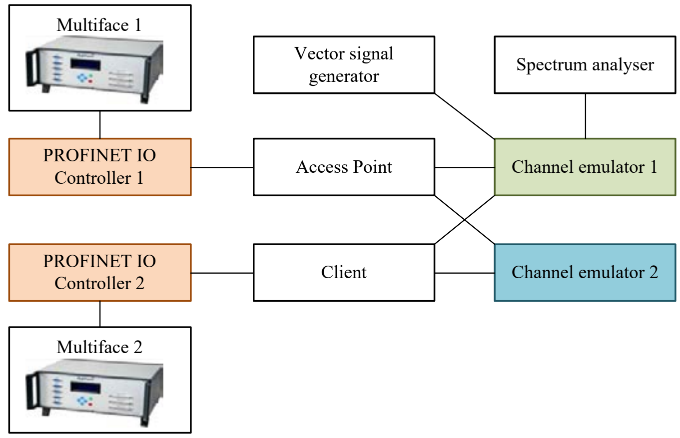

Fig. 3: Multifaces [13].

TABLE I: Case 1 with device distances of 10 m.

Parameters		TT	UT	LMS	MLR	CML
L1	MTL	0.04275	0.00064	0.06003	0.000009	0.00005
	DPLC	0.03855	0.00068	0.05701	0.00087	0.00005
L2	MTL	0.02714	0.00024	0.0	0.00001	0.00006
	DPLC	0.02412	0.00021	0.00008	0.00005	0.00005
L3	MTL	0.02603	0.00198	0.00216	0.00018	0.00006
	DPLC	0.01716	0.00147	0.00219	0.00038	0.00006
Mean	MTL	0.03197	0.00095	0.02073	0.00039	0.00006
	DPLC	0.02661	0.00078	0.01976	0.00038	0.00005

three logical links, named L_1, L_2, and L_3. Note that all data should be normalized as the method in Reference [13].

We make comparative experiments between the Multi-learning (MTL) model [13] and the proposed model. In both models, we set 12-time steps for input data. The batch size is 200, the epoch is 200, and the optimizer is Adam with a learning rate 0.005.

We conducted experiments on the three data sets, respectively. Fig. 4 shows the dependability prediction results of logical link 1 from data set 1 that has been divided into TT, UT, LMS, LMR, and CML, respectively, and it illustrates that the proposed model has a better mean squared error than the MTL model. Note that the DPLC abbreviated from dependability prediction with logical link correlation is the proposed model.

Tables I-III list all parameter comparisons of prediction MSE between the proposed and MTL models, where we also

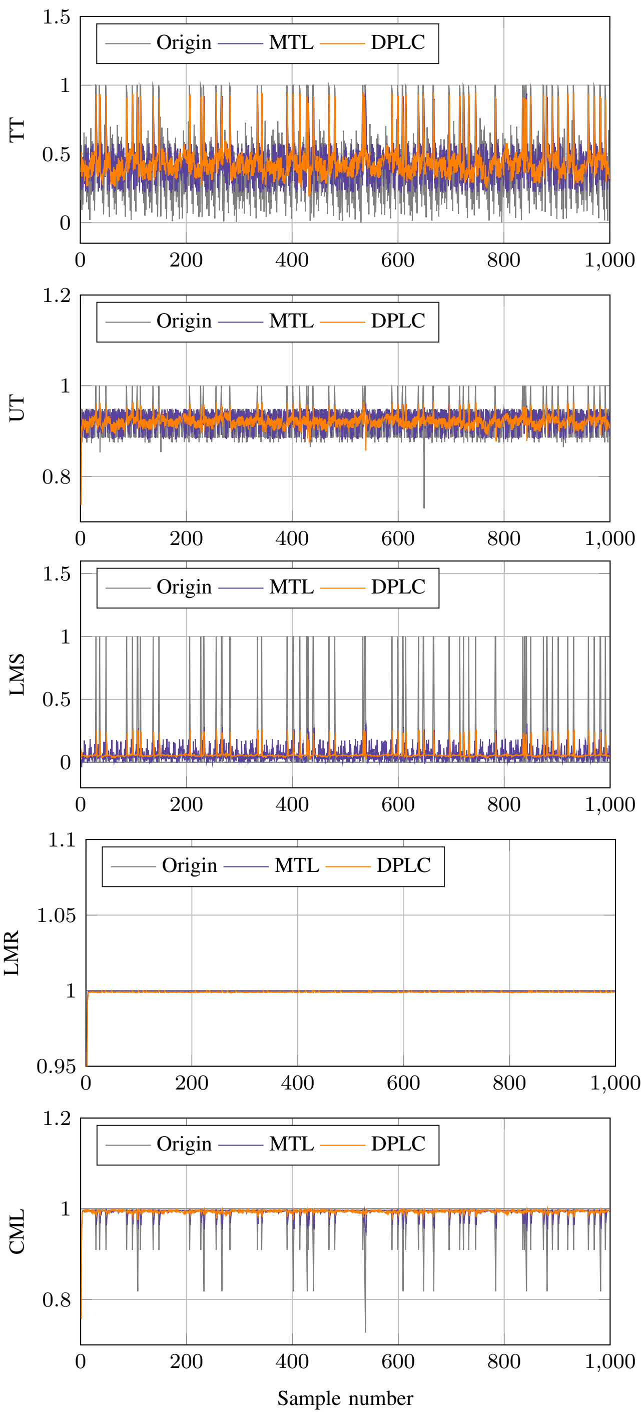

Fig. 4: Dependability prediction result of logical link 1 from data set 1.

calculate the mean of the results of the three logical links. In general, the proposed model always outperforms the MTL model. Particularly in Case 1, the proposed model has bigger superiority than Cases 2 and 3, where the improvement of the TT prediction mean is up to 17%. The reason is that the data in Case 2 and 3 have bigger fluctuation than in Case 1 which means a larger solution space, and the fluctuation is caused by the longer distance between wireless devices. However, in these two harsh cases, the DPLC still has a better prediction effect than the MTL model.

TABLE II: Case 2 with device distances of 100 m.

Parameters		TT	UT	LMS	MLR	CML
L1	MTL	0.05716	0.00275	0.08443	0.00254	0.00066
	DPLC	0.05653	0.00271	0.08463	0.00243	0.00006
L2	MTL	0.05466	0.00208	0.05724	0.00147	0.00006
	DPLC	0.05111	0.00209	0.05728	0.00149	0.00006
L3	MTL	0.04911	0.00068	0.03445	0.00039	0.00005
	DPLC	0.04838	0.00054	0.03475	0.00038	0.00005
Mean	MTL	0.05364	0.00184	0.05871	0.00147	0.00006
	DPLC	0.05198	0.00178	0.05889	0.00142	0.00005

TABLE III: Case 3 with device distances of 150 m.

Parameters		TT	UT	LMS	MLR	CML
L1	MTL	0.10844	0.00078	0.22141	0.00089	0.00006
	DPLC	0.10844	0.00076	0.21381	0.00075	0.00005
L2	MTL	0.08891	0.00038	0.23317	0.00048	0.00005
	DPLC	0.08603	0.00037	0.23374	0.00047	0.00005
L3	MTL	0.08892	0.00037	0.23302	0.00045	0.00006
	DPLC	0.08607	0.00039	0.23349	0.00048	0.00006
Mean	MTL	0.09542	0.00051	0.22921	0.00061	0.00006
	DPLC	0.09351	0.00051	0.22701	0.00056	0.00005

IV. Conclusion

This paper proposed an sequence to sequence model based on the LSTM and attention mechanism, which leverages the correlation between logical links to improve the prediction performance. The sequence to sequence part is used mainly for dimension reduction and prediction while the attention mechanism is set for learning the correlation between logical links. We measured three realistic data sets considering different device distances of 10 m, 100 m, and 150 m, respectively. Then, we conducted comparative experiments on these data sets which prove the effectiveness of the proposed model.

In future work, we attend to replace all LSTM cells as attention mechanisms and test more data sets to prove the robustness of the proposed model. Further, we will design these attention mechanisms in a low-complexity way to meet the resource-constrained condition of the wireless devices.

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