An Evaluation Method for C2 Cyber-Physical Systems Reliability Based on Deep Learning

HE Ming, ZOU Qingbing, CHEN Xiliang, LUO Chen, KANG Kai

College of Command Information Systems, PLA Science and Technology University, Nanjing 210007

Abstract: As the battle space for Command and Control (C2) has grown more complex, the C2 reliability that threatens their ability is facing many new challenges. The Cyber-Physical System (CPS) technology is brought into C2 systems, C2 CPS architecture is structured, and a real-time online method for evaluating the reliability of C2 CPS is designed. The method establishes an assessment framework with use of deep learning, implements an online rank algorithm, and achieves the online analysis and evaluation of the reliability of the C2 CPS. The simulation experiments show the validity and correctness of the assessment method is verified. The system reliability has been greatly improved.

Key words: C2 CPS; online assessment; deep learning

1 Introduction

Command and Control (C2) Systems was mostly constituted of four general types of elements: sensors, command posts, computers, and communications networks. As the battle space for C2 has grown more complex, the C2 reliability that threatens their ability is facing many new challenges. To enable commanders and their staffs to achieve effective and efficient work processes, C2 systems must be reliable. [1] A reasonable and scientific assessment of C2 systems helps find ways to improve their reliable operation and provide continuing operation command.

Cyber-Physical System (CPS) is an intelligent system, through the organic and depth fusion of computing, communication and control technology, it realizes the combination and coordination of computing resources and physical resources. [2][3] It provides a new way for the development of C2 systems to combine with communication, calculation and control technology. According to the development trend, we can lead the CPS technology in C2 systems to establish C2 CPS. Deep learning is a set of algorithms in machine learning that attempt to model high-level abstractions in data by using architectures com-posed of multiple non-linear transformations.[4][5] In view of the C2 CPS with large scale processing data, continuous uninterrupted online operation, and the operator can only be closed feedback etc, urgent need to implement the real-time reliability evaluation for C2 CPS. Based on this back-ground, this paper proposes a deep learning based online evaluation method to improve the reliability of CPS.

2 Theoretical basis

2.1 The raise of the problem

With the continuous development of technology, C2 systems warfare evolved into the joint operations C2 systems, under the condition of the existence of the complexity, variability, uncertainty and difficult to control, we require the system must be effective and reliable. Networking, intelligentization and versatility is the inevitable development trend of C2 systems.

One of the main causes of C2 systems failure is the failure of system components. In the face of growing demand, charges system must guarantee the high running reliably, and should also be as much as possible to use existing infrastructure in order to reduce the cost. It inevitably contains some of the old, unreliable electrical components, this added a lot of hidden trouble for C2 systems reliability.

2.2 The architecture of C2 CPS

Considered the characteristics of C2 systems, the design of the C2 CPS architecture is shown in Figure 1:[6-13]

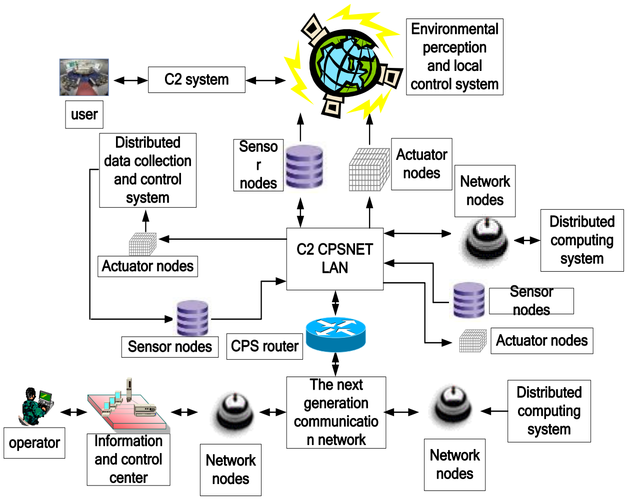

Figure 1 The architecture of C2 CPS

The whole system structure of C2 CPS includes C2 network and information network. Information network mainly includes a variety of sensors, distributed computing, CPS real time network.

3 Design and implementation of the algorithm

Bayes method is widely used in reliability analysis, and usually uses the reliability information of each unit of the system as the prior information of the system. By compositing the prior information and less test data, we can obtain system reliability estimate.[14]

In order to ensure the reliability of C2 CPS, the system components are sorted by confidence drawn from the history data, use it as an expert opinion model[15]. We use deep learning to build online queuing algorithm, with the effective integration of multiple models, we get the system forecast. When forecasting system failure may occur, we improve the hidden trouble parts of marked, thereby improving the reliability of C2 CPS.[16][17]

3.1 Construction component queue

Using the method mentioned in literature [18], we obtain the component confidence lower limit, by the analysis of empirical data, system component life approximately satisfy the exponential distribution.

Assuming the C2 CPS system consists of k components, by the reliability testing data of the system, we obtain the prior distribution of the reliability is $\pi(R) = LG(R; r_1, \eta_1)$. By Bayes theorem we get that $\pi(R \mid r, \eta) = LG(R; r_1 + r, \eta_1 + \eta)$. The confidence lower limit of component R is

$$R_L = \exp[-\chi^2_{1-\alpha}(2r_1 + 2r + 1)/(2\eta_1 + 2\eta)].$$

And η is the system equivalent number of tasks.

We order the components according to the confidence lower limit, and create components queue. That is an expert opinion model.

3.2 Online queuing algorithm

According to deep learning based on expert opinion thought, we construct online queuing algorithm, and use the method proposed by 3.1 to sort components periodically, which will produce multiple queue model, each model is an expert opinion. Mix a plurality of expert opinion together and we get a meta model, namely the final prediction queue. The meta model is the weighted average of a plurality of expert opinion.

The variables used in the algorithm and their meanings are shown in table 1:

Table 1 variables

Variable name	Meaning
M	Representation model set, also known as expert opinion, brings together all the queuing model
L	Represents the upper limit number of elements in M
Q	Model queue, generated by the performance of the model
λ	Unit of time
$age(m_i)$	The exist time that m_i in M
γ	The range is [0,1], for the weight update function to adjustment model weights, the greater it is, the more slowly of learning
Δ	The number of model that participate in the prediction
ω_{new}	The initial weight that distributed to the new model
ω_{min}	The minimum weight of the model in M
ω_{max}	The maximum weight of the model in M
τ	The percent in [ω_{min}, ω_{max}], used to determine the size of the distribution values for the new model
d_i	The loss of the model in the last system fault
z_i	The reliability of the model
z_{best}	The best reliability of the model in the component queue
z_{worst}	The worst reliability of the model in the compo-

	nent queue
θ	Used to set the exponential decay of time for the model

With the formula (1) to distribute initial weight for the new model, and it is related to the already had model:

$$\omega_{new} = \tau \times (\frac{\omega_{\max} + \omega_{\min}}{2}) \qquad (1)$$

Each weights of the model in M changes dynamically with time, formula (2) is the weight update function, to update the model weights:

$$\omega_i = \omega_i \times \gamma^{d_i} \qquad (2)$$

d_i is calculated by formula (3):

$$d_i = \frac{z_{best} - z_i}{z_{best} - z_{worst}} \qquad (3)$$

Because of the model based on the unit time λ added, in order to avoid the model set M infinite increase, when the model number exceeds the limit L, that is $|M| > L$, use weights of model and service time to queue the models, and create queue Q. Exponential with parameter $\theta \in (0,1)$ to set the model using time decay, remove the model at the end of Q.

Finally, average the weighted of the Δ model with the function of $Weighed\_average(\{\omega_i \times Ranking_i(t))$, the good performance of the model will be given a higher weight, the predictions of the model results will be fused and get the final forecasting result, i.e. meta model.

Figure 2 is the pseudo code of online queuing algorithm. In the algorithm, we set up a current model set M, every unit of time λ, a new model is increased to M, delete the worst model of Q when $|M| > L$.

$OnlineRank(L, \Delta, \gamma, \theta, \tau, \lambda)$
initialize L
while{$true$}
do at time t
    $Ranking_i(t) \leftarrow m_i(Capture(t))$ for $m_i \in M$
    $\Lambda \leftarrow$ the modle that at the front of Q and the number is Δ
    $Ranking(t) \leftarrow Weighed\_average(\{\omega_i \times Ranking_i(t) | m_i \in \Lambda\})$
    if new fault happens
        then z_i for $m_i \in M$
            $z_{best} \leftarrow \max(z_1, z_2, ..., z_{|M|})$
            $z_{worst} \leftarrow \min(z_1, z_2, ..., z_{|M|})$
            for $m_i \in M$
            do $d_i = \frac{z_{best} - z_i}{z_{best} - z_{worst}}$
                $\omega_i = \omega_i \times \gamma^{d_i}$
    if after time interval λ
        then add a new model into $M \longleftarrow m_{|M|+1}$
            $\omega_{new} \leftarrow \omega_{\min} + \tau \times (\omega_{\max} - \omega_{\min})$
            $\omega_{|M|+1} \leftarrow \omega_{new}$
            $M \leftarrow M \cup \{m_{|M|+1}\}$
            if $|M| > L$
            then delete the worst model according to $\omega_i \times \theta^{age(m_i)}$

Figure 2 online queuing algorithm pseudo code

4 Reliability assessment method

4.1 General framework

In order to evaluate the reliability of C2 CPS, presented an automatic online method for assessing the reliability of C2 CPS based on deep learning. As shown in Figure 3, the algorithm assesses C2 CPS lucidly and automatically, they work parallelly, and will not have any effect on each other.

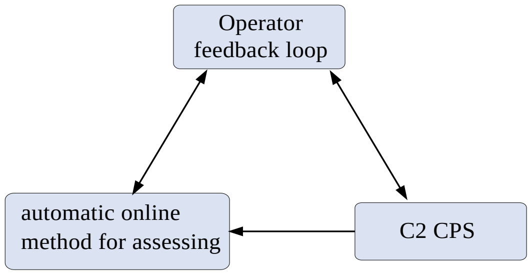

Figure 3 Automatic online assessment framework

According to the prescribed time interval of the system to queue the components, and then get expert model, integrate a number of model to get the final prediction model, predict the most likely element that will cause the next system fault, and the information feed back to the operator real-time, so the operator can take timely measures to avoid the system failure, and effectively improve the C2 CPS reliability.

4.2 The work flow

The entire work process consists 4 steps:

Step 1, gain experience data of components and state information from C2 CPS;

Step 2, according to the information collected by online queuing algorithm to construct meta-model, to evaluate the system reliability;

Step 3, the predicted meta-model as a result of the assessment, feed back to the operator interface with the form of alarm;

Step 4, according to the alarm information, the operator take corresponding measures on the components that may trigger the next failure of C2 CPS to ensure trouble free operation.

The whole evaluation process works online and circularly, and keep pace with the C2 CPS, effectively improved the reliability of the system.

5 The experimental simulation

For the system state information, in the data classification experiment, classification model trained with the data of 80%, with the remaining 20% do blind test data.

The following settings for the online queuing algorithm's parameters were used in the experiments: $\gamma = 0.7$, $L = 30$, $\Delta = 10$, $\lambda = 5$, $\theta = 0.9$,and the parameter that determine the initial weight value of the new model $\tau = 0.7$.

Respectively, within in a month, simulate the condition that the C2 CPS equipped with online assessment methods and not equipped, the reliability of the system are shown in figure 4:

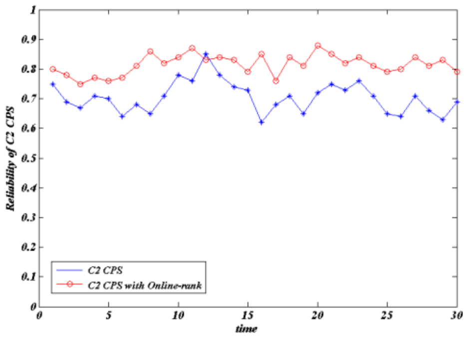

Figure 4 The experimental results

Simulation results show that after equipped with the online assessment method, the reliability of the C2 CPS remains at about 0.8, has been significantly improved.

6 Conclusion

In this paper, we study the reliability of C2 CPS. An automatic online method for assessing the reliability of C2 CPS based on deep learning is presented. The next step is mainly for C2 CPS model, algorithm and implementation tools and so on. In particular, the system topology and structure can make the component failure, loss or functional decline, at the same time, considering that C2 CPS is in ceaseless development, and intelligent electronic equipment will be constantly added to the system, the way of accessing empirical data also need further study.

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