Acta Technica 62 (2017), No. 5A, 245–254

Active early warning technology of information system operating state based on deep learning

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Abstract. In order to effectively prevent the malfunction problem of information system, this paper has presented an active early warning technology based on deep learning, which has realized the effective combination of the advanced learning and the early warning technology of the information system, and is beneficial to the real-time monitoring of different problems in information system operation. This technology can divide the conflicting types of information into different sets of information in the sharing operational status, and requires that the similar nature of the information subset can be assigned to share the same knowledge operating status, and therefore can prevent the schedulable loss by the information blocking each other in the system operation. Our experiment results show that, compared with similar technologies, the provided technology can split the information subsets, and allocate them to the running status of the same information system according to the information relevance evaluation results. At the same time, it can move the disassembled information to the current running state of the lightest information system to reduce the system spin loss.

Key words. Deep learning, proactive warning technology, information system; information collection.

[1]Acknowledgment - This research is supported by the project “Research and Application of Early Warning and Fault Diagnosis Technology for Information System Operation”. In this project, after the information system running data collection and cleaning is completed, the next step that needs to be carried out is to analyze and excavate the historical data of historical operation and maintenance. This is essentially a big data mining analysis. Big Data Mining mines the hidden, previously unknown, useful information for decision-making from large data sets (which may be incomplete, noisy, indeterminate, various forms of storage). In this project, it is necessary to analyze and correlate mining data according to the collected operational data to realize the overall perception of operational status of the information system, including comprehensive analysis of operation and maintenance data, real-time warning of operation and maintenance risks and to achieve pre-solve the problem of active operation and maintenance to achieve intelligent operation of aided decision-making.

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1. Introduction

Deep learning and active warning of the information are needed in different running status of information systems in order to give full play to the ability of active early-warning technology for deep learning in the running status of information systems [1−3] .To minimize the impact on the operation status of different information systems, the dependence between the information and mutual blockage is caused by the waste of resources of the system [4−6]. Active warning technology in the information system running state must be set to keep all information independent of each other [7−8] Problem is similar to solve the technical information system to complete the active state of the warning [9]. Although the overhead of this technology is small, we should not ignore the constraints of information between the synchronization [10];

This paper presents a deep learning-based information system operating status of active warning technology. This technology is used for the information system operating conditions of the various information classification and processing of a number of information sub-set, and the relevant information to the same subset of moving can effectively prevent the phenomenon of information congestion in the operation state of the information system. If the information subset cannot be allocated to the same operation state, the information correlation analysis can be used to decompose these information elements to avoid the system's overall utilization due to the congestion of information occurring during the operation of the information system.

2. Operational status model of information system

Periodic depth learning *Task* (i) is expressed in the form of a triplet τ_i =(T_i, C_i, π_i) where T_i represents the period of information, and π_i represents the priority, and C_i represents the worst execution time. Whenever a period occurs, $\mathrm{T}_i$is in the ready state first, and then there is no release jitter. Each execution of τ_i represents an instance of information, which is usually denoted by J_i. The relative deadline of information is consistent with its period.

Definition 1: ui is the CPU utilization of τ_i, which is equal to the result of the ratio between the worst execution time of τ_i and the period, which is expressed by the equation u_i=C_i/T_i. Periodic information set of Γ={τ_1, τ_2, ..., τ_n } is the operating state processor of the isomorphic information system P={p_1, p_2, ..., p_m}, where $\mathrm{p}(\tau_i)$ represents the operating state of the information system where τ_i is located , and $\tau(\mathrm{p}_k)$ represents all the information sets assigned to the information of system operating state p_k, which consists of q shared operating states of Φ={ρ_1, ρ_2, ..., ρ_q}, where Θ_i Φ means $\mathrm{T}_i$must satisfy the exclusive access condition ρ_s Θ_i in the shared operating state accessed by $\tau_{i.}$. When ρ_s is only allocated to the same information system running state and accessed by information, it should be referred to as local resources and vice versa Resources.

3. Information blocking analysis of information system operating status

Blocking of access to information occurs when the global resource is locked by other information system operating conditions during the requested access, and the information needs to be kept in a spinning state to wait for global resources as required by the MSRP protocol. When information waits for some same global resource at the same time, MSRP chooses FIFO spin method to prevent starvation.

Lemma 1: Suppose that τ_j is the maximum time required for a visit to the global resources $\rho_{s,}$ and the longest time is $\xi_{j,s}$, then it will satisfy any τ_i p$_k$ ρ_s has the visit requests for the longest time is expressed as follows:

$$W_{k,s} = \sum_{p_r \neq p_k} \max_{\tau_j \in \tau(p_r)} \xi_{j,s} \tag{1}$$

Definition 2: The spin loss (S_k) is equal to the ratio of the longest spin-wait time to $tLCM$ for each item of information in the operating state of the information system in the $tLCM$ period. The $tLCM$ is equal to the least common multiple of the information periods in the information system operating state.

In order to ensure the real-time schedulable of the system, a reasonable processor resource needs to be reserved so as to ensure that the system can achieve the deadline standard required for real-time information under any state. Therefore, Spin loss method can reduce the system's overall resource consumption, and thus effectively improve system utilization.

Theorem 1: For arbitrarily scheduled τ_i p$_k$, the system schedulable loss is caused by it and $\tau_i$are equal to the spin loss S$_k$(i) formed by p$_k$, and that will satisfy:

$$S_k\left(i\right) = \frac{\sum_{\forall \rho_s \in \Theta_i \cap \Phi_G} n_{i,s} \bullet W_{k,s}}{T_i} \tag{2}$$

4. System state active early warning technology for deep learning

4.1. Active state of information system active warning technology

The implementation process of this technique is as follows: firstly, we can classify all the information that exists in Γ into conflict with each other as a set of information, and learn all the information in the same information subset deeply into the same information system. Randomly selected two information τ_1 and τ_2 to access the resource ρ_1, while τ_2 and τ_3 can access to the resource ρ_2, and then the above three information belong to the same information subset, and the results are shown in Figure 1.

It will be active in the information system to any active warning state, and to the operation of any information system will not cause the phenomenon of obstruction.

We can use the following recursive technology to complete the active warning of the state of the information system.

Technology 1 can be achieved through the following treatment ideas:

(1)Assume that the messages remain independent of each other in their initial state (IndependentTRUE) and are not grouped (linkNONE).

(2)If all the information is not related to link, and this time is the end of the technology. On the other hand, we can select a group of unprocessed information, and the group status of the information can be modified to linki, and then we will judge whether to share the running status with other information.

(3) If τ_i and the same shared operation status is accessed simultaneously with some other information, set the status of these two messages are set to FALSE at the same time, and then set the status of the packets to τ_i.link, and group them into the same information element set ofτ_i, and then use recursive method from the beginning to re-perform this step.

(4)Analyze$\tau_i$and follow-up if we want to access the same shared running status, and then go to step (3)when we need to access the same shared running status. Otherwise, we can skip to step (2).

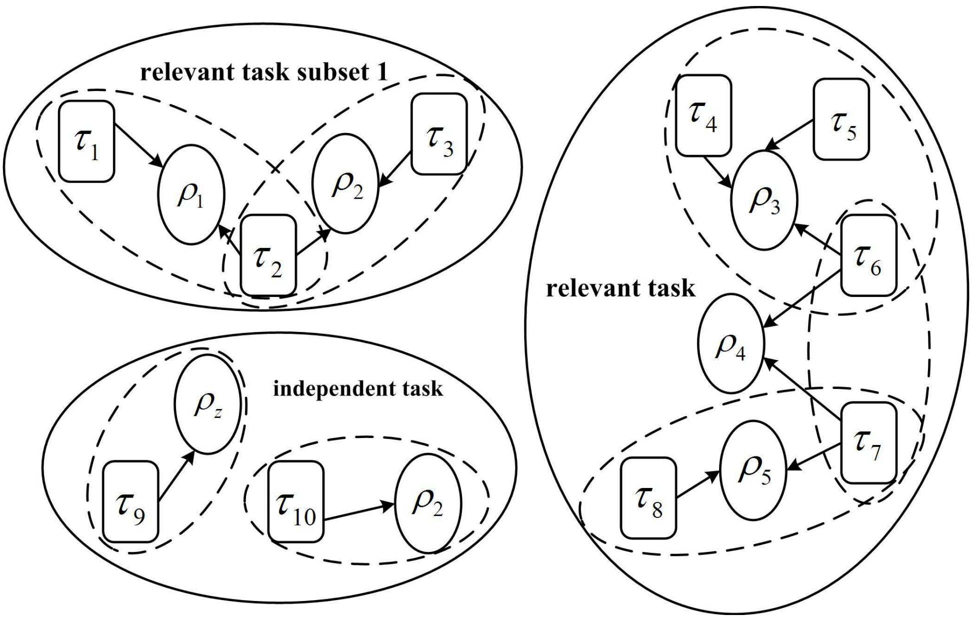

Fig. 1. Information system operating status of active warning technology

4.2. The relevance of information system operating status evaluation

This paper presents a method of evaluating the relevance of information as follows:

Lemma 2: For the sum of anyτ_i, spin loss formed on p_k withτ_j $\tau(\mathrm{p}_k)$ is the sum of the p_k spin losses each has the following equation:

$$S_k(i+j) = S_k(i) + S_k(j) \tag{3}$$

The matrix U represents the longest time that x($1 \leq x \leq n$) information needs to access shared operation state. The element $u_{i,s}$ represents the longest time that i-th information needs to access shared operation state of$\rho_s$according to Lemma 1 of $u_{i,s=}\xi_{c},_s$. If $u_{i,s=}0$, then the shared operating status of$\rho_s$is not accessed.

$$U_{x\times q} = \begin{pmatrix} u_{1,1} & u_{1,2} & \cdots & u_{1,q} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,q} \\ \vdots & \vdots & \ddots & \vdots \\ u_{x,1} & u_{x,2} & \cdots & u_{x,q} \end{pmatrix} \tag{4}$$

Theorem 2: Let $\text{Ƒ} = \{\tau_a, \tau_b, \cdots, \tau_c\}$ $(x = |\text{Ƒ}| \leq n)$ is the subset of information obtained for technique 1, which be expressed as the time taken to access the shared operating stateƑby x×q (q is the number of shared operating states) matrix U. Arbitrarily and assignƑto the information system operating state of p_r while all the other information present in it is deeply learned into the information system operating state p_k(rk), and then the information system Ƒof operating state p_k is generated by the remaining information spin loss as follows:

$$S_k\left(\text{Ƒ}^i\right) = \sum_{d\in[1,x]\wedge d\neq c} \frac{\sum_{s=1}^{q} a_{c,d}}{T_{f(d)}} \tag{5}$$

$$a_{c,d,s} = \begin{cases} u_{c,s} \times n_{f(d),s}, u_{c,s} \times u_{d,s} \neq 0 \\ 0, \qquad\qquad u_{c,s} \times u_{d,s} = 0 \end{cases} \tag{6}$$

Where$\text{Ƒ}^i = \text{Ƒ} - \{\tau_i\}$, and F(d) is the information sequence number corresponding to the *d-th* row of matrix U$x\times q$.

The spin losses obtained by Theorem 2 are derived from within and from information Ƒaccess to the same shared operating stateτ_i, and $S_k\left(\text{Ƒ}^i\right)$ can be seen that the correlation between the remaining information existing within the data$\tau_i$that can be quantitatively analyzed by means of spin lossƑ. This paper is used as a result of the correlation between the evaluation and the remaining information ofτ_i.

4.3. Basic theoretical knowledge of deep learning

The original subset of information is assigned to the information system operating state p_k, and$\tau_i \in$ Ƒis assigned to p_r(rk) in the first splitting process. The split information ofτ_u is then distributed to pr or to the remaining information system state of p_y. Combining Lemma 1, we can see that the maximum value of the time for information access to the information system operating state p_k is max($\xi_{i,s,m}$) when pr and $\rho_s$are assigned to the same shared operating state of $\xi_{u,s}$. The maximum waiting time for information can access to the information system operating state p_k if we assign p_y to $\xi_{i,s}$+ $\xi_{u,s}$. According to Theorem 1 and Lemma 1, splitting information and deeply learning is the same information system$\rho_s$operating condition that can significantly reduce the information ofτ_u, and congestion time of information systems is operating conditions, and thereby we can avoid additional spin loss.

When the information obtained by splitting is all deeply learned to the same information system running status, it can be regarded as a whole deep learning information, which is realized by integrating the information logic to be split up, and the original deep learning information each split is equivalent to the original information from a subset of split to get a deep learning information. The specific process is shown in Figure 2. If we want to split from the information subset of $\tau_3\backslash\tau_1$ (this time the split ofτ_1 has been completed), we can process as a process of logically combining to obtain a deep learning message ofτ^*, and then split it to separate from the original information subset ofτ^*.

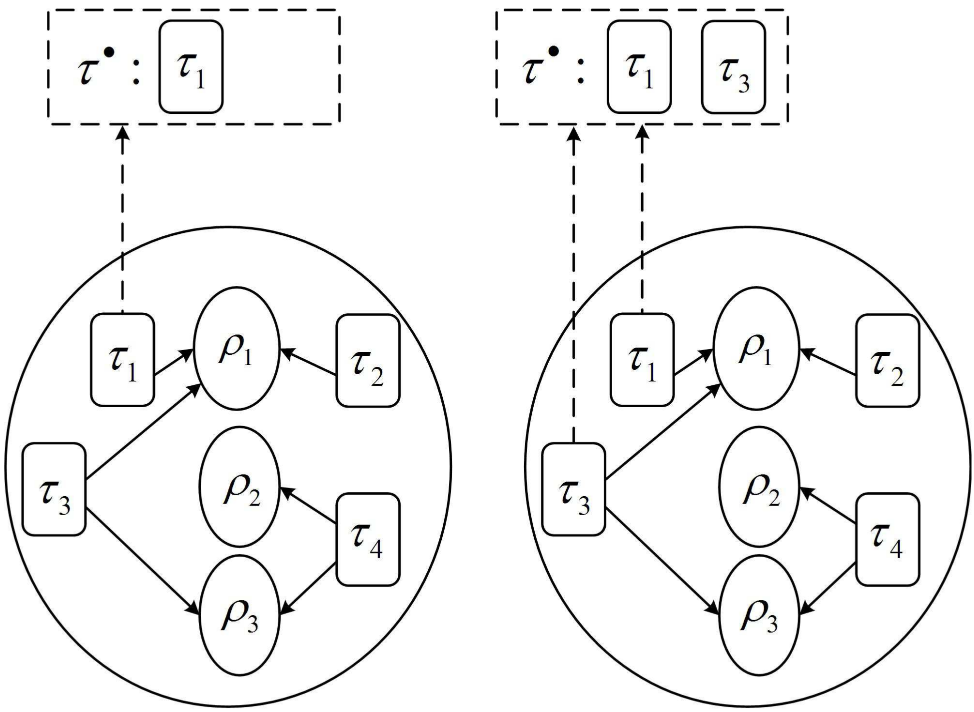

Fig. 2. composition method of deep learning information

Since each row vector of matrix U represents a piece of information, the information logic can be merged with the transformation of row vectors, and set$\text{Ŧ} = \{\tau_a, \tau_b, \cdots, \tau_c\}$ $(x = |\text{Ŧ}| \leq n)$ as the relevant information subset obtained from technique 1 and the matrix U.

Let the depth learning information correspond to the v-th row$\tau_i$of the matrix U, which is the c-th piece of information that is obtained by splitting, and then the following transformations are performed on the elements ($u_{v,s}$) of the vth and sth columns in the matrix U as follows:

$$\forall s \in [1, q], u_{v,s} = \max(u_{v,s}, u_{i,s}) \tag{7}$$

Theorem 3: If the original information system ofFis assigned to the operating state p_k at the same time, and all the information ofFobtained from the split is assigned to the information system operating state p_r, and then rk, and the remaining information ofFin the waiting is for the depth of learning during the period of information, and spin loss will occur to the information system operating state p_k, and the maximum value is$S_k(Ғ^i)$.

According to Theorem 3, $S_k(Ғ^*)$can be used as an index of the correlation between the depth learning information of$\tau^*$and the remaining information ofFin the evaluation. Considering that the deep learning information is obtained by combining a great deal of information through merging, if all the information corresponding to the minimum value is split, it is possible to ensure that the spin-down of the operating system of the information system$S_k(Ғ^*)$caused by the remaining information after the completion of the splitting is minimized.

5. Experiment and analysis

5.1. Performance index

In this paper, the acceptance rate of information set is used to evaluate the performance of the active warning technology of the operating status of the information system, and the selected processor platform type is the running status of the information system 8. Suppose each experiment will generate N=10000 random information sets, depth learning technology A of maximum of M information sets can be scheduled. At this time, the acceptance rate of the information set corresponding to technology A is equal to M/N. If the obtained information set has a large acceptance rate, the efficiency of the technique is correspondingly higher. Also compared with different systems have the average spin loss of the system, which is defined as follows:

$$\alpha = \frac{\sum_{\forall \Gamma} \sum_{\forall p_k \in P, \forall \tau_i \in \tau(p_k)} S_k(i)}{N} \tag{8}$$

5.2. Information System Operating State Simulation

The number of messages n depends on the distribution of CPU utilization u_i, and the utilization of the system of$SU = \frac{\sum_{\forall \tau_i \in \Gamma} u_i}{m}$(0 <SU<1) is occupied by each message, and at the same time the parameters satisfy the following conditions:

(1) $u_i$was obtained from [0.1,0.3] in a random manner by the Unifast-Discard technique.

(2) T_i is obtained randomly from [100, 1000], and its natural logarithm is uniformly distributed to simulate various types of real-time information.

(3) The execution time of C_i depends on the period of the message and its CPU utilization while satisfying the condition $C_i = T_i \times v$.

(4)The information has the same priority as the Rate Monotonic (RM) technology. The higher the satisfaction period is, the lower the priority is.

(5) A group of running states contains 16 shared resources, which can be randomly accessed by 8 pieces of information.

(6)Each message contains a maximum of 6 critical sections. The shared operating states obtained from the subgroups should be selected to obtain the shared operating states of the critical sections.

(7)The access critical time to share the running status is in the range of [1, 20].

5.3. Experimental Analysis

(1)Acceptance rate of information set Figure 3 shows the relationship between system utilization rate of SU and aggregate acceptance rate, when the critical length is equal to 4 and the critical number of each piece of information is 2. From Figure 3, It can be seen that there is a monotonous decreasing relationship between SU ??acceptance rates and SU. When the WFD and Syn-aware technology are under the condition of SU> 0.6, the information set will have non-schedulable features and SR-aware technology. It is necessary to meet the conditions of SU> 0.7 before the non-schedulable of information aggregation. Comparison of these two technologies shows that Syn-aware technology has a greater acceptance rate of information collection.

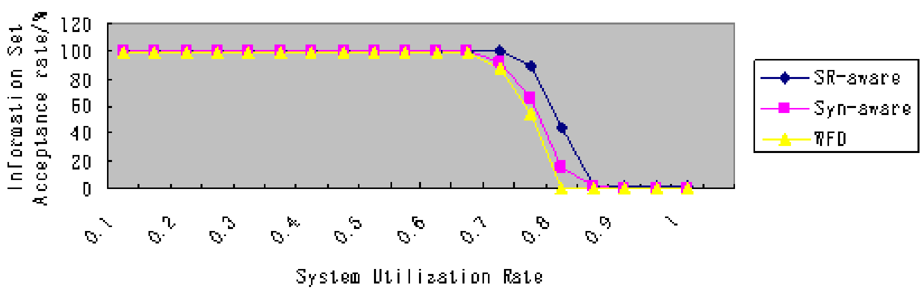

Fig. 3. Relationship between collection rates of acceptance and system utilization

Figure 4 shows the different technical performance and the relationship is between the length of the critical area, and from the figure we can see that the information is composed of two critical areas with SU=0.65. When the length of the critical area increases, the need to wait the spin-up time of information also increases, and the acceptance rate of technical information set may also decrease. If all the information subsets cannot be allocated to the same information system running status, SR-aware technology is combined with the results of correlation analysis of the information split, and then assigned to the same state of the information system operation, information only for specific information system operating state information spin wait, and effectively reducing the spin loss. Syn-aware technology uses a random way to split and distribute the information combination, therefore the longer the critical section length will lead to a significant increase in system utilization loss .Because Syn-aware technology to split the information subset has a greater randomness, therefore its performance and WFD technology is similar.

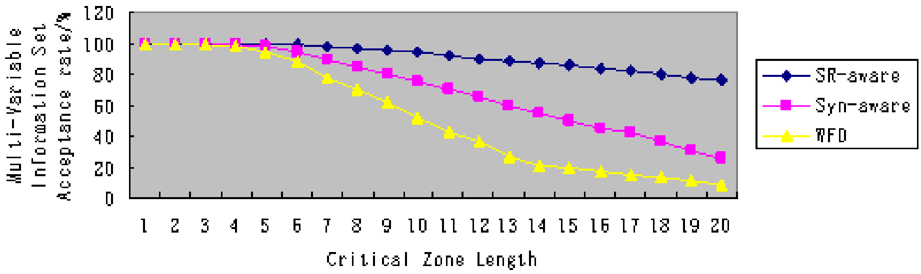

Fig. 4. Acceptance curves of the critical zone length and the information collection rate

Figure 5 shows the relationship between the number of information critical sections and the information set acceptance rate, when the critical section length is equal to 4 and SU=0.65. When the number of information critical sections increases, the spin-waiting has shared operating state results. The loss of system resources will also increase, ultimately resulting in different acceptance rates of different sets of technical information to a lesser extent. In addition, the information will be interlinked and evolved into a larger subset of information during the access to the shared operating state. If the number of critical sections of information is high, Syn-aware and SR-aware techniques require multiple subdivisions of the subset of information. Because SR-aware technology has a more efficient deep learning technique, information collection acceptance rate is higher.

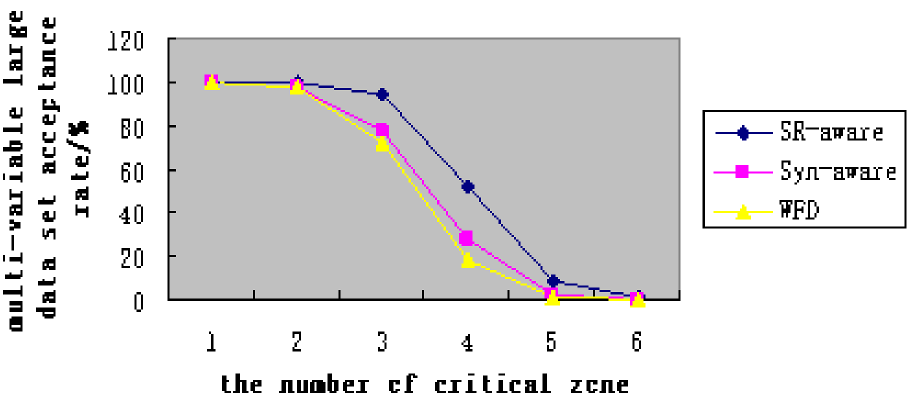

Fig. 5. Relationship between the acceptance rate of information collection and the number of critical sections of information

6. Conclusion

This paper presents a deep learning-based information system operating status of active early warning technology, which is through the application of deep learning and information system operating status of active early warning technology, and effectively prevent the different information systems operating conditions occurred in the information blocking phenomenon. In order to increase the system, this paper also compares the performance of the technology with the rest of the technology, and the results show that using this new technology to proactively alert information collection technology has more efficiency than Syn-aware and WFD.

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Received November 16, 2017