Equipment Health Assessment Based on Node Embedding

Jian Li, Xiao Chen, Chao Zhang, Hao Wu, Xin Yu, Shiqi Liu and Haolei Wang

March 7, 2023

Equipment Health Assessment Based on Node Embedding

Jian Li, Xiao Chen, Chao Zhang, Hao Wu, Xin Yu, Shiqi Liu, and Haolei Wang*

State Grid Zhoushan Electric Power Supply Company of Zhejiang Power Corporation, Zhejiang Zhoushan 316021, China
88018211@163.com, 18768070482@163.com, 948451226@qq.com, 44979592@qq.com, gentlefox@163.com, 543854141@qq.com, 151491628@qq.com

Abstract. Equipment health assessment is a fundamental task in predictive equipment maintenance practice, which aims to predict the health of equipment based on information about the equipment and its operation, thus avoiding unexpected equipment failures. In the current context, equipment health assessment based on sequential deep learning methods is becoming more and more popular, however, such methods ignore the inter-device correlations, leading to their lack of readiness for health assessment of a large number of devices. To address this problem, this paper proposes a node-embedding-based device health assessment method, which creatively introduces a graph model for device health assessment and effectively improves the performance of health assessment. Firstly, this paper proposes a way to define equipment association graphs. Secondly, we introduce the node embedding technique to extract graph information. Finally, an equipment health assessment method based on the equipment association graph is proposed. Experiments show that the proposed method outperforms the existing prevailing methods.

Keywords: Health Assessment, Node Embedding, Association Graph

1 Introduction

With the improvement of information equipment automation [15, 29] and integration [28, 33, 34] technology, the classic equipment asset management method can no longer satisfy the requirements of current equipment management. A large number of basic information data [?, ?, ?] and operation status data [?, ?, ?] derived from routers, switches [22, 27, 32] and professional production equipment are beyond the analysis capability of traditional expert experience, and there is an urgent need for intelligent analysis methods [24, 26] to migrate and apply.

Most of the existing equipment health assessment methods are based on the *Reliability-Centered Maintenance* (RCM) concept, which describes historical failure data through quantitative modeling, combined with expert evaluation to

* Corresponding author: 151491628@qq.com

determine the life and reliability of equipment, so as to make preventive maintenance decisions to reduce potential downtime losses [1, 35, 36, 45]. Among these approaches, traditional methods are generally based on statistic definition and regression analysis techniques, among which the relative healthiness model and its improvement models are typical [2, 5, 21, 23]. However, such methods are unable to effectively extract high-level features from the data, and their classification or prediction capabilities are insufficient, resulting in poor health assessment accuracy and limited guidance for maintenance of equipment in production environments. The development of machine learning technology has introduced new ways of approaching equipment health assessment. The machine learning-based methods improve the evaluation accuracy to a certain extent [3, 38, 44, 46], but it also relies on the introduction of expert knowledge and has insufficient migration capability for different application scenarios and different device states [6, 19, 39, 43]. In recent years, deep learning-based methods have also been applied [4, 13, 18]. Some methods use sequential models to predict the future health of equipment [17, 20, 42] , however, these methods are only applicable to a single device and consume a large amount of computational resources, making it difficult to land applications in real scenarios with a large number of equipment [7, 41, 47].

To address these problems, this paper aims to provide a graph structure that can characterize the association between equipment operation information and equipment, and propose a method for equipment health assessment based on equipment association graphs, so that equipment health assessment can be free from the reliance on expert knowledge. Specifically, this paper first proposes the definition of a device association graph model and defines the node features in the device association graph by feature extraction; subsequently, the graph features are extracted based on the node embedding method; finally, the labels of unknown labeled nodes are predicted based on the perceptron and the information of known labeled nodes.

The main contributions of this paper can be summarized as follows:

1. This paper proposes a new equipment association graph definition and construction method. The traditional method tends to focus on the historical operation data [8, 11, 16] of a single equipment, and the analysis of the association between equipment is limited to the similarity of weights in the regression equation brought by the association of basic information such as the same manufacturer, without obtaining the influence of the association such as the physical location of the equipment. In contrast, the proposed equipment association graph can effectively characterize the complex associations between equipment and can more accurately reflect the effect of the influencing factors on equipment health, thus obtaining more accurate health values.

2. In this paper, we introduce node embedding based on random walk and Word2Vec into the field of equipment health assessment, which brings a new

perspective to the research and development of this field. Compared with the existing methods based on statistics and machine learning, the node embedding method reduces the dimensionality of the feature vector, which reduces the complexity for the subsequent calculation; on the other hand, the vector value of a device after embedding is influenced by the devices with which it has a strong association, which can extract higher-level features and achieve a more accurate health assessment.

3. This method is based on the graph structure for equipment health assessment, and is able to predict the health of all unknown devices through a single uniform node embedding, which solves the shortcomings of existing deep learning-based equipment health assessment methods that focus on single device health prediction.
4. We define the equipment characteristics through the most intuitive basic information and operation information of the equipment, and get rid of the dependence of the existing method on expert knowledge. For different types of equipment, the method can operate properly without the exclusive characteristics defined by expert knowledge, and accurately achieve equipment health assessment, reducing the threshold of personnel and data completeness for applying the method.

2 Related Work

There are many studies on equipment health assessment models, including traditional statistical models, machine learning models, and deep learning models. Most approaches are based on RCM concept and assess equipment health centered around remaining useful life.

2.1 Statistical Models

Earlier approaches modeled equipment health assessment based on expert knowledge defining statistics under application scenarios, by such as equipment operation indicators, equipment temperature, relevant product technical indicators, etc.; and then implemented statistical techniques such as multiple regression and entropy correction to calculate the weights of the statistics, and finally used the obtained relative health model to predict the health of equipment.

For example, statistical methods including hypothesis testing [21], extreme value theory [5] and maximum-likelihood estimation [2,23] are widely used in the field of equipment health assessment [37,40]. However, such methods rely on manual feature construction and have difficulty in obtaining complex fusion features, which leads to a strong dependence on feature construction for their accuracy, further affecting their accuracy and usability.

2.2 Machine Learning Models

Existing machine learning-based methods are also based on expert knowledge to define key equipment features, such as basic equipment information, operating indicators, etc., followed by feature modeling using machine learning algorithms such as XGBoost [14] and clustering [40], and training with large amounts of data [9, 10, 31] to obtain a good classification or prediction model.

Besides, other commonly used machine learning methods include support vector machines [3, 46], Gaussian regression [38, 44], the gamma process [43], least squares regression [6], hidden Markov model [19], and the Wiener processes [1, 39]. Compared with statistical-based methods, this type of method improves the model's ability to fit the data, thus enhancing the evaluation accuracy, but it still relies on expert knowledge and feature selection, and its automatic feature extraction capability still needs further improvement.

2.3 Deep Learning Models

Deep learning techniques are also applied in this field, but limited by the amount of data [12, 25, 30] and the number of labels required for deep learning models, the migration of related technologies is still at a preliminary stage, and some researchers have used sequential models to predict the future health of a single device [4,13,18], but the related accuracy rate needs to be improved [17,20,42,47]. For example, [20] proposes a competition learning-based method for predicting long-term machine health status and [42] combines multiple sensor signals and *Long Short-Term Memory* (LSTM) models for modeling. In addition, there are also many approaches based on combining GAN models with sequence models to obtain better performance [17,47]. In addition, other network structures, such as *Convolutional Neural Networks* (CNN), are gradually applied to equipment health assessment [7,41]. For example, [7] combines CNN and LSTM to improve the accuracy of equipment remaining useful life estimation. However, as an important part of deep learning, deep graph models have been rarely applied in device health assessment. In particular, the graph node embedding-based approach has not yet been migrated to the field. This makes existing methods applicable only to a single device, ignoring practical application scenarios with a large number of devices.

3 Method

The health assessment method proposed in this paper is divided into two stages. First, a graph structure is defined to characterize the association between equipment operation information and equipment in order to free the health assessment method from the reliance on expert knowledge, and node features in the equipment association graph are defined by feature extraction. Second, the equipment association graph is embedded based on the node embedding method and the health level of the equipment to be evaluated is assessed. In this section, we first

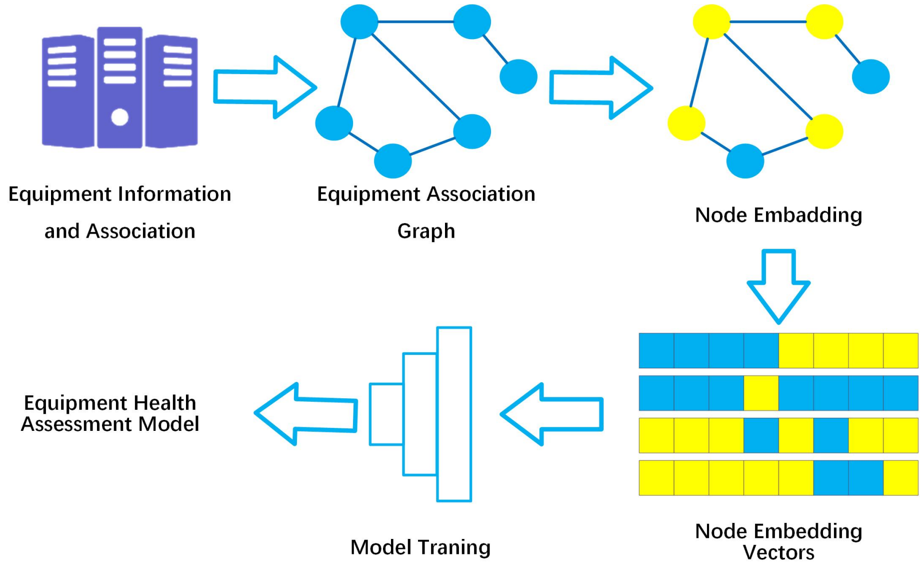

Fig. 1. Flow chart of the proposed method

define and explain the concepts and graph structure related to equipment association graphs, then we explain how equipment association graphs are constructed, and finally we discuss the methods for equipment health assessment based on equipment association graphs. The complete flow of the proposed method is shown in Fig. 1.

3.1 Definition of Concepts

Equipment information Equipment information includes basic equipment information, equipment usage information and other information for specific equipment types. Among them, the basic information of equipment includes manufacturer, factory time, equipment type, etc.; equipment usage information includes physical location of equipment, average daily working time, average daily failure times, average daily temperature, etc.; other information for specific equipment type refers to the working information based on equipment type, for example, network switch includes average daily forwarding volume, average daily fan speed, etc. Based on specific scenarios and equipment, equipment information can be added without upper limit, thus forming a more complete device characteristic.

Equipment association Equipment association refers to the association between equipment information. If a piece of information of two equipment is the same, it is considered that there is an association between two equipment. In

Algorithm 1 Equipment Association Graph Construction

Input: Node Set $V\{v_i\}_{i=1}^{n}$ where n denotes the size of nodes. Equipment information Set $I = \{I_i\}_{i=1}^{n}$ where I_i denotes the equipment information of nodes v_i. Size T of equipment information I_i.
Output: Equipment Association Graph $G = (V, E)$.

```
1: for v_i ∈ V, v_j ∈ V do
2:     E_ij = 0
3:     for t ∈ 0, ··· , T do
4:         if I_i^t = I_j^t then
5:             E_ij ← E_ij + 1
6: G = (V, E)
7: return G
```

the actual production environment, the stronger the association, the more similar the health of the equipment. For example, equipment of the same batch, or equipment running at the same temperature.

3.2 Definition of Equipment Association Graph

To effectively describe the information of equipment and the association between the equipment, a equipment association graph needs to be constructed. As a class of graph structures, a equipment association graph can be represented as $G =< V, E >$, where V denotes the set of nodes and E denotes the set of edges. Therefore, the definition of a equipment association graph is the definition of its edges and nodes.

Node The proposed equipment association graph defines that each node characterizes a piece of equipment and the attributes of the node are the feature vectors composed of information about that equipment, where continuous values are normalized to the $[0, 1]$ interval by the following equation and discrete values are treated as one-hot encodes. The normalized processing equation is as Equation (1).

$$y_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where y_i denotes to the normalized result of feature i, x_i denotes to the value of this device on feature i, and $\max(x)$ and $\min(x)$ denote to the maximum and minimum values of all devices on feature i.

Subsequently, the labels of the nodes are used as the health of the equipment. Since the health of the training set data is known, the values are directly assigned to the corresponding nodes as labels.

Edge Each edge in the proposed equipment association graph links two nodes, and the edges have no direction but have a weight. The construction of edges follows the following flow.

1. Let the weight of the edge between any two nodes be 0.
2. For any two nodes, information about their corresponding equipment is examined. For each identical field in the equipment information, the weight of the edge between these two nodes is increased by 1.
3. Generate edges between nodes with ownership greater than 0.

Specifically, to generate the equipment association graph, we first process the raw data and, for each equipment, generate its equipment information vector as equipment characteristics; subsequently, we construct nodes for each equipment, add the equipment characteristics vector as attributes, or as labels if the health degree is known; finally, we calculate the weights between the nodes two by two and generate edges with corresponding weights greater than 0. The equipment association graph construction algorithm is summarized as Algorithm 1.

3.3 Equipment health assessment based on node embedding

To perform equipment health assessment based on the equipment association graph, we first a) perform a random walk on the graph to obtain node sequences based on the equipment association graph; subsequently b) compute node embedding vectors based on the node sequences using the Woed2Vec algorithm; and finally c) predict node labels for all labeled locations based on a three-layer perceptron with the node embedding vectors and known labels as inputs.

First, most of the existing random walk methods can be applied to structures such as heterogeneous graphs and heterogeneous information networks. Equipment association graphs are a static class of homogeneous graphs, so the transfer probability of random walk needs to be adjusted. Specifically, we adjust the probability of being currently at node v, which will be transferred to node t in the next step, as Equation (2) and (3).

$$P(t \mid v) = \begin{cases} \frac{weight(t,v)}{N_w(v)}, (t,v) \in E \\ 0, otherwise \end{cases} \tag{2}$$

$$N_w(v) = \sum_{t_i} weight\left(t_i, v\right) \tag{3}$$

where $weight(t,v)$ denotes the weight of the edge between node t and node v, $N_w(v)$ denotes the sum of weights of edges between node v and all neighboring nodes. We select the number of nodes in the path obtained by the random walk to be 10.

Second, the Word2vec algorithm is an encoding approach and we adapt it to a graph node embedding algorithm that embeds nodes into vectors and makes the embedding vectors obtained by nodes with similar attributes as close as possible.

For any node v in $n_{v-c}, ..., n_{v+c}$ of the paths obtained by random walks in the previous step, the objective function to be maximized by word2vec is

$$\sum_{v=1}^{v} \log P\left(n_{v-c}, \ldots, n_{v-1}, n_{v+1}, \ldots, n_{v+c}\right) \tag{4}$$

The probability in the Equation (4) can be transformed into a product of a series of probabilities, and the final objective function can be transformed into

$$\frac{e^{V_{n_v}^{\top} V'_{n_{v+j}}}}{\sum_{i=1}^{V} e^{V_{n_v}^{T} V'_{n_v}}} \tag{5}$$

where V_{n_i} denotes the input vector of node n_i (i.e., its attributes), V'_{n_i} denotes the output vector of node n_i (i.e., its embedding vector), and V denotes the number of all nodes. During the calculation of i growth to V, the above equation calculates the embedding vector of all the nodes.

Finally, we use the embedding vectors of the nodes corresponding to all equipment with known health as the input to the three-layer perceptron, and their health values are used as the labels to be fitted to train the perceptron model. After the training is completed the embedding vectors of the nodes with unknown labels are fed into the perceptron model and the obtained output is the predicted health of the corresponding nodes, i.e., the corresponding equipment.

Each layer in the three-layer perceptron is a fully connected layer, and each neuron obeys the following formula.

$$output = f(net - \theta) \tag{6}$$

$$net = \sum z_i \cdot v_i \tag{7}$$

Where z_i denotes the output value of the ith neuron in the previous layer, v_i is the weight of the ith neuron linking this neuron in the previous layer. θ is the deviation value of this neuron, which we set to θ. $f(x)$ is the activation function, and we set the activation function which is the sigmoid function.

4 Experiments

4.1 Dataset

The dataset is the equipment information and equipment association information of servers, disk arrays, network routers, network switches, firewalls, IPS, IDS, WAF, etc. from an enterprise in operation in China, and the comprehensive evaluation is carried out based on the relevant information.

We use equipment information as equipment characteristics and equipment association information as the basis for constructing equipment association diagrams, and experts are invited to evaluate the health of the equipment in the dataset in terms of years in operation, failure conditions, and product support periods, and use the health as the dataset label.

We finally constructed a dataset consisting of 1952 devices, which were randomly divided into training, validation, and test sets in the ratio of 8:1:1. Subsequently, all the data are used to construct an equipment association graph according to their relationships as input data for the proposed equipment health assessment method. Besides equipment information, we construct features such as years in operation, defect level, cumulative failures, percentage of failures in the most recent year, business system data loss, average trouble-free operation time, product support period, and repeated maintenance.

4.2 Evaluation

We compare our approach with the mainstream machine learning and deep learning methods. All methods use raw numerical features for normalization and category features for one-hot encoding as input features. We not only use RMSE and MAE as indicators of health assessment error, but also discretize health judgments into healthy and unhealthy (with a cut-off of whether health is greater than 0.5) to compare the accuracy of health trend assessment.

Among them, RMSE can be expressed as:

$$\mathrm{RMSE}(X,h)=\sqrt{\frac{1}{m}\sum_{\mathrm{i}=1}^{m}(h(x_i)-y_i)^2} \tag{8}$$

where X denotes the test dataset, m denotes the test dataset size, h denotes the health assessment model, $h(x_i)$ denotes the result of the ith test data predicted by the model, and y_i denotes the label of the ith test data. MAE can be expressed as:

$$\mathrm{MAE}(X,h)=\frac{1}{m}\sum_{i=1}^{m}\left|h(x_i)-y_i\right|. \tag{9}$$

The experimental results are shown in the Table 1.As shown in the table, the proposed method has reduced 6.1% and 2.2% in RMSE and MAE of health prediction and improved 2.3% in accuracy compared to recent deep learning methods [7]. The results show that the proposed method can effectively improve the performance of equipment health assessment and is closer to the expert assessment results than previous methods.

4.3 Ablation

To verify the validity of the proposed method, we compared the experimental results of the proposed method with the results of the equipment health assessment without node embedding.

Method	RMSE	MAE	Accuracy
SVM	42.3	33.2	78.0
XGBoost	34.8	25.1	85.2
CNN	35.6	27.9	81.8
LSTM	30.9	23.7	86.7
CNN+LSTM [7]	28.4	21.0	88.3
Proposed method	**22.3**	**18.8**	**90.6**

Table 1. Experimental results of comparison with prevailing methods (%)

The experimental results are displayed in Table 2, and it can be seen that the proposed method is effective in enhancing the final assessment results. Since the same model is used for training in both methods, the results namely show that the proposed method can effectively improve the feature representation without over-relying on expert knowledge.

Method	RMSE	MAE	Accuracy
Proposed method	**22.3**	**18.8**	**90.6**
without node embedding	38.5	26.6	80.2

Table 2. Experimental results of comparison with the methods without node embedding (%)

4.4 Hyperparameters and model selection

As mentioned earlier, we divided a portion of the training data as the validation set. In the training, we use MSE loss as the loss function, and compare the loss on the validation set for models trained with different combinations of hyperparameters to select the model parameters. Specifically, we select stochastic gradient descent as the optimizer, the number of walking steps from 1,2,3,4,5, the learning rate and weight decay from 0.0001,0.0005,0.001,0.005,0.01,0.05,0.1,0.5, and the number of epochs from 100,150,200,250. The final parameters are shown in Table 3.

5 Conclusion

In this paper, we propose a node-embedding based equipment health assessment method that introduces a graph model in the equipment health assessment task, which significantly reduces the RMSE and MAE of equipment health assessment

Hyperparameter	Value
Walking Steps	4
Learning Rate	0.005
Weight Decay	0.001
Epochs	200

Table 3. Selected hyperparameter value

and improves the task accuracy. Compared with previous methods, although the proposed method has been decoupled from expert knowledge to a large extent, it still requires a certain amount of expert annotation. In the next stage, combining the method with semi-supervised and unsupervised methods to further reduce the reliance on expert annotation may help to reduce the cost of the equipment health assessment to further enhance its application value.

6 Acknowledgements

This work was supported by State Grid Zhoushan Electric Power Supply Company of Zhejiang Power Corporation under grant No. B311ZS220002 (Research on hyperautomation for information comprehensive inspection).

References

1. An, D., Kim, N.H., Choi, J.H.: Practical options for selecting data-driven or physics-based prognostics algorithms with reviews. Reliability Engineering & System Safety **133**, 223–236 (2015)
2. Awate, S.P.: Adaptive, nonparametric markov models and information-theoretic methods for image restoration and segmentation. Ph.D. thesis, School of Computing, University of Utah (2006)
3. Benkedjouh, T., Medjaher, K., Zerhouni, N., Rechak, S.: Health assessment and life prediction of cutting tools based on support vector regression. Journal of intelligent manufacturing **26**(2), 213–223 (2015)
4. Chen, C., Liu, Y., Sun, X., Di Cairano-Gilfedder, C., Titmus, S.: An integrated deep learning-based approach for automobile maintenance prediction with gis data. Reliability Engineering & System Safety **216**, 107919 (2021)
5. Clifton, D.A., Clifton, L.A., Bannister, P.R., Tarassenko, L.: Automated novelty detection in industrial systems. In: Advances of Computational Intelligence in Industrial Systems, pp. 269–296. Springer (2008)
6. Coppe, A., Haftka, R.T., Kim, N.H.: Uncertainty identification of damage growth parameters using nonlinear regression. AIAA journal **49**(12), 2818–2821 (2011)
7. Fu, H., Liu, Y.: A deep learning-based approach for electrical equipment remaining useful life prediction. Autonomous Intelligent Systems **2**(1), 1–12 (2022)
8. Gai, K., Qiu, M., Elnagdy, S.: A novel secure big data cyber incident analytics framework for cloud-based cybersecurity insurance. In: IEEE BigDataSecurity conf. (2016)

9. Gai, K., Qiu, M., Liu, M., Xiong, Z.: In-memory big data analytics under space constraints using dynamic programming. FGCS **83**, 219–227 (2018)
10. Gai, K., Zhang, Y., et al.: Blockchain-enabled service optimizations in supply chain digital twin. IEEE TSC (2022)
11. Gai, K., et al.: Electronic health record error prevention approach using ontology in big data. In: IEEE 17th HPCC (2015)
12. Gao, X., Qiu, M.: Energy-based learning for preventing backdoor attack. In: KSEM (3). pp. 706–721 (2022)
13. Hashemian, H.M.: State-of-the-art predictive maintenance techniques. IEEE Transactions on Instrumentation and measurement **60**(1), 226–236 (2010)
14. Jia, Z., Xiao, Z., Shi, Y.: Remaining useful life prediction of equipment based on xgboost. In: The 5th International Conference on Computer Science and Application Engineering. pp. 1–6 (2021)
15. Li, J., Ming, Z., et al.: Resource allocation robustness in multi-core embedded systems with inaccurate information. J. of Sys. Arch. **57**(9), 840–849 (2011)
16. Li, Y., Gai, K., et al.: Intercrossed access controls for secure financial services on multimedia big data in cloud systems. ACM TMCCA (2016)
17. Liu, C., Tang, D., Zhu, H., Nie, Q.: A novel predictive maintenance method based on deep adversarial learning in the intelligent manufacturing system. IEEE Access **9**, 49557–49575 (2021)
18. Liu, J., Pan, C., Lei, F., Hu, D., Zuo, H.: Fault prediction of bearings based on lstm and statistical process analysis. Reliability Engineering & System Safety **214**, 107646 (2021)
19. Liu, Q., Dong, M., Peng, Y.: A novel method for online health prognosis of equipment based on hidden semi-markov model using sequential monte carlo methods. Mechanical Systems and Signal Processing **32**, 331–348 (2012)
20. Malhi, A., Yan, R., Gao, R.X.: Prognosis of defect propagation based on recurrent neural networks. IEEE Transactions on Instrumentation and Measurement **60**(3), 703–711 (2011)
21. Markou, M., Singh, S.: Novelty detection: a review—part 1: statistical approaches. Signal processing **83**(12), 2481–2497 (2003)
22. Niu, J., Gao, Y., et al.: Selecting proper wireless network interfaces for user experience enhancement with guaranteed probability. JPDC **72**(12), 1565–1575 (2012)
23. Pecht, M.: Prognostics and health management of electronics. Encyclopedia of structural health monitoring (2009)
24. Qiu, H., Dong, T., et al.: Adversarial attacks against network intrusion detection in IoT systems. IEEE IoT J. **8**(13), 10327–10335 (2020)
25. Qiu, H., Kapusta, K., et al.: All-or-nothing data protection for ubiquitous communication: Challenges and perspectives. Information Sciences **502**, 434–445 (2019)
26. Qiu, H., Zheng, Q., et al.: Topological graph convolutional network-based urban traffic flow and density prediction. IEEE Trans. on ITS (2020)
27. Qiu, M., Chen, Z., et al.: Energy-aware data allocation with hybrid memory for mobile cloud systems. IEEE Sys. J. **11**(2), 813–822 (2014)
28. Qiu, M., Jia, Z., et al.: Voltage assignment with guaranteed probability satisfying timing constraint for real-time multiproceesor DSP. J. of Signal Proc. Sys. (2007)
29. Qiu, M., Li, H., Sha, E.: Heterogeneous real-time embedded software optimization considering hardware platform. In: ACM sym. on Applied Comp. pp. 1637–1641 (2009)
30. Qiu, M., Qiu, H.: Review on image processing based adversarial example defenses in computer vision. In: IEEE 6th Intl Conf. BigDataSecurity. pp. 94–99 (2020)

31. Qiu, M., Qiu, H., et al.: Secure data sharing through untrusted clouds with blockchain-enabled key management. In: 3rd SmartBlock conf. pp. 11–16 (2020)
32. Qiu, M., Xue, C., Shao, Z., et al.: Efficient algorithm of energy minimization for heterogeneous wireless sensor network. In: IEEE EUC Conf. pp. 25–34 (2006)
33. Qiu, M., Xue, C., et al.: Energy minimization with soft real-time and DVS for uniprocessor and multiprocessor embedded systems. In: IEEE DATE Conf. pp. 1–6 (2007)
34. Qiu, M., Yang, L., Shao, Z., Sha, E.: Dynamic and leakage energy minimization with soft real-time loop scheduling and voltage assignment. IEEE TVLSI **18**(3), 501–504 (2009)
35. Qiu, M., Khisamutdinov, E., Zhao, Z., Pan, C., Choi, J.W., Leontis, N.B., Guo, P.: Rna nanotechnology for computer design and in vivo computation. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **371**(2000), 20120310 (2013)
36. Qiu, M., Xue, C., Shao, Z., Sha, E.H.M.: Energy minimization with soft real-time and dvs for uniprocessor and multiprocessor embedded systems. In: 2007 Design, Automation & Test in Europe Conference & Exhibition. pp. 1–6. IEEE (2007)
37. Roberts, S.J.: Novelty detection using extreme value statistics. IEE Proceedings-Vision, Image and Signal Processing **146**(3), 124–129 (1999)
38. Seeger, M.: Gaussian processes for machine learning. International journal of neural systems **14**(02), 69–106 (2004)
39. Si, X.S., Wang, W., Hu, C.H., Chen, M.Y., Zhou, D.H.: A wiener-process-based degradation model with a recursive filter algorithm for remaining useful life estimation. Mechanical Systems and Signal Processing **35**(1-2), 219–237 (2013)
40. Sutharssan, T., Stoyanov, S., Bailey, C., Yin, C.: Prognostic and health management for engineering systems: a review of the data-driven approach and algorithms. The Journal of engineering **2015**(7), 215–222 (2015)
41. Wang, B., Lei, Y., Li, N., Yan, T.: Deep separable convolutional network for remaining useful life prediction of machinery. Mechanical systems and signal processing **134**, 106330 (2019)
42. Wang, D., Liu, K., Zhang, X.: A generic indirect deep learning approach for multisensor degradation modeling. IEEE Transactions on Automation Science and Engineering (2021)
43. Wang, X., Balakrishnan, N., Guo, B., Jiang, P.: Residual life estimation based on bivariate non-stationary gamma degradation process. Journal of Statistical Computation and Simulation **85**(2), 405–421 (2015)
44. Wilson, A., Adams, R.: Gaussian process kernels for pattern discovery and extrapolation. In: International conference on machine learning. pp. 1067–1075. PMLR (2013)
45. Wu, G., Zhang, H., Qiu, M., Ming, Z., Li, J., Qin, X.: A decentralized approach for mining event correlations in distributed system monitoring. Journal of parallel and Distributed Computing **73**(3), 330–340 (2013)
46. Yan, J., Liu, Y., Han, S., Qiu, M.: Wind power grouping forecasts and its uncertainty analysis using optimized relevance vector machine. Renewable and sustainable energy reviews **27**, 613–621 (2013)
47. Zhang, L., Lin, J., Liu, B., Zhang, Z., Yan, X., Wei, M.: A review on deep learning applications in prognostics and health management. Ieee Access **7**, 162415–162438 (2019)