Proceedings of the 1st IEEE International
Conference on Micro/Nano Sensors for AI, Healthcare and Robotics
December 5-7, 2018, Shenzhen, China

Conceptual Framework of Smart Factory based on OPC UA and LSTM Encoder-Decoder

1st Xianhe Wen
Shenzhen Academy of Robotics
Shenzhen 518000, *China*
wenxianhe@szarobots.com

2nd Heping Chen
Shenzhen Academy of Robotics
Shenzhen 518000, *China*
chen@szarobots.com

3rd Binhe Wen
AECC Aero Engine Control System
Wuxi Jiangsu 214063, *China*
bhwen5516521@126.com

4th Jiang Liu
Shenzhen Academy of Robotics
Shenzhen 518000, *China*
jiangliu@szarobots.com

5th Yaonan Li
Shenzhen Academy of Robotics
Shenzhen 518000, *China*
ynli@szarobots.com

6th Ning Xi
Shenzhen Academy of Robotics
Shenzhen 518000, *China*
xining@szarobots.com

***Abstract*—OPC UA (Open Platform Communications Unified Architecture) is key for multi-heterogeneous software and hardware information integration. Some studies have proposed to apply OPC UA to smart factory information integration, but most tend to propose concepts and lack application research. While, LSTM Encoder-Decoder (Long Short-Term Memory based Encoder-decoder) is an unsupervised learning method not requiring labeled data. It has good performance in time series data analysis, but few researches relate it with smart factory predictive analysis. This paper proposed a conceptual framework of smart factory based on OPC UA and LSTM Encoder-Decoder technology. Specifically, first, the theories are discussed including the general architecture of smart factory, information integration architecture based on OPC UA and LSTM Encoder-decoder model for smart factory predictive analysis. Then, we introduced the simulation result analysis. Finally, the conclusion was given.**

***Keywords*—smart factory, opc ua, lstm encoder-decoder, information integration, predictive analysis**

I. Introduction

As early as 2004, Bauer M [1] and others began research on Smart Factory. They proposed ubiquitous mobile computing technology to optimize production systems. Based on ubiquitous computing technology, Dominik Lucke [2] further proposed the definition, challenges and possible enabling technologies of Smart Factory. Wieland M [3] et al. studied intelligent workflow technology based on context-aware integration and applied the technology to a simplified smart factory environment, simulating machine maintenance and individual customer order processing business processes. SmartFactory^{KL} built smart factories by applying information and communication technologies to automation systems and studied possible technical challenges in this process [4]. Hameed B [5] et al. studied RFID-based intelligent real-time factory with environmental awareness. Zamfirescu C B [6] and others proposed that as long as there is no unified heterogeneous software and hardware control and communication system method, many problems encountered in the information-physical system (CPS) cannot achieve automatic decision-making. Helmuth Ludwig [7] pointed out that the success of Amberg's smart factory is due to the integration of three key technologies: product lifecycle management (PLM), Manufacturing Execution System (MES) and automation systems. Cadavid J [8] et al. proposed Model Based Definition (MBD), which is designed to solve the problem of too complex and hard to reuse in the construction of computer integrated manufacturing systems. Kassner LB [9] et al. proposed a conceptual framework for amplifying production process anomalies by mining and analyzing unstructured data at different stages of the product manufacturing life cycle; Lee J [10] proposed a 5C smart factory architecture covering connection, information conversion, cyber, cognition and configuration. However, most of the researches are at the early stage, and the specific implementation technical routes are being industriously explored.

In this Article, we mainly focus on implementation of smart factory based on OPC UA and LSTM Encoder-Decoder. According to the reviews above, information integration and predictive analysis are the two most key technologies for Smart factory. In terms of information integration, OPC UA is suitable for multi-heterogeneous software and hardware information integration [11] [12]. Many studies [13] [14] have proposed to apply OPC UA to smart factory information integration, but most of them tend to propose concepts and lack application research. In terms of predictive analysis, many researchers have applied machine learning algorithms to predictive analysis for devices [15] [16], but most of them are based on supervised learning methods [17] [18], which require a large amount of labeled data, which is not suitable for factory environments. LSTM Encoder-Decoder [19] [20] is a non-supervised learning method which does not require labeled data. It has a good performance in predictive analysis. This paper integrates OPC UA and LSTM Encoder-Decoder technology for the first time to realize the two key technologies of smart factory information integration and predictive analysis.

The rest of the article is organized as follows. In section 2, the theories are discussed including the overall architecture of smart factory, information integration architecture based on OPC UA and LSTM Encoder-decoder model for smart factory anomaly detection. In section 3, we proposed the simulation result analysis. Finally, the conclusion was given.

II. Theories

A. Smart Factory Architecture

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. If you are using US letter-sized paper, please

The project is partially supported by the Shenzhen Overseas High Level Talent (Peacock Plan) Program KQTD20140630154026047 and China Postdoctoral Science Foundation (Grant No. 2018M633158).

978-1-5386-9408-4/19/$31.00 © 2018 IEEE

close this file and download the Microsoft Word, Letter file.

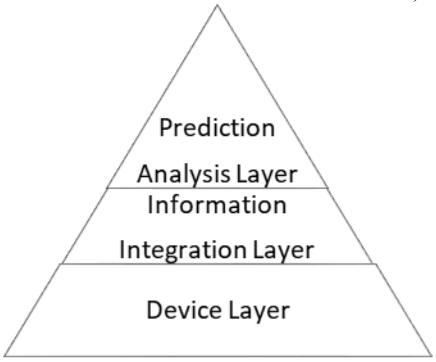

Fig. 1. General Architecture of Proposed Smart Factory

Fig.1 shows the general smart factory architecture proposed in this paper. The smart factory completes various work activities of the workshop by a number of intelligent devices (work robots, intelligent storage equipment and intelligent logistics equipment, etc.). These devices are connected by a set of information integration software and hardware to achieve interconnection and interoperability. The analysis software completes the predictive analysis of workshop order, resource scheduling, equipment health and future capacity. In this paper, information integration will be realized by OPC UA and prediction analysis will be based on LSTM Encoder-Decoder model.

Based on this architecture, information integration architecture based on OPC UA and LSTM Encoder-Decoder reconstruction model for smart factory predictive analysis will be summarized as follows.

B. Information Integration Architecture based on OPC UA

OPC UA is a standard communication protocol (IEC 62541), designed to enable secure and reliable connections for interconnecting various systems in industrial automation and other communication areas where measurement data or event notifications are transferred. This enables soft real-time transfer of current and historical data and events, including alarm management. OPC UA is also selected as the backbone of the German government driven Industry 4.0 program, which targets to increase flexibility in production automation [21]. Fig.2 depicts the OPC UA-based smart factory information integration framework, which connects

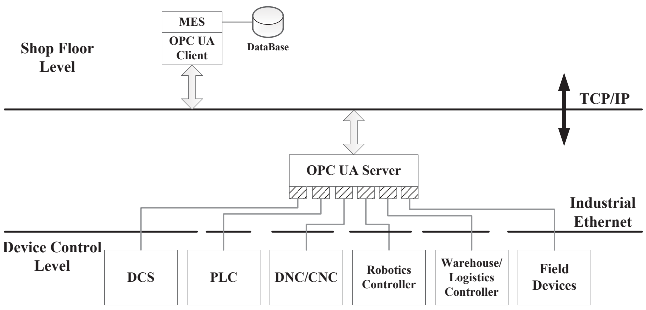

Fig. 2. OPC UA Information Integration Architecture

the controllers (DCS, PLC, DNC/CNC, Robotics/Motion Controller, Smart Warehouse/Logistics Controller, Field Devices) of various devices in the smart factory via Ethernet to the OPC UA server, and the OPC UA client accesses the

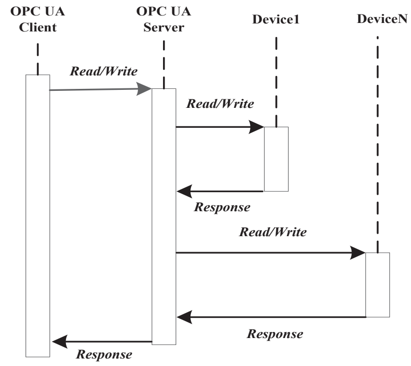

Fig. 3. Sequence diagram of Read/Write call of OPC UA

OPC UA server through TCP/IP to realize interconnection and information integration of the intelligent devices. The sequence diagram of a Read/Write call from OPC UA client to OPC UA server and from OPC UA server to devices (e.g. Robots) is illustrated in Fig.3.

C. LSTM Encoder-Decoder reconstruction model for smart factory predictive analysis

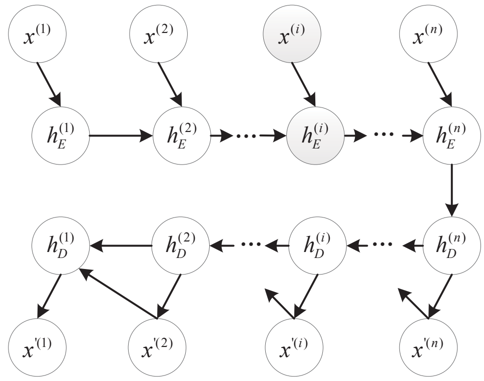

Fig. 4. The structure of LSTM Encoder-Decoder

The smart factory predictive analysis includes predicting future orders based on past order data, predicting future productivity based on order execution data and equipment operation data, and predicting equipment maintenance time nodes based on equipment status monitoring from sensors' data. This article, taking equipment predictive maintenance as an example, introduces the smart factory predictive analysis, observes the abnormal signal in the device status sensor data through the LSTM Encoder-Decoder algorithm, and discovers the abnormal signs of the equipment in advance, which is the key of predictive maintenance.

Consider a time-series $X=\{x^{(1)},x^{(2)},\ldots,x^{(n)}\}$ of length n, where each point $x^{(i)}\in R^m$ is an m-dimensional vector of readings for m sensors of an equipment in the factory at time-instance t_i. As shown in fig.4, we train an LSTM Encoder-Decoder to reconstruct instances of normal time-series, and the reconstructed time-series is $X^{'}=\{x^{'(1)},x^{'(2)},\ldots,x^{'(n)}\}$, anomalies can be detected by unexpected high reconstruction errors.

$H_E=\{h_E^{(1)},h_E^{(2)},\ldots,h_E^{(n)}\}$ is the hidden layer state value series of the encoder, and $H_D=\{h_D^{(1)},h_D^{(2)},\ldots,h_D^{(n)}\}$ is the hidden layer state value series of the decoder. Fig. 5 illustrates the inner structure of one LSTM Cell in Fig.4. It explains how to derive $h_E^{(t)}$ from $x^{(t)}$ and $h_E^{(t-1)}$. Similarly, it can also explain how $h_D^{(t-1)}$ and $x'^{(t)}$ are derived from $h_D^{(t)}$.

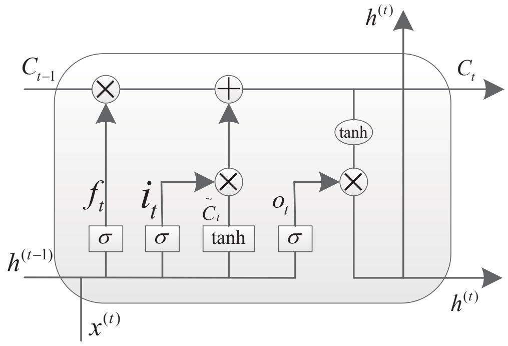

Fig. 5. The structure of LSTM Cell

Where σ represents activation function sigmoid, and tanh represents activation function tanh.

Consider S_{train} is the normal time series used to train the model. Then, the model is trained to minimize the objective,

$$\sum_{S_{train}} \sum_{i=1}^{n} \left\| x^{(i)} - x'^{(i)} \right\|^2 \tag{7}$$

After the training of the reconstruction model is finished using the normal sensor data from the equipment, we can use the model to detect anomaly of the equipment by injecting the newly collected sensor data of the equipment to the model and calculating the anomaly score. The reconstruction error vector for t_i,

$$e^{(i)} = \left| x^{(i)} - x'^{(i)} \right| \tag{8}$$

Anomaly score,

$$a^{(i)} = (e^{(i)} - \mu)^T \Sigma^{-1} (e^{(i)} - \mu) \tag{9}$$

μ is the mean vector of the error, and Σ is the co-variance matrix of the error.

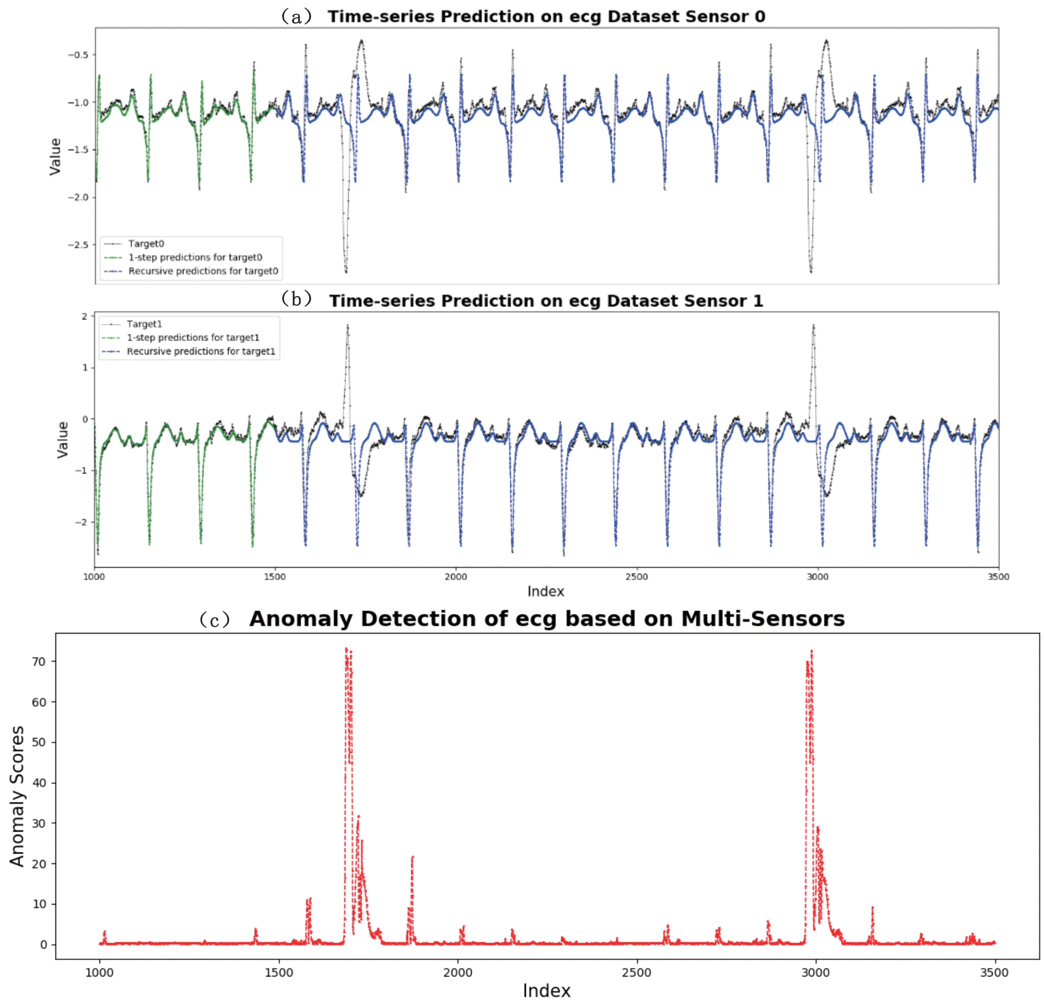

Fig. 6. simulation result of the LSTM Encoder-Decoder based on ecg dataset

Then, the bigger the value of $a^{(i)}$ means the higher probability of anomalous the data at t_i.

III. SIMULATION RESULT ANALYSIS

A. Information integration simulation

We simulate the smart factory equipment with the ABB IRB 1200 robot, which is managed by the IRC5 robot controller. The ABB IRC5 OPC Server is connected to the robot controller via Ethernet. The KEPServerEX 6 plays the role of OPC UA Server, communicates with the ABB IRC5 OPC Server via Ethernet and encapsules the OPC Server into an OPC UA server. Based on Visual C# 2017, we have designed the OPC UA client software.

The OPC UA client software communicate with the OPC UA server in OPC UA protocol. Through the above process, the OPC UA client can read and write the robot controller, and realize the information integration of the robot. At the same time, the OPC UA client software accesses the SQL Server database and realizes real-time synchronous acquisition and storage of the process data of the robot.

B. Predictive analysis simulation

We use the electrocardiograph (ecg) data as the simulation data. Website of the data is: http://www.cs.ucr.edu/~eamonn/discords/ ECG_data.zip. The LSTM Encoder-Decoder model is designed in Python 3.5 environment based on the PyTorch framework. Then, model learning and anomaly detection are performed in the case where the learning rate is set to 0.0002, the epoch is set to 800, and the batch size is set to 64, the output results are obtained as in Fig. 6.

C. Simulation result analysis

From Fig.6(c), it can be found that the point with the highest anomaly scores appear at the position around the 1700th and 3000th data point which is identical with time-series prediction of sensor0 and sensor1 respectively portrayed in Fig.6(a) and Fig.6(b) . This indicates that our algorithm is effective on anomaly detection based on multi-sensors. Therefore, it also can be used for smart factory equipment predictive analysis.

IV. CONCLUSIONS

In summary, based on the OPC UA information integration method proposed in this paper, the smart factory software at the floor layer successfully integrates with the hardware at the equipment layer, and successfully collects important data from each axis of the IRB 1200 robot. This method can be extended to information integration of various heterogeneous devices and software, solving the smart factory information integration problem caused by various incompatible device and software protocols.

In addition, the artificial intelligence learning method LSTM Encoder-Decoder has been successfully tested in anomaly detection of ecg data. In actual scenarios, the anomaly may be early failure of internal components of robots or other smart factory equipment. Through the method proposed in this paper, early failures can be predicted in advance by analyzing multi-sensor real-time data collected from the equipment, which can guide early maintenance, thereby reducing sudden failures, improving production efficiency and reducing maintenance costs.

After solving the production automation problem, the key to the success of the smart factory lies in information integration and big data analysis. Based on the OPC UA method and the artificial intelligence learning method LSTM Encoder-Decoder, this paper carries out the comprehensive application research of information integration and big data analysis for the first time. We believe this is of great significance to the research and application of smart factory.

REFERENCES

[1] Bauer M, Jendoubi L, Siemoneit O. Smart factory–Mobile computing in production environments[C]//Proceedings of the MobiSys 2004 Workshop on Applications of Mobile Embedded Systems (WAMES 2004). 2004.

[2] Lucke D, Constantinescu C, Westkämper E. Smart factory-a step towards the next generation of manufacturing[J]. Manufacturing systems and technologies for the new frontier, 2008, pp. 115-118.

[3] Wieland M, Kaczmarczyk P, Nicklas D. Context integration for smart workflows[C]//Pervasive Computing and Communications, 2008. PerCom 2008. Sixth Annual IEEE International Conference on. IEEE, 2008, pp. 239-242.

[4] Zuehlke D. Smart factory–from vision to reality in factory technologies[J]. IFAC Proceedings Volumes, 2008, 41(2) , pp. 14101-14108.

[5] Hameed B, Minguez J, Wörner M, et al. The smart real-time factory as a product service system[M]//Functional Thinking for Value Creation. Springer, Berlin, Heidelberg, 2011, pp. 326-331.

[6] Zamfirescu C B, Pirvu B C, Schlick J, et al. Preliminary insides for an anthropocentric cyber-physical reference architecture of the smart factory[J]. Studies in Informatics and Control, 2013, 22(3) , pp. 269-278.

[7] Hessman T. The dawn of the smart factory[J]. Industry Week, 2013, 14, pp. 14-19.

[8] Cadavid J, Alférez M, Gérard S, et al. Conceiving the model-driven smart factory[C]//Proceedings of the 2015 International Conference on Software and System Process. ACM, 2015, pp. 72-76.

[9] Kassner L B, Mitschang B. MaXCept--Decision Support in Exception Handling through Unstructured Data Integration in the Production Context: An Integral Part of the Smart Factory[C]//System Sciences (HICSS), 2015 48th Hawaii International Conference on. IEEE, 2015, pp. 1007-1016.

[10] Lee J. Smart factory systems[J]. Informatik-Spektrum, 2015, 38(3), pp. 230-235.

[11] Imtiaz J, Jasperneite J. Scalability of OPC-UA down to the chip level enables "Internet of Things"[C]//Industrial Informatics (INDIN), 2013 11th IEEE International Conference on. IEEE, 2013, pp. 500-505.

[12] Harrison R, Vera D, Ahmad B. Engineering the smart factory[J]. Chinese Journal of Mechanical Engineering, 2016, 29(6) , pp. 1046-1051.

[13] Faltinski S, Flatt H, Pethig F, et al. Detecting anomalous energy consumptions in distributed manufacturing systems[C]//Industrial Informatics (INDIN), 2012 10th IEEE International Conference on. IEEE, 2012, pp. 358-363.

[14] Pauker F, Ayatollahi I, Kittl B. Service Orchestration for Flexible Manufacturing Systems using Sequential Functional Charts and OPC UA[J]. Dubrovnik, 2015, 9, pp. 11-09.

[15] Lee D, Pan R. Predictive maintenance of complex system with multi-level reliability structure[J]. International Journal of Production Research, 2017, 55(16) , pp. 4785-4801.

[16] Liao L, Ahn H. Combining deep learning and survival analysis for asset health management[J]. International Journal of Prognostics and Health Management, 2016.

[17] Tian Z, Wong L, Safaei N. A neural network approach for remaining useful life prediction utilizing both failure and suspension histories[J].

Mechanical Systems and Signal Processing, 2010, 24(5) , pp. 1542-1555.

[18] Kim H E, Tan A C C, Mathew J, et al. Machine prognostics based on health state estimation using SVM[M]//Asset Condition, Information Systems and Decision Models. Springer, London, 2012, pp. 169-186.

[19] Malhotra P, Ramakrishnan A, Anand G, et al. LSTM-based encoder-decoder for multi-sensor anomaly detection[J]. arXiv preprint arXiv:1607.00148, 2016.

[20] Cho K, Van Merriënboer B, Gulcehre C, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation[J]. arXiv preprint arXiv:1406.1078, 2014.

[21] Jouni Aro, Heikki Tahvanainen. OPC UA Enables Secure Data Transfer and System Integrations in Private and Public Networks[J]. Automaatio XXI seminar 17.-18.3. 2015.