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A Soft Measurement Method for Air Supply Systems of Railway Vehicles Based on Improved Multivariate Support Vector Regression

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Abstract

Aiming at the problem that the air supply system of railway vehicles lacks sensor data and most of the measurement points are not easy to measure directly, a soft measurement method based on improved multivariate support vector regression (IMSVR) was proposed. By analysing the structure composition and working principle, intake temperature, intake pressure and exhaust pressure of the air supply system were selected as auxiliary variables of the variable to be measured. In order to make full use of the acquired data information, the phase space reconstruction technology was introduced, and a soft measurement model between the variables to be measured and auxiliary variables of the air supply system was established based on the improved multivariate support vector regression (IMSVR) algorithm, and the particle swarm optimization (PSO) algorithm was used to optimize the kernel parameter *g* and the penalty parameter *c*. By installing pressure and temperature sensors on a typical air supply system and carrying out performance tests and fault injection tests on the modified air supply system test bench, the air supply system experimental data set was obtained. Finally, taking the fuel injection temperature as an example, the validity and accuracy of the method proposed in this paper were verified based on the experimental data set. The research result provides a reference for the fault early warning, diagnosis and maintenance of the air supply system.

Keywords: railway vehicle, air supply system, soft measurement, improved multivariate support vector regression.

1 Introduction

Air supply system (Figure 1) provides clean and dry compressed air necessary for the normal operation of railway vehicle's braking system and other air-using equipment. Its reliability directly affects the service safety, operation efficiency and maintenance costs of railway vehicles. However, due to its complex structure, frequent start and stop, as well as harsh working environments [1,2], such as vibration and shock caused by track irregularities, sand and dust intrusion, and electromagnetic interference, the performance of air supply system and its key components will inevitably deteriorate, and some functional failures such as insufficient air supply and high oil temperature have been reported [3,4]. Fault warning is an important technology to reduce accident risk and improve system reliability and safety. However, current air supply system has only a few pressure and temperature switches for control feedback, and lacks sensor data for fault warning.

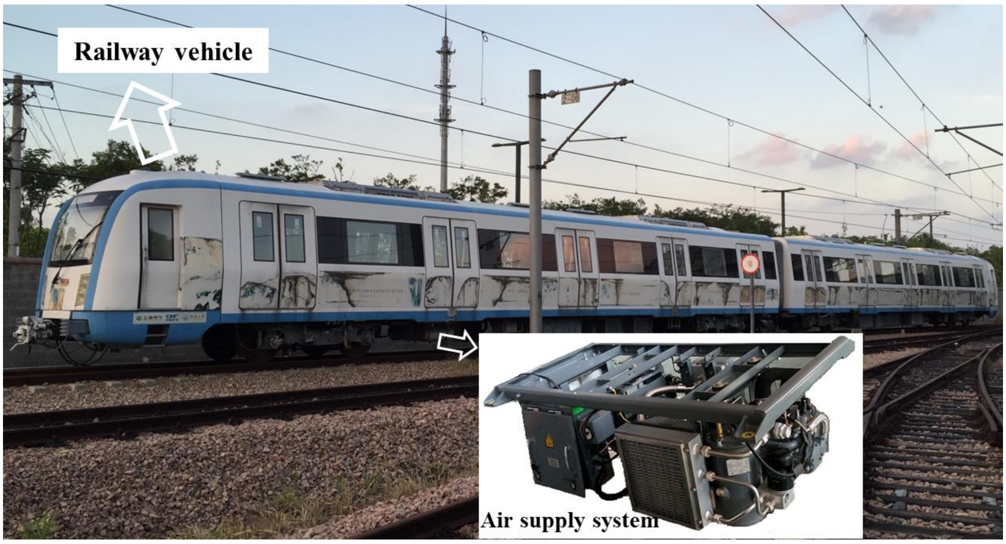

Figure 1: Air supply system of a railway vehicle.

With the rapid development and application of machine learning and big data analysis technologies, the demand for intelligent equipment of railway vehicle has gradually increased. It is foreseeable that intelligent air supply system will be equipped with some pressure, temperature and other sensors to monitor the key components. However, considering the installation space, economic cost, and data transmission reliability, the pressure or temperature at some locations still cannot be measured directly. To this end, soft measurement method is proposed. Soft measurement methods mainly include traditional regression analysis and machine learning methods [5]. Due to the time-varying nonlinear characteristics of the pressure and temperature time series of air supply system, machine learning methods such as artificial neural network (ANN) [6] and support vector regression (SVR) [7] have been widely used. Actually, ANN adopts a learning method based on the empirical risk minimization criterion, which requires a large number of training samples, leads to overfitting easily and affects the generalization ability, while SVR is based on the structural risk minimization criterion, which can effectively overcome the shortcomings of ANN [8].

In order to realize the fault warning of the air supply system of railway vehicles, the soft measurement method for the key components of air supply system was studied in this paper.

2 Methods

In order to establish the soft measurement model of air supply system, appropriate auxiliary variables should be selected firstly. By analysing the structure composition and working principle of air supply system, it is found that air supply system performance is mainly affected by the intake pressure, intake temperature, exhaust pressure and operation rate. Therefore, they were used as auxiliary variables in this paper, as shown in Figure 2.

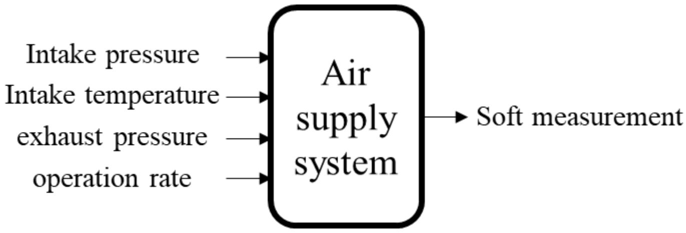

Figure 2: Schematic diagram of the soft measurement of the air supply system.

Take $P_i(t)$, $T_i(t)$, $P_e(t)$ and $w(t)$ as input, $S(t)$ as output, and the soft measurement model can be expressed as Equation (1).

$$S(t)=f[P_i(t), T_i(t), P_e(t), w(t)] \quad (1)$$

where, $S(t)$ represents the variable to be measured in the air supply system, $P_i(t)$ represents the intake pressure, $T_i(t)$ represents the intake temperature, $P_e(t)$ represents the exhaust pressure, $w(t)$ represents the operation rate, and t is the sample time.

Secondly, data collection should be carried out for modelling. As air supply system has only a few pressure and temperature switches, corresponding sensors were arranged in the air supply system test bench, and performance tests and fault injection tests were conducted on the modified air supply system test bench (Figure 3) to obtain normal and fault experimental data set of the key components of the air supply system.

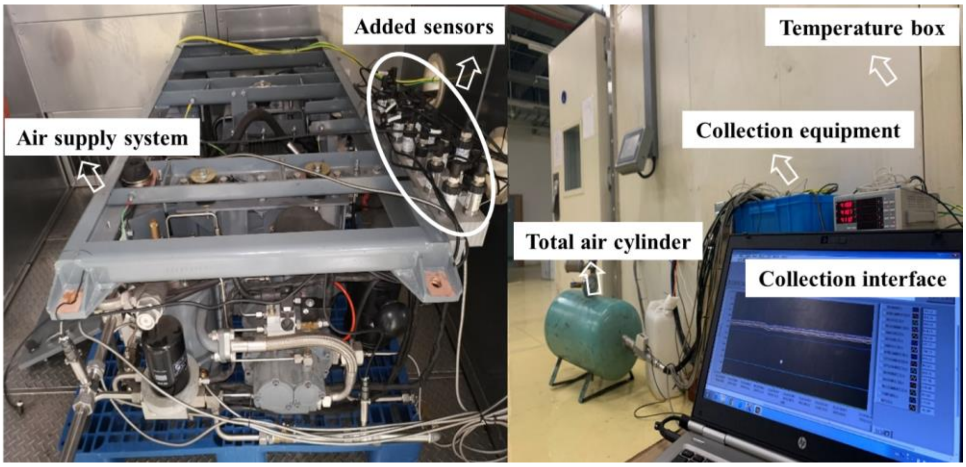

Figure 3: Modified air supply system test bench.

Sensor layout details were listed in Table 1.

No.	Name	No.	Name
1	intake pressure	8	front and rear pressure of oil and gas separator
2	intake temperature	9	front and rear temperature of air cooler
3	rear pressure of intake filter	10	front and rear pressure of dust filter
4	fuel injection flow	11	front and rear temperature of oil cooler
5	cooling oil flow	12	front and rear pressure of oil filter
6	fuel injection temperature	13	total air cylinder flow
7	compressor head exhaust temperature	14	exhaust pressure

Table 1: Sensor layout details of modified air supply system test bench.

Thirdly, in order to make full use of the acquired data information, phase space reconstruction technology was introduced, and an improved multivariate support vector regression (IMSVR) algorithm was used to establish the soft measurement model by considering the memory function of time series. Moreover, PSO algorithm was used to select the model parameters, and the mean squared error (MSE) and the mean absolute error (MAE) were used to evaluate the modelling effect.

3 Results

In this paper, a case analysis on the fuel injection temperature of the air supply system was carried out. Based on the modified air supply system test bench, the performance test and the high oil temperature simulation experiment of air supply system were conducted, and the operation rate was set as 40%. Figure 4~6 shows the change curves of the three auxiliary variables $P_i(t)$, $T_i(t)$, and $P_e(t)$ during the whole working process of the air supply system.

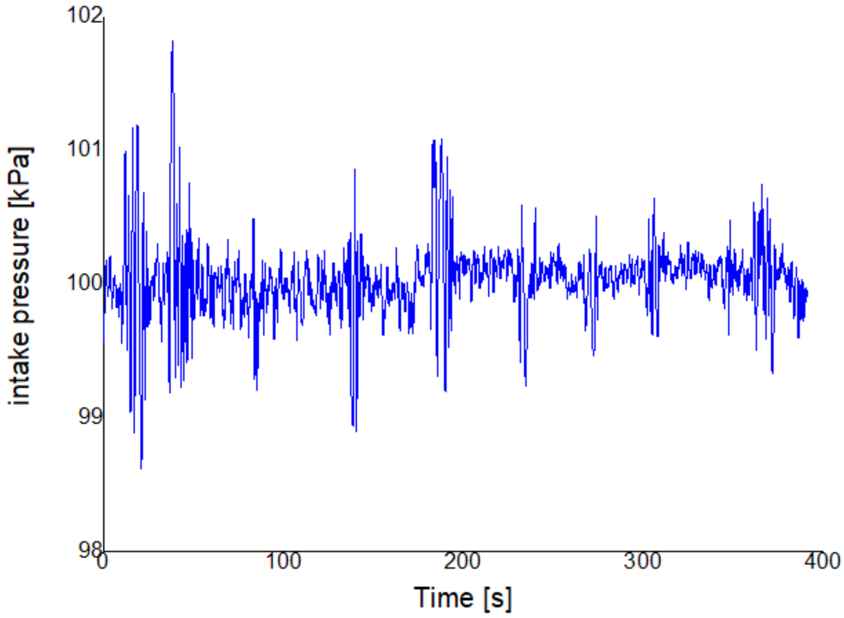

Figure 4: Intake pressure curve of air supply system.

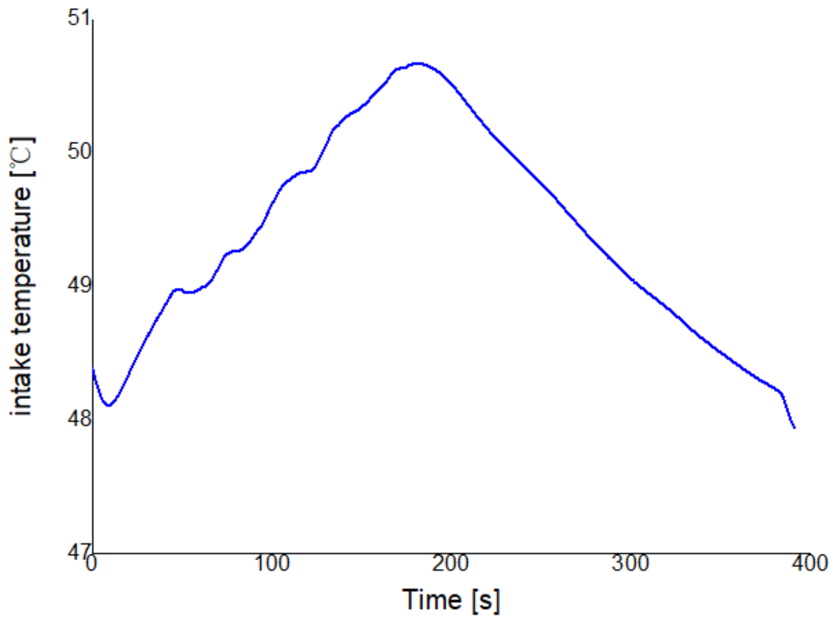

Figure 5: Intake temperature curve of air supply system.

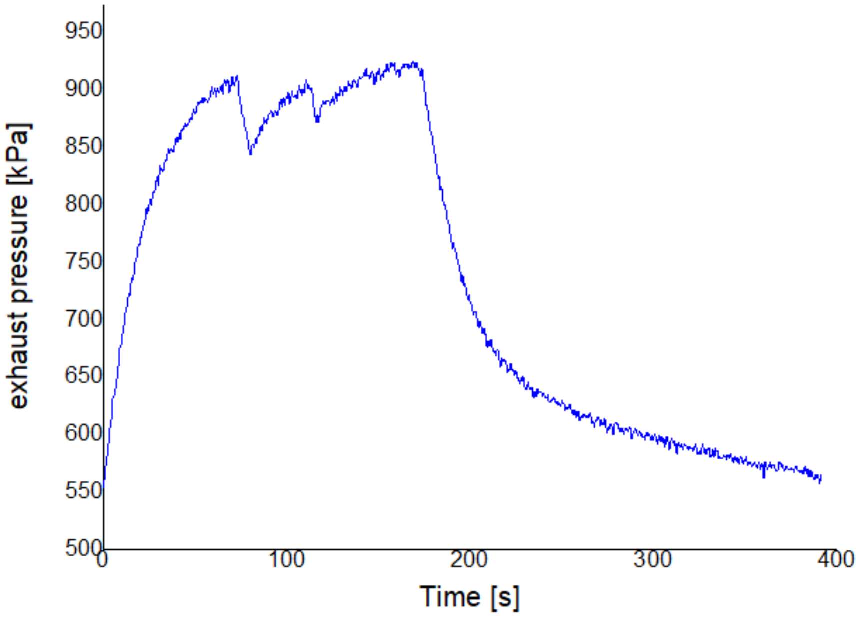

Figure 6: Exhaust pressure curve of air supply system.

Figure 7 shows the change curve of the measured fuel injection temperature during the whole working process of the air supply system.

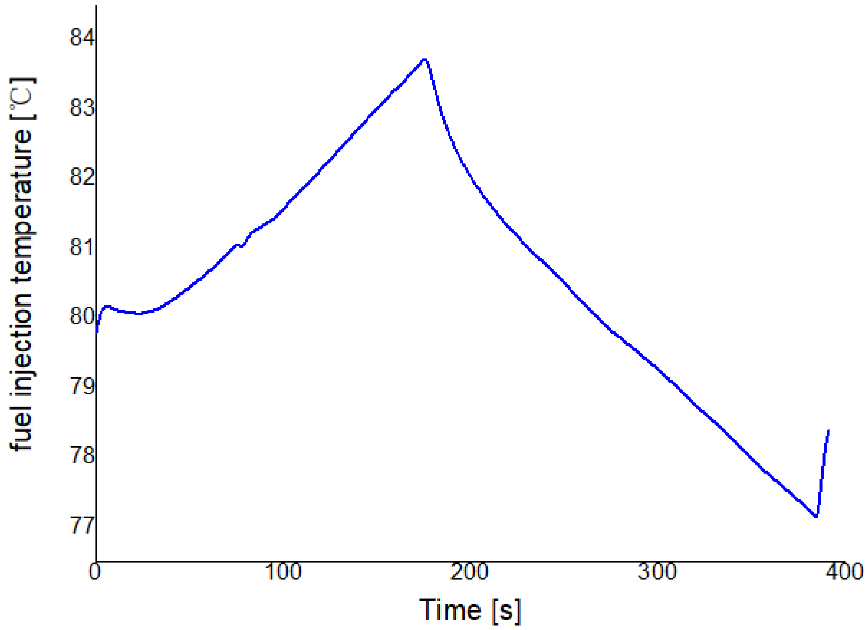

Figure 7: Measured fuel injection temperature curve of air supply system.

After moving average filtering and normalization, $P_i(t)$, $T_i(t)$, $P_e(t)$, and $w(t)$ were used to establish the soft measurement model of the fuel injection temperature based on the method proposed in this paper. The comparison curves between the soft measurement value of the fuel injection temperature and the measured one can be obtained, as shown in Figure 8.

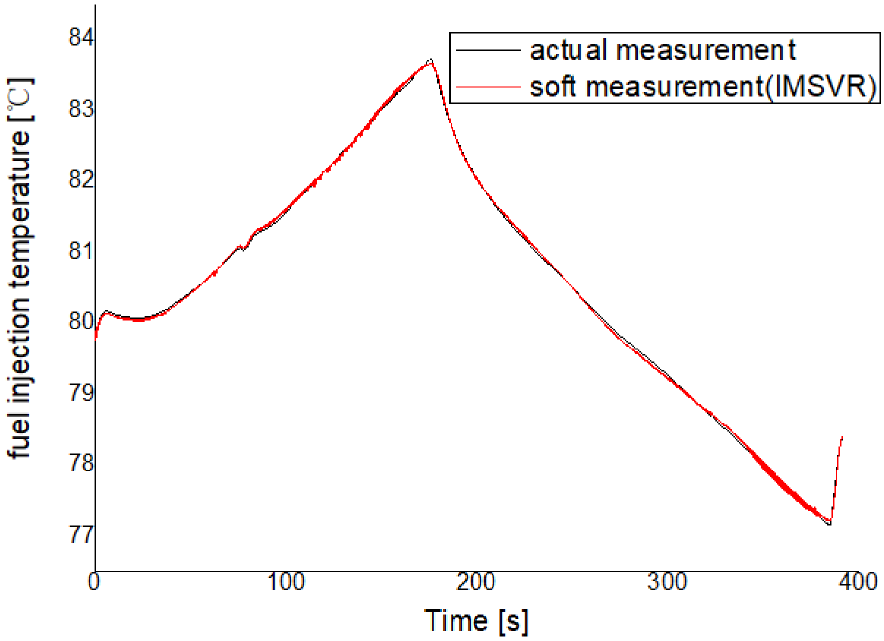

Figure 8: Comparison curves between soft measurement value and actual measurement value.

In order to verify the accuracy of IMSVR, the output of soft measurement model based on traditional MSVR was shown in Figure 9.

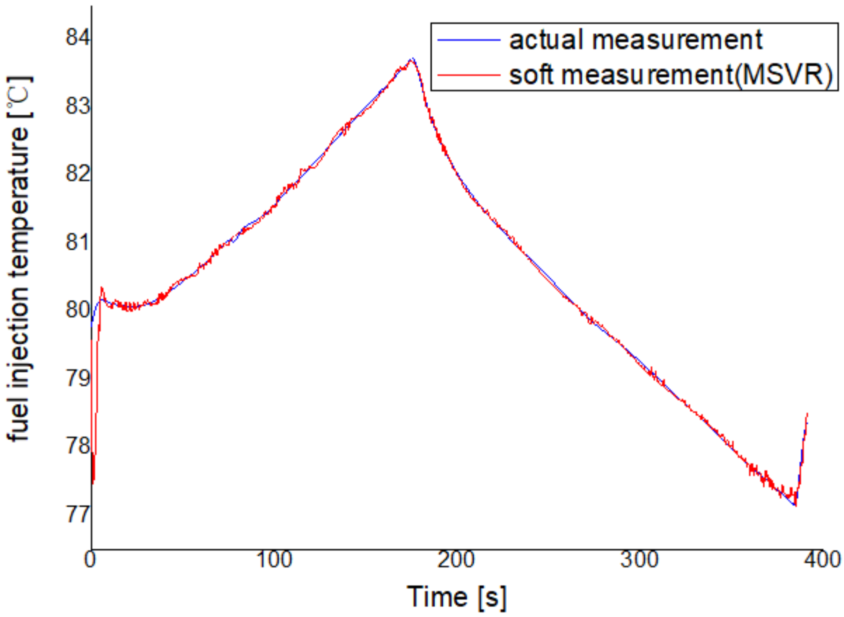

Figure 9: Comparison curves between soft measurement value based on MSVR and actual measurement value.

The modelling effect of soft measurement model based on traditional MSVR and IMSVR was shown in Table 2.

Evaluation indicators	MSVR	IMSVR
MSE	0.0354	0.0013
MAE	0.0548	0.0308

Table 2. Modelling effect.

It can be seen from Figure 8~9 and Table 2 that the soft measurement result of fuel injection temperature based on the method proposed in this paper can correspond to the measured ones well, and the modelling effect of IMSVR is better than MSVR.

4 Conclusions and Contributions

Air supply system is a key equipment of railway vehicles, however, air supply system has only a few pressure and temperature switches and most of the measurement points are not easy to measure directly, which limits its fault warning ability. In this paper, considering the nonlinearity of air supply system, a soft measurement method for air supply systems of railway vehicles was proposed based on an improved multivariate support vector regression algorithm, which can reduce the cost and improve the observability of air supply system.

The case analysis results show that the proposed method could effectively and reliably measure the state variables of key components of air supply system. Moreover, soft measurement result based on IMSVR is more accurate than that based on traditional MSVR, which further shows the accuracy of the method.

The research provides a reference for monitoring the service state of air supply system, and the fault warning of the air supply system could be realized by comparing soft measurements with preset thresholds, which would reduce the potential safety hazards caused by abnormal shutdown, and improve the operation safety and efficiency.

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References

[1] W.J. Wang, G.Q. Li, J.C. Han, et al. “Influence rule of dynamic stress of high-speed train gearbox housing”, Journal of Traffic and Transportation Engineering, 2019,19(1):85-95.

[2] Z.S. Ren, Z.M. Liu. “Vibration and frequency domain characteristics of high speed EMU”, Journal of Mechanical Engineering, 2013, 49(16):1-7.

[3] Q.W. Wang, R.W. Fan, Z. Jin, et al. “Analysis and Discuss of Main Pipe Under Pressure Fault of the Brake System in Beijing Subway Changping Line”, Railway Locomotive & Car, 2019, 39(1):123-126.

[4] J. Liu. “Fault analysis and treatment of high temperature in GKD_3 locomotive’s screw pump air compressor”, Railway Locomotive and Motor Car, 2013(11): 46-48+11.

[5] H. Pei, C.H. Hu, X.S. Si, et al. “Review of Machine Learning Based Remaining Useful Life Prediction Methods for Equipment”, Journal of Mechanical Engineering, 2019, 55(8): 1-13.
[6] G.W. You, S. Park, D. Oh. “Real-time state-of-health estimation for electric vehicle batteries: A data-driven approach”, Applied Energy, 2016, 176: 92-103.
[7] Y.H. Gao, Y.B. Li. “Fault Prediction Model Based on Phase Space Reconstruction and Least Squares Support Vector Machines”, “Proceedings of 2009 Ninth International Conference on Hybrid Intelligent Systems”, IEEE Computer Society, 2009:464-467.
[8] F.M. Huang, J.S. Huang, S.H. Jiang, et al. “Prediction of groundwater levels using evidence of chaos and support vector machine”, Journal of Hydroinformatics, 2017, 19(4):586-606.