Development of an Operational Digital Twin of a Locomotive Braking System Solenoid Valve for Fault Classification

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ABSTRACT

In recent years, a growing role in digital technologies has been filled by model-based digital twinning. A digital twin produces a mapping of a physical structure, operating in the digital domain. Combined with sensor technology and analytics, a digital twin can provide enhanced monitoring, diagnostic, and optimization capabilities. This research harnesses the significant capabilities of digital twining for the unmitigated challenge of fault type classification of a locomotive braking system solenoid valve. We develop a digital twin of the solenoid valve and suggest a method for fault type classification based on the digital twin. The diagnostic ability of the approach is demonstrated on a large experimental dataset.

1. INTRODUCTION

Solenoid valves are widely used in industry because of their simple operating mechanism (Fan et al., 2019; J. Y. Oh et al., 2012; Yoon et al., 2013). However, malfunctioning valves can cause serious injury and/or financial damage. Predictive maintenance strategies have been developed to mitigate unexpected failures (Escobar et al., 2011; Kwon et al., 2016; H. Oh et al., 2015; Park et al., 2016; Wang et al., 2018). Existing failure detection methods often use vibration signals. For example, Tsai et al (Tsai & Tseng, 2010) develop a dynamic model-based method for detecting damage to valve stems and valve seats for electronic diesel injection systems, while Guo et al (H. Guo et al., 2017) propose a data-driven method for detecting magnet wear in brake systems. Although vibration signal-based methods have high detection sensitivity, they require the installation of invasive sensors in the target valves, which can be a practical burden. Non-invasive current signal based fault detection methods are advantageous in this regard (B.Orner et al., n.d.; W. Guo et al., 2018). However, these models have not produced robust fault type classification algorithms due to significant differences between simulated data and real data measured under actual operating conditions. To address this problem, this study proposes a digital twin approach (DT) for classifying faults that occur in a solenoid valve of a locomotive braking system. Digital twins are virtual representations of physical systems. They are used to monitor systems, predict their behavior and optimize their performance (Chen et al., 2001; El Mejdoubi et al., 2016). Here, the proposed DT is based on a physical model of the brake system solenoid valve and is optimized using a machine learning approach. A learning model is trained to diagnose faults in the real twin (RT, i.e., the physical structure) based on the residual signal between the real life measured data of the RT and the estimated data of the DT. Implementing DTs is challenging because it is difficult to ensure that the DT accurately represents the system (Seo et al., n.d.). One a is to use machine learning algorithms to improve the accuracy of mathematical models using sensor data (Tsai & Tseng, 2010), which can compensate for the differences between simulation and reality and provide DT improvements.

DTs are becoming increasingly popular in various industries such as manufacturing, transportation, energy, and healthcare (Angadi et al., 2009; Trappey et al., 2015) because they provide accurate and reliable predictions of a system's behavior and state, allowing for longer time intervals between maintenance routines (Kawashima et al., 2004). DTs can be particularly useful for optimizing the performance of complex systems such as those found in manufacturing and transportation (Kawashima et al., 2004; Luomala & Hakala, 2015).

The contribution of this study is twofold: (i) to develop a DT of a solenoid valve for locomotive braking systems and (ii) to develop a robust diagnosis of various faults in a solenoid valve for locomotive braking systems by estimating the internal latent physical variables within a DT and training a learning model on the residuals. The study is divided into five sections. Section 2 provides a theoretical background and introduces the new DT, Section 3 presents the new algorithm based on DT, and Section 4 demonstrates the algorithm using experimental data. The study is summarized in Section 5.

2. THEORETICAL BACKGROUND

In the following sections, the solenoid valve of the locomotive braking system and the new DT of a locomotive solenoid valve are introduced. In Section 2.1 the solenoid and its role in the braking system are explained. The development of the physical model underlying the behavior of the DT and the relationship between the measured data of the RT and the internal latent physical variables of the DT are described by the equations presented in Section 2.2.

2.1. Solenoid Valve in the Braking System

The locomotive of type JTBW42 and other train locomotives have a solenoid valve that plays a critical role in ensuring rail vehicle safety. This valve is an essential part of the braking system. When the pressure in the system drops below a certain threshold, it triggers the solenoid valve to apply the brakes as soon as a brake signal is received. The structure of the braking system is shown in Fig.1. The position of the solenoid valve between the relay valve and the pressure control valve is crucial for reliable emergency braking.

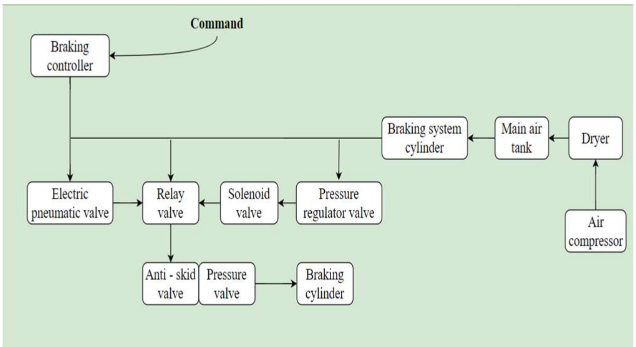

Figure 1. Structure of the braking system in trains

According to the statistics of the Israeli Railway maintenance department, the probability of solenoid valve failure on JTBW42 locomotives increases sharply when mileage exceeds 800,000 km. Many situations are responsible for solenoid valve failure, e.g. situations where the solenoid valve cannot be completely sealed due to corrosion inside the valves, loss of power or mechanical wear [1, 2].

As shown in Fig.2, the solenoid valve controls the operation of a moving iron core in a solenoid coil to open or close the exhaust valve by turning the solenoid coil on or off. Of course, the solenoid valve is a switch-like component that can easily fail due to wear. Therefore, it is important to accurately assess the condition of the solenoid valve.

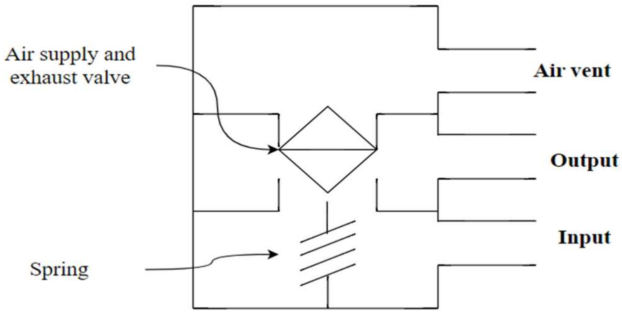

Figure 2. Structure of the solenoid valve

2.2. DT of a Locomotive Solenoid Valve in the Braking System

Fig.3 depicts a cylindrical ferromagnetic steel shell with a movable cylindrical steel piston inserted inside it. The piston is connected to a spring. A coil connected to a DC power source is positioned inside the casing. The coil, when excited, transforms electrical energy into magnetic field energy. This electromagnetic force moves the piston in the positive $\boldsymbol{x}$-coordinate direction and reduces the reluctance of the magnetic circuit, which increases the inductance. Once the piston reaches an operating point where the electromagnetic force equals the spring force, the system is in equilibrium. If an external mechanical force, $\boldsymbol{f_o}$, is applied suddenly and the piston moves, the inductance decreases, and the mechanical energy of the spring transfers the magnetic energy of the applied coupling. When the electromagnetic force equals the restraining force, a new operating point is reached. Once the mechanical force $\boldsymbol{f_o}$ drops to zero, the system returns to the starting point, and the mechanical energy of the spring transfers to the coupling field. However, part of the energy is dissipated during transients and due to friction losses in the circuit.

Using Kirchhoff's Voltage Law (2nd low) and assuming magnetically linear system, the solenoid valve electrical subsystem is described as follows:

$$
\begin{aligned}
&v_0 = R \cdot i + \frac{d\delta}{dt}; \\
&\delta = L(x) \cdot i; \\
&v_0 = R \cdot i + L(x) \cdot \frac{di}{dt} + i \cdot \frac{dL(x)}{dx} \cdot \frac{dx}{dt} \\
&\frac{di}{dt} = \frac{1}{L(x)} \cdot \left[v_0 - R \cdot i - i \cdot \frac{dL(x)}{dx} \cdot \frac{dx}{dt} \right]
\end{aligned} \tag{1}
$$

where R is the resistance, i is the current, v is the voltage, x is the piston displacement, δ is the flux linkage, L is the inductance and t is time.

Using Newton's second law the solenoid valve mechanical subsystem is described as follows:

$$\sum F = M \cdot a = M \cdot \frac{dV}{dt} = M \cdot \frac{d^2x}{dt^2};$$
$$f_{fld} - k \cdot (x - x_0) - C \cdot \frac{dx}{dt} - f_0 = M \cdot \frac{d^2x}{dt^2}; \quad (2)$$
$$\frac{d^2x}{dt^2} = \frac{1}{M}\left[f_{fld} - C \cdot \frac{dx}{dt} - k \cdot (x - x_0) - f_0\right]$$

where k is the spring constant, x_0 is the initial piston displacement, C is the damping coefficient, x is the piston displacement, f_0 is a force acting on the piston, f_{fld} is the electromagnetic force and M is mechanical parts mass.

Knowing the reluctance of the system, the Inductance could be derived:

$$R_M = \frac{g}{\varphi_0 \cdot \pi \cdot x \cdot d}\left(\frac{a+x}{x}\right);$$
$$L(x) = \frac{N^2}{R_M} = \frac{\varphi_0 \cdot \pi \cdot x \cdot d \cdot N^2}{g}\left(\frac{x}{a+x}\right) \quad (3)$$
$$L' = \frac{\varphi_0 \cdot \pi \cdot x \cdot d \cdot N^2}{g} \rightarrow L(x) = L' \cdot \left(\frac{x}{a+x}\right)$$

where R_M is the reluctance of the system, d is the piston diameter, a is the cylindrical steel shell geometrical size (see Fig.3), g is the gap between the piston and the cylindrical steel shell and N is the windings around the coil.

Knowing that the magnetic system is linear and that the current was kept constant during the change of the working point, the electromagnetic force can be derived as follows:

$$f_{fld} = \frac{dWf}{dx} = \frac{i^2}{2} \cdot \frac{dL(x)}{dx} = \frac{i^2}{2} \cdot \frac{a \cdot L'}{(a+x)^2}$$
$$\frac{dL(x)}{dx} = \frac{a \cdot L'}{(a+x)^2} \quad (4)$$

Two parameters were routinely measured on the tested locomotives. They are presented in Fig. 4: the solenoid valve current, marked by i_A, the solenoid valve displacement, marked by x and the solenoid valve voltage U_A. In the current study, the internal latent physical variables (R, k and L) are estimated by solving a least squares problem, where the variables minimize the constraints presented in Eq. 5. This is achieved in Eq. 6, also known as a least squares estimation:

$$\theta_i, \ldots, \theta_j = arg \min_{\theta_i,\ldots,\theta_j} \sum_{n=1}^{N}\left(\sum_{k=i}^{j} \theta_k x_k[n] - y[n]\right)^2 \quad (5)$$

$$\vec{\theta} = (X^T X)^{-1} X^T y \quad (6)$$

where $x_k[n]$ represents the corresponding values of the internal parameters θ_k in the coordinate n [e.g., for θ_1 in time t, the corresponding value is $U_A\left(\frac{t}{\Delta t}\right)$], $y[n]$ represents the measured parameters in the coordinate n and X is the matrix of $x_k[n]$ with N rows and $j-i+1$ columns.

The internal variables (θ_1, θ_2 and θ_3) can be used to calculate the process coefficients presented in Eq. 7:

$$R = \theta_1, L = \theta_2, k = \theta_3 \quad (7)$$

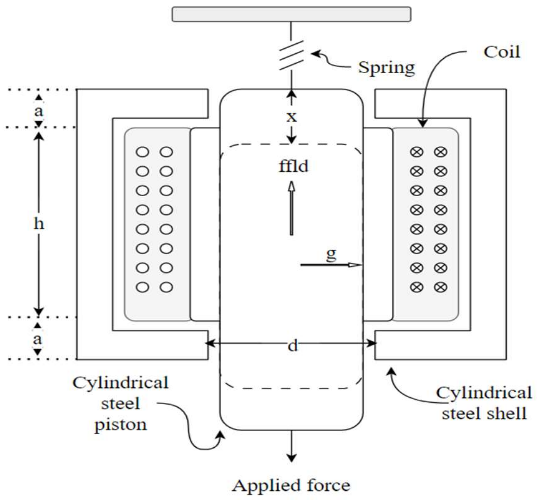

Figure 3. Schematic description of the solenoid structure

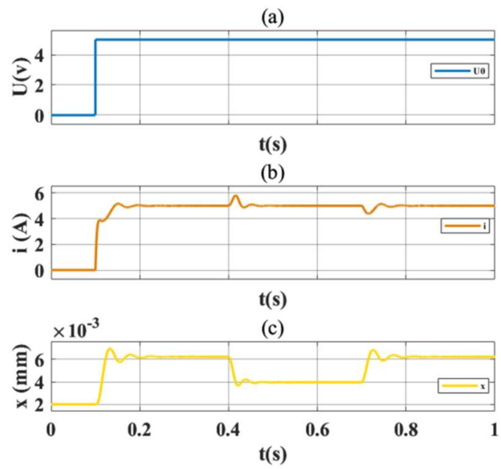

Figure 4. Measured parameters; (a) $\boldsymbol{U_A}$ (blue), (b) $\boldsymbol{i_A}$ (orange), (c) $\boldsymbol{x}$ (yellow).

3. THE PROPOSED ALGORITHM

The proposed algorithm is integrated in the locomotive DT. It consists of five steps, illustrated in Fig. 5.

1. For each RT in the training set, an individualized DT is generated by estimating the internal variables (θ_1, θ_2 and θ_3). These variables are estimated by the least squares method presented in Eq. 5, as explained in Section 2.2.
2. Based on the internal estimated parameters, the DT calculates the residuals between the measured and estimated signals.
3. From each residual, five features are extracted: mean, variance, maximal value, kurtosis, and absolute sum.
4. A model of Deep Neural Network (DNN) is trained on the extracted features where, at first, the training set is divided into 80% training and 20% validation, and the number of trees is set to have maximal accuracy on the validation set.
5. The trained model is used to predict the classes of the test set.

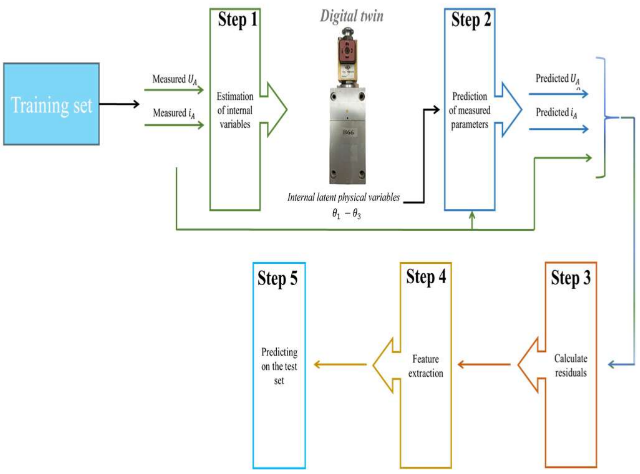

Figure 5. The new suggested algorithm.

We analyze the computational, time, and resource demands, especially with respect to large data sets, to provide a comprehensive understanding of the practical implementation of the algorithm. To improve the interpretability of the model, we also explore various methods such as layer-wise propagation of relevance, attention mechanisms, and sensitivity analysis. These additions aim to shed light on the decision-making process of the deep neural network ensemble and provide meaningful explanations for its predictions. By improving the interpretability of the model, we aim to address the black-box characteristics of deep neural networks and make provide transparency in the diagnostic process, which will promote the applicability of our approach in safety-critical train operations and maintenance activities.

4. DEMONSTRATION ON AN EXPERIMENTAL DATASET

In this section, the new algorithm described in Section 3 is tested and compared with other algorithms:

A regular machine-learning algorithm consists of Steps 3, 4, and 5 of the new algorithm described in Section 3. This algorithm extracts the features directly from the measured signals, i.e., i_A and U_A, and a model of deep neural network is trained on these extracted features, as described in Step 4 in Section 3. This algorithm does not use the DT.

The comparison process between the new algorithm and the regular machine-learning algorithm demonstrates the contribution of the DT concept.

These two algorithms, i.e., the regular machine-learning algorithm, and the new suggested algorithm, were tested on an experimental dataset consisting of a 5,500 RT training set and a 250 RT test set. An example of the two measurements of an RT in the training set is depicted in Fig. 4. Overall, five classes were tested, one healthy and four types of faults: damage coil, voltage sensor bias, current sensor bias, and damage spring Fig.6. The fault types were divided uniformly across different classes.

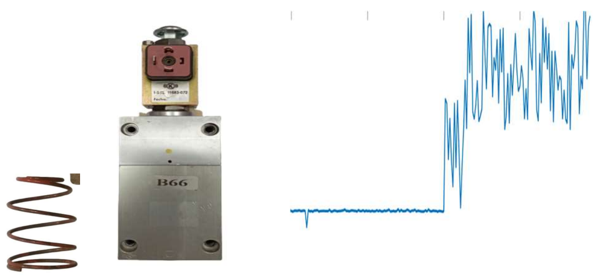

Figure 6. Illustration of the damaged spring signal.

The results of the two tested algorithms are presented in Fig. 7 on 250 test examples, 50 from each condition. As can be seen in Fig. 7(a - c), the new algorithm achieved a significant improvement from accuracy of 68% to 87.1%. The error is reduced by more than a factor of 2. This result demonstrates the ability of the DT to improve diagnosis by incorporating physical knowledge of the system.

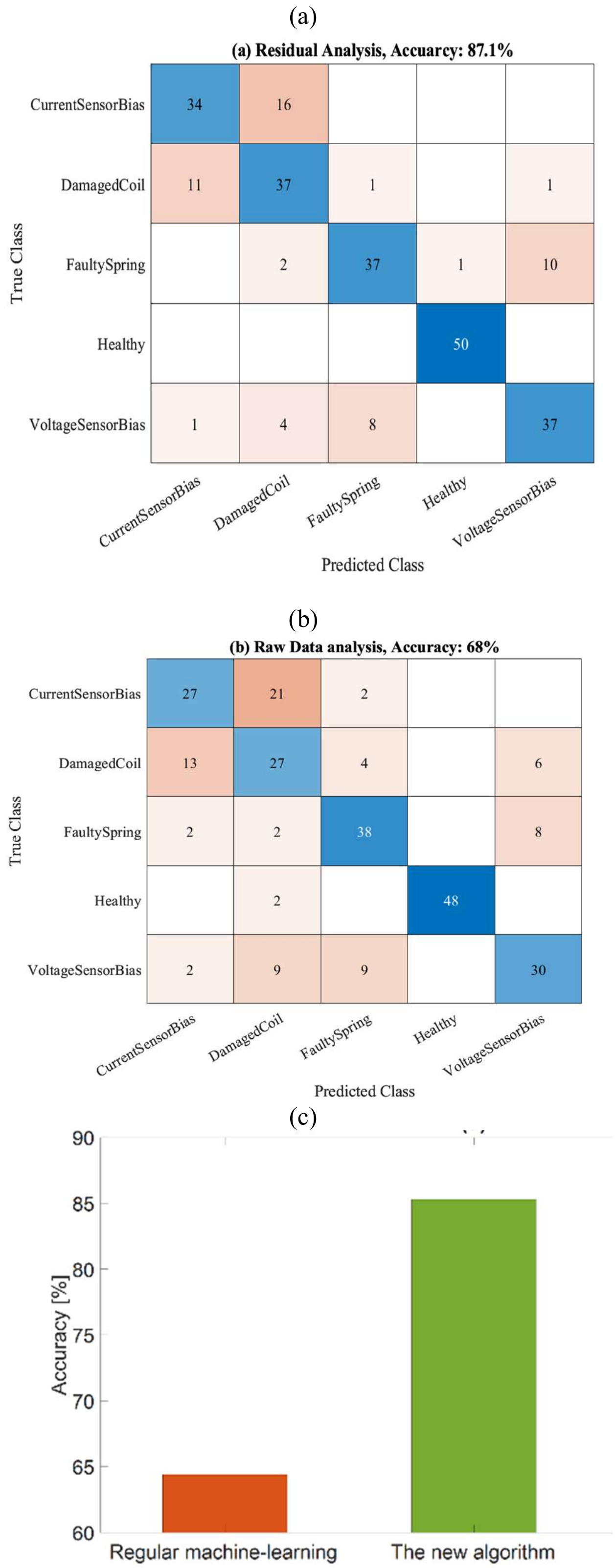

Figure 7. Results of the new suggested algorithm. (a) The new suggested algorithm, (b) Regular machine-learning algorithm without the DT, the summarized accuracies of (a–b**).** Each table presents the confusion matrix after applying the tested algorithm on the test set

5. CONCLUSION

This paper presents a DT algorithm for diagnosing faults in solenoid valves of locomotive brakes. The algorithm involves five steps, including estimation of internal DT variables, computation of residuals, feature extraction, training of a deep neural network ensemble, and prediction. The dataset used for testing consists of 5,500 training RTs and 250 test RTs. The results show a significant improvement in accuracy from 68% to 87.1 % compared to traditional machine learning algorithms. The approach DT improves diagnosis by incorporating physical knowledge about the system.

Unlike traditional fault detection methods, the method described is based on a physically derived solenoid valve model of the braking system, making it applicable to a wide range of operating points and easily transferable to other solenoid valves. In addition, the symptoms are easy to interpret and understand.

This model-based approach DT has a broader impact than traditional engineering design, as it can improve train operations and maintenance activities by diagnosing and correcting maintenance faults. Ultimately, the greatest benefit of such DT is its impact on customer experience and operating costs. The paper shows how performance-based engineering, where real-time performance provides the input to an adaptive system packaged in a digital layer - the DT - can create significant value.

REFERENCES

Angadi, S. V., Jackson, R. L., Choe, S. yul, Flowers, G. T., Suhling, J. C., Chang, Y. K., Ham, J. K., & Bae, J. il. (2009). Reliability and life study of hydraulic solenoid valve. Part 2: Experimental study. *Engineering Failure Analysis*, *16*(3), 944–963. https://doi.org/10.1016/j.engfailanal.2008.08.012

B€ O Orner, M., Straky, H., Weispfenning, T., & Isermann, R. (n.d.). *Model based fault detection of vehicle suspension and hydraulic brake systems*.

Chen, P., Toyota, T., & He, Z. (2001). Automated Function Generation of Symptom Parameters and Application to Fault Diagnosis of Machinery Under Variable Operating Conditions. In *SYSTEMS AND HUMANS* (Vol. 31, Issue 6).

El Mejdoubi, A., Oukaour, A., Chaoui, H., Gualous, H., Sabor, J., & Slamani, Y. (2016). State-of-Charge and State-of-Health Lithium-Ion Batteries' Diagnosis According to Surface Temperature Variation. *IEEE Transactions on Industrial Electronics*, *63*(4), 2391–2402. https://doi.org/10.1109/TIE.2015.2509916

Escobar, R. F., Astorga-Zaragoza, C. M., Tllez-Anguiano, A. C., Jurez-Romero, D., Hernndez, J. A., & Guerrero-

Ramrez, G. V. (2011). Sensor fault detection and isolation via high-gain observers: Application to a double-pipe heat exchanger. *ISA Transactions*, *50*(3), 480–486. https://doi.org/10.1016/j.isatra.2011.03.002

Fan, X., He, Y., Cheng, P., & Fang, M. (2019). Fuzzy-Type Fast Terminal Sliding-Mode Controller for Pressure Control of Pilot Solenoid Valve in Automatic Transmission. *IEEE Access*, *7*, 122342–122353. https://doi.org/10.1109/ACCESS.2019.2937847

Guo, H., Wang, K., Cui, H., Xu, A., & Jiang, J. (2017). A Novel Method of Fault Detection for Solenoid Valves Based on Vibration Signal Measurement. *Proceedings - 2016 IEEE International Conference on Internet of Things; IEEE Green Computing and Communications; IEEE Cyber, Physical, and Social Computing; IEEE Smart Data, IThings-GreenCom-CPSCom-Smart Data 2016*, 870–873. https://doi.org/10.1109/iThings-GreenCom-CPSCom-SmartData.2016.179

Guo, W., Cheng, J., Tan, Y., & Liu, Q. (2018). Solenoid Valve Fault Diagnosis Based on Genetic Optimization MKSVM. *IOP Conference Series: Earth and Environmental Science*, *170*(4). https://doi.org/10.1088/1755-1315/170/4/042134

Kawashima, K., Ishii, Y., Funaki, T., & Kagawa, T. (2004). Determination of flow rate characteristics of pneumatic solenoid valves using an isothermal chamber. *Journal of Fluids Engineering, Transactions of the ASME*, *126*(2), 273–279. https://doi.org/10.1115/1.1667888

Kwon, D., Hodkiewicz, M. R., Fan, J., Shibutani, T., & Pecht, M. G. (2016). IoT-Based Prognostics and Systems Health Management for Industrial Applications. *IEEE Access*, *4*, 3659–3670. https://doi.org/10.1109/ACCESS.2016.2587754

Luomala, J., & Hakala, I. (2015). Effects of temperature and humidity on radio signal strength in outdoor wireless sensor networks. *Proceedings of the 2015 Federated Conference on Computer Science and Information Systems, FedCSIS 2015*, 1247–1255. https://doi.org/10.15439/2015F241

Oh, H., Choi, S., Kim, K., Youn, B. D., & Pecht, M. (2015). An empirical model to describe performance degradation for warranty abuse detection in portable electronics. *Reliability Engineering and System Safety*, *142*, 92–99. https://doi.org/10.1016/j.ress.2015.04.019

Oh, J. Y., Park, Y. J., Lee, G. H., & Song, C. S. (2012). Modeling and validation of a hydraulic systems for an AMT. *International Journal of Precision Engineering and Manufacturing*, *13*(5), 701–707. https://doi.org/10.1007/s12541-012-0091-6

Park, J., Ha, J. M., Oh, H., Youn, B. D., Choi, J. H., & Kim, N. H. (2016). Model-Based Fault Diagnosis of a Planetary Gear: A Novel Approach Using Transmission Error. *IEEE Transactions on Reliability*, *65*(4), 1830–1841. https://doi.org/10.1109/TR.2016.2590997

Seo, B., Jo, S.-H., Oh, H., & Youn, B. D. (n.d.). *Solenoid Valve Diagnosis for Railway Braking Systems with Embedded Sensor Signals and Physical Interpretation*.

Trappey, A. J. C., Trappey, C. V., Ma, L., & Chang, J. C. M. (2015). Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions. *Computers and Industrial Engineering*, *84*, 3–11. https://doi.org/10.1016/j.cie.2014.12.033

Tsai, H. H., & Tseng, C. Y. (2010). Detecting solenoid valve deterioration in in-use electronic diesel fuel injection control systems. *Sensors*, *10*(8), 7157–7169. https://doi.org/10.3390/s100807157

Wang, K., Guo, H., Xu, A., Jameson, N. J., Pecht, M., & Yan, B. (2018). Creating Self-Aware Low-Voltage Electromagnetic Coils for Incipient Insulation Degradation Monitoring for Smart Manufacturing. *IEEE Access*, *6*, 69860–69868. https://doi.org/10.1109/ACCESS.2018.2880266

Yoon, J. Il, Truong, D. Q., & Ahn, K. K. (2013). A generation step for an electric excavator with a control strategy and verifications of energy consumption. *International Journal of Precision Engineering and Manufacturing*, *14*(5), 755–766. https://doi.org/10.1007/s12541-013-0099-6

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