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Mechanical Transmission Model and Numerical Simulation Based on Machine Learning

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ABSTRACT

Mechanical transmission is one of the earliest transmission modes in human society. With the continuous progress of science and technology, effective simulation and calculation research on mechanical transmission has gradually become an important link in the study of mechanical transmission. In the actual engineering practice, reliable and accurate data are difficult to obtain due to the complexity and low accuracy of the traditional mechanical transmission process. Machine learning (ML), a model trained by data, was used to analyze the response of the system through different parameters and drew scientific and reasonable conclusions. ML is more intuitive, easier to operate, and faster in calculation than the traditional methods. In many mechanical structures, due to the large number of processing parts and data, numerical simulation of this important equipment requires a considerable time to adjust and optimize accordingly.

KEYWORDS

Edge Computing, Internet of Things, Machine Learning, Mechanical Transmission

INTRODUCTION

With the continuous improvement of technology and industrial production level, mechanical transmission technology has been widely used. Specifically, it is used to connect motion transmission belts of various large mechanical equipment and engineering machinery in industrial production, as well as the transmission between various industries and machinery. It is among the indispensable fields with great development potential in current industrial applications given its advantages, such as high transmission accuracy, good reliability, low noise, and few moving parts. The method based on machine learning (ML) provides a theoretical basis and technical means for optimizing transmission systems, exhibiting great importance for various complex transmission systems.

Mechanical transmission is a widespread concern for the industrial manufacturing community, and many scholars have carried out research on this subject. Zhang et al. (2019) proposed a power return hydromechanical transmission system and modeled the speed ratio, torque ratio, efficiency, capacity,

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and other characteristics of the return hydromechanical transmission system to ensure the dynamic torque ratio and improve the efficiency of the automatic transmission system. Compared with the hydraulic mechanical split transmission, the return flow hydraulic mechanical transmission system can achieve higher efficiency while ensuring the starting torque ratio. Blagonravov et al. (2017) considered the stepless mechanical transmission with the vibration motion of internal components and outlined the basic principle of the automatic control of transmission with internal force function according to the vibration amplitude of the internal components. Asgari and Yazdizadeh (2018) proposed a robust fault diagnosis scheme for wind turbine generator sets and established a comprehensive mathematical model of the mechanical transmission system and gearbox dynamics of wind turbine generator sets operating in a wind farm. Farrage and Uchiyama (2018) believed that the friction occurring in mechanical systems is an important issue to achieve high-precision performance. They also believed that friction would not only adversely affect the motion accuracy of the drive shaft but also consume excessive energy and that the sliding mode control verified the effectiveness of the proposed friction model in the dual axis feed drive system. Kim et al. (2019) analyzed the transmission strength of a tractor's transmission gear by using the equivalent torque during plowing. The load measurement system consists of engine speed sensor, torque gauge, four-shaft speed sensor, and a pressure sensor of two hydraulic pumps. The analysis method using equivalent torque showed lower stress and higher safety factor than that using maximum torque. Therefore, the equivalent torque method would support a more reliable product development when designing tractors with an actual working torque. Yang et al. (2019) mentioned that the hydraulic mechanical transmission (HMT) is suitable for high-power vehicles and established the speed model of HMT in power shift, considering HMT as the research object. Baek et al. (2020) proposed a quantitative method of reliability distribution to solve the reliability distribution problem of the mechanical transmission system. Their case analysis results proved that the method can provide certain reference for reliability distribution of the mechanical transmission system. The research theory of the mechanical transmission is relatively rich, but its application is still limited.

ML is applied in many fields. Pathan et al. (2019) proposed the data analysis application and ML monitoring to accurately predict the macro stiffness and yield strength of unidirectional composite materials under lateral loading. These researchers showed that predictions can be obtained without performing physics-based calculations by analyzing the image of material microstructure and the constitutive model knowledge of fiber and matrix. Moghadam et al. suggested that ML and deep learning algorithms become important tools in the field of materials and mechanical engineering. According to these researchers, ML models trained from large material datasets associate structures, attributes, and functions at multiple hierarchical levels, providing a new approach for rapid exploration of design space. Shen et al. (2019) showed how the strength of ML trained through a multilevel simulation combination can predict the performance of metal organic frameworks and introduced the ML algorithm to predict the mechanical performance of existing and future metal organic frameworks in seconds. Maley et al. (2010) evaluated the mechanical properties by using molecular dynamics simulation and ML technology. These researchers showed that the mean squared error of the ML prediction of the mechanical properties is several orders of magnitude smaller than the actual value of each attribute, indicating that the model has good training results. Shamsirband and Khansari (2021) believed that the most powerful methods for detecting damage are ML and deep learning. They discussed advanced ML methods and their applications in detecting and predicting material damage. These researchers showed that according to performance, deep learning and integration-based technology have the highest application and robustness in the field of damage diagnosis. Talebjedi et al. (2022) proposed the optimization strategy for refining the mechanical energy saving by combining ML algorithm and heuristic optimization method. Najjar et al. (2022) used the micromechanical model, finite element simulation of micro-indentation, and ML to predict the mechanical properties of the 2O3 nanocomposites. They established a micromechanical model on the basis of the evolution law of mixture, grain, and grain boundary size. The application of ML in machinery still has limitations.

The application of ML in the mechanical transmission has been researched, and the satisfaction, speed, periodicity, safety, and efficiency of the mechanical transmission have been analyzed to improve the performance of mechanical transmission in all aspects and to promote its further development in the industry.

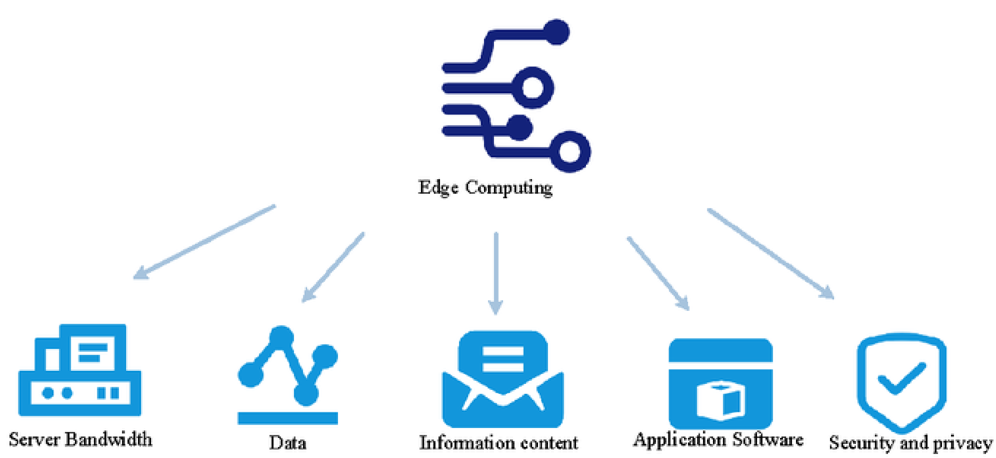
EDGE COMPUTING, ML, AND MECHANICAL TRANSMISSION

Relationship Between Edge Computing and ML

ML is a technical complement in edge computing. In ML, the generated data would be transmitted to the ML system software to generate an analytical decision model. ML has two methods in the IoT and edge computing scenarios. ML optimization algorithm requires considerable computing power to make decisions in cloud computing (Sangaiah, 2019). The data collected from the edge would be transmitted to the ML system software to form a decision mode for learning, training, and analysis, and then the entity model information would be transmitted to the edge of the network. With this method, all edge devices can be analyzed and managed. In this entity model, edge devices would be used for collection, analysis, and application to the cloud to improve the level of intelligence. The edge computing architecture can be used to improve the performance of cloud computing systems, so that they can process and analyze data at the edge of the network and be closer to the data source. In this approach, data can be collected and processed around the device compared with sending data to the cloud or data management center. The advantages of edge computing are shown in Figure 1.

Edge computing can reduce the server bandwidth required by sensors and central cloud computing, as well as the pressure on the entire information technology (IT) architecture. Data are stored and processed on edge devices without using data links. This approach eliminates continuous high-bandwidth network connections. Based on boundary computing, node devices provide only the information required by cloud computing, and not the original data. This approach is beneficial to reduce the connectivity of cloud architecture and save costs. It is very beneficial when a large number of industrial production machines and devices are used for edge analysis, and only excessive data information is transmitted to the cloud, resulting in considerable savings in IT infrastructure. The individual behavior of the edge device is similar to the actual cloud computing class by mathematical operation. Applications can be executed rapidly and can establish reliable and highly corresponding communication with nodes.

Figure 1.
Relationship between edge computing and ML



With regard to security and privacy of data based on boundary computing, compared with unsecure data transmission, sensitive data are generated, processed, and stored on edge devices, and the centralized data management center may be damaged. An edge computing system can provide common countermeasures for each edge to achieve data consistency and privacy.

Mechanical Transmission

Mechanical transmission is the most commonly used in mechanical engineering. It realizes power and motion through mechanical form. It mainly has two types: one is driven by the friction between the mechanical parts, and the other is driven by the meshing of the driving parts or by the meshing of intermediate parts to achieve power and movement. Many types of mechanical transmission are available, and they can be divided into two categories: friction transmission and gear transmission.

The transmission of power is realized through friction, including belt drive, rope drive, and friction wheel drive. Friction transmission can easily realize stepless speed regulation. Most of them can be applied to the driving occasions with a large wheelbase. Overload slip can be used as a damping and protection transmission mechanism, but it is usually inapplicable to high-power occasions and cannot ensure an accurate transmission ratio.

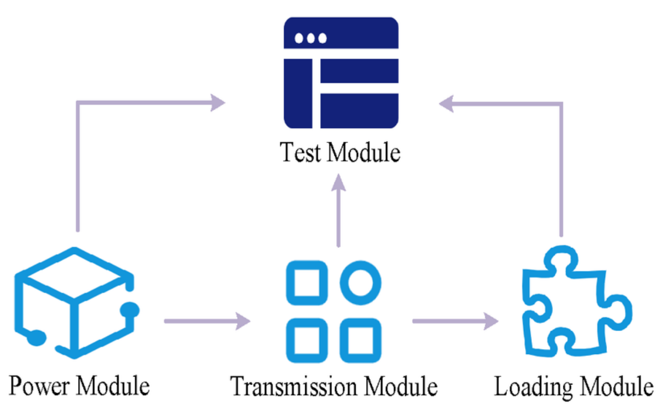
Gear transmission, chain transmission, spiral transmission, and harmonic transmission are meshed with the transmission device to achieve transmission and movement. Gear transmission can be used in high power occasions with an accurate transmission ratio, but usually requires high machining accuracy and assembly accuracy. Basic product categories include reducer, brake, clutch, coupling, CVT, lead screw, and slide rail.

INFLUENCE OF ML ON MECHANICAL TRANSMISSION

Mechanical Transmission Test Platform

The mechanical transmission test platform consists of four modules: transmission, power, test, and loading. The transmission module is mainly the mechanical transmission equipment for bag test. Common transmission equipment includes gear transmission, belt transmission, and chain transmission. The power module is the main power input equipment of the entire test platform, mainly including the motor and frequency converter. The loading module simulates the load of the transmission system; the test module collects data signals. Common devices include pressure sensor, encoder, speed torque sensor, temperature sensor, vibration sensor, and noise sensor. The mechanical transmission test platform is shown in Figure 2.

Figure 2.
Mechanical drive test rigs



Mechanical Transmission Structure Composition

Transmission shaft: it is composed of several tooth-shaped gears and is used to transmit rotary torque or rotary motion. Coupling between teeth: when the gear and end cover are assembled together, a device or component that transmits torque is formed between the shaft end and end cover. The end cover is usually fixed with tooth keys, locking pins, or bolts, and the end cover should always be clean. Installation of shaft: the end cover is generally fixed with a shaft to bend the shaft end inward. Coupling: the transmission shaft is composed of two cams, and a coupling is installed between the cams. Transmission teeth: tooth-bonded or meshed gear sets are used; they are usually composed of two cylindrical gears and four spur gears. The mechanical transmission structure is shown in Figure 3.

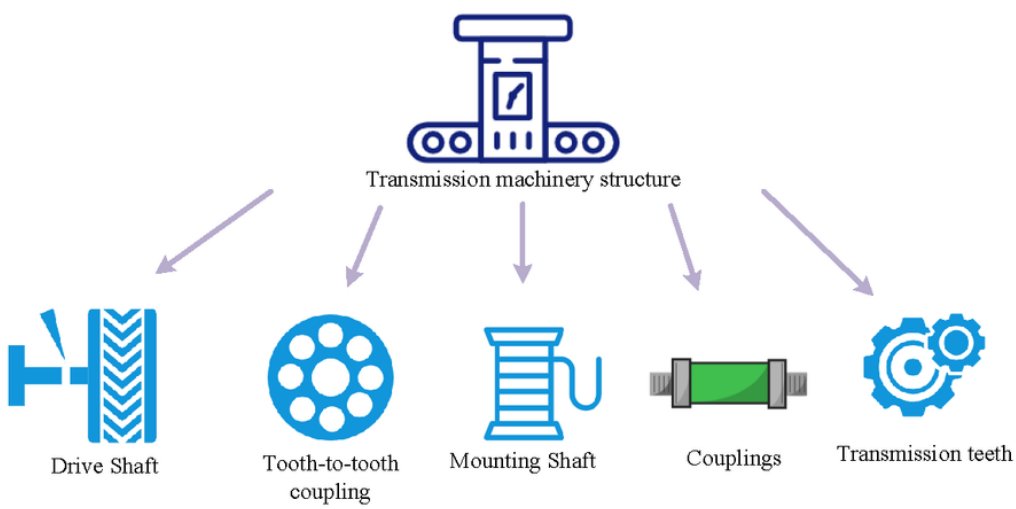
Gear transmission mainly uses gears and cams to transmit force and torque and can also use cams to adjust the rotation angle. It has the following advantages:

- **Stepless speed regulation:** Under low-speed conditions, the torque generated by gear meshing is small.
- **Simple structure:** The design and manufacture are relatively simple while maintaining the transmission ratio and running stability.
- **High transmission efficiency, small size, and light weight:** The transmission shaft generally adopts hollow bearing or rolling bearing and is equipped with cam or cam gear to realize torque transmission.
- **High transmission reliability:** Transmission can be realized without maintenance and replacement of parts.

Application of ML in Mechanical Transmission

ML allows experts to easily learn and process complex inputs. The algorithm provided by ML can improve the analysis quality and work efficiency. If a robot is used to assemble a machine, then all parts of the car need to be installed on a central platform. These parts would be assembled on the car. The robot would use ML algorithms to program and then compare it with the current car to determine which parts are better on the current car. If a sensor system is installed in front of the car, then the car would track obstacles in front of the car, and then the sensor would judge whether the car would

Figure 3.
Mechanical drive structure composition



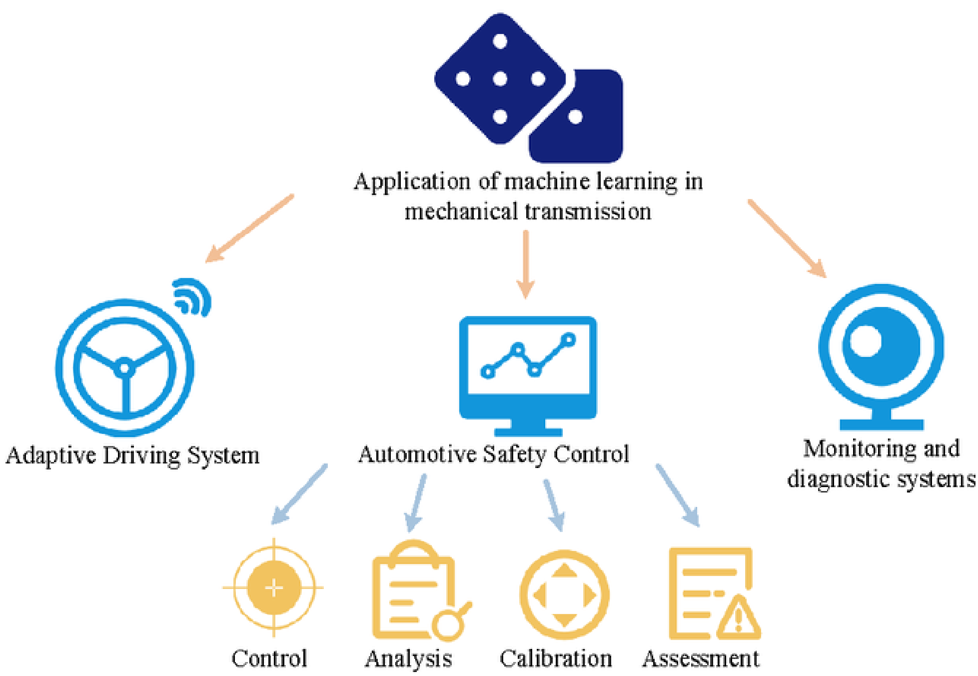
turn through the body or other positions. Finally, the robot would obtain information from the sensors installed on other vehicles near it for calibration and adjustment. During these processes, if the car does not deviate from its intended route or deviates from its lane or stop line, then it would send an alarm, and the car would start to repair itself. The application of ML in mechanical transmission is shown in Figure 4.

Vehicle Safety Control

The traditional driving simulation system needs to be realized through data collection. These processes include all tests conducted in the test environment, such as sensors installed in the center of the car, testing and calibration systems, simulation of operating software, and simulation of steering wheel steering. With the continuous development and maturity of ML technology, achieving real-time control, real-time analysis and feedback, real-time calibration, and safety assessment of the autodrive system in the test environment is currently possible.

The ML system also optimizes any unexpected situations that occur in the vehicle while driving. The regression and measurement theory in ML is used to collect various event data identified by the current car drivers, traffic lights, and other traffic signs, thereby adjusting the autodrive system and enabling the car to drive autonomously (Gupta et al., 2019). In addition, for the problems faced by the autodrive system, interaction interference may be observed among many sensor systems involved in the challenges faced by the autodrive system and other sensor systems closely related to the entire system. The interaction interference between sensors would lead to problems. For example, the sensors cannot obtain accurate information (similar to the current vehicle, with either people or obstacles) about the current car and other vehicles for analysis and for determining the impact on the speed of information transmission to improve the ability of interaction delay between automation systems and sensors. Therefore, a combination of a complete set of ML technology and advanced sensor technology should be established to achieve fully autonomous vehicle automatic driving function and safe control system status.

Figure 4.
Application of ML in mechanical transmission



Adaptive Driving System

The adaptive driving system includes multiple independent cameras and microphones, both of which can capture video and audio information while driving. In a typical use case, when an autonomous vehicle enters a lane on the road, it detects the speed and direction of the car in front. When the car turns, accelerates, or decelerates, it recognizes the danger signal and sends an alarm. The sensor can analyze these signals and negotiate with the driver to predict the driver's action through the steering angle and speed. The vehicle system detects whether obstacles exist or whether the driving direction of the vehicle is within a reasonable speed range and does not interfere with the vehicle or change its route or speed. The vehicle would encounter different road conditions (such as rainy and snowy weather and slippery roads) during actual use. Thus, the adaptive driving system needs to constantly adjust the algorithm to ensure that the vehicle moves in the right direction and maintains a safe distance from other vehicles.

Automobile Maintenance Monitoring and Diagnosis System

ML can monitor the status of vehicles in real time. With the help of sensors, computer vision, and other technologies, ML systems can collect various data to further improve vehicle performance. If the vehicle cannot brake at the right time and position, then the vehicle would encounter problems in some cases. The ML system achieves this goal through classification, statistics, and description of measured data (Groensfelder et al., 2020). The measurement data contain different structural features, location, and working modes of the sensors or systems; thus, they can support the decision-making of the artificial intelligence software and algorithms. Contrary to the traditional vehicle-centered measurement data, the ML system can analyze, detect, diagnose, track, and even control vehicles and maintain them and other relevant data.

MECHANICAL TRANSMISSION MODEL ALGORITHM OF EDGE COMPUTING

Robert Edge Detection Operator

The Robert edge detection operator uses a local difference operator to find edges.

The gradient of a function is defined as shown in equation (1):

$$\nabla r\left(a,b\right) = \frac{\lambda r\left(a,b\right)}{\lambda a} i_a + \frac{\lambda r\left(a,b\right)}{\lambda a} i_b \tag{1}$$

The modulus of $\nabla r\left(a,b\right)$ gradient is the gradient of the digital image. In digital image processing, the difference method is generally used to obtain better differential results. The Robert operator determines the edge by using a local difference operator; that is, edge detection is performed by the difference between two adjacent pixels in the diagonal direction. The difference value is considered as shown in equations (2) and (3):

$$\nabla_a r\left(a,b\right) = r\left(a,b\right) - r\left(a+1,b+1\right) \tag{2}$$

$$\nabla_b r\left(a,b\right) = r\left(a,b+1\right) - r\left(a+1,b\right) \tag{3}$$

The gradient of the image is obtained by the formula shown in equation (4):

$$\left|\nabla r\left(a,b\right)\right| = \sqrt{\nabla_a^2 r + \nabla_b^2 r} \tag{4}$$

It is simplified to the formula shown in equation (5):

$$\left|\nabla r\left(a,b\right)\right| = \left|\nabla_a r\right| + \left|\nabla_b r\right| \tag{5}$$

The corresponding convolution template is shown in equation (6):

$$\nabla_a r = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \nabla_y r = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{6}$$

According to the calculation formula, the gradient amplitude $\nabla r\left(a,b\right)$ can be obtained. Then, the threshold value should be obtained through actual inspection and testing. If the threshold is TH, then TH would be used as the standard for comparison and judgment.

Optimal Distribution of Motion Accuracy

- **Design Variable:** The meta-action chain includes *m* transmission pairs, and the standard deviation of the motion error of each transmission pair is considered the design variable, as shown in equation (7):

$$0 \le \varepsilon\left(\delta'_{n-1,n}\right) \le \varepsilon\left[\delta NK\right] \prod_{k=n}^{m-1} i_{k+1,k} \tag{7}$$

- **Objective Function:** The distribution value of the motion error of each transmission pair is introduced into the motion error of the element action chain, and the difference between the result and the design value is considered the objective function, as shown in equation (8):

$$g_1 = \varepsilon\left[\delta NK\right] - \left[\left(\frac{\varepsilon\left(\delta'_{1,2}\right)}{\prod_{k=n}^{m-1} i_{k+1,k}}\right)^2 + \cdots + \left(\frac{\varepsilon\left(\delta'_{n-1,n}\right)}{\prod_{k=n}^{m-1} i_{k+1,k}}\right)^2 + \cdots \left(\frac{\varepsilon\left(\delta'_{n-2,n-1}\right)}{i_{k+1,k}}\right)^2 + \varepsilon\left(\delta'_{n-1,n}\right)^2\right]^{1/2} \ge 0 \tag{8}$$

- **Cost Function:** In the optimal allocation of motion accuracy of the element action chain, its manufacturing cost is mainly the total equipment cost of each element action unit. The cost is measured by the complexity of unit comprehensive assembly, and the cost function is obtained by the formula shown in equation (9):

$$\delta_{n-1,n} = \frac{Y_{x,n-1} Y_{x,n}}{\sum_{n=2}^{m} Y_{x,n}} \tag{9}$$

In the formula, $\delta_{n-1,n}$ is the weighted coefficient of the transmission pair assembly cost.

- **Robust Function:** To minimize the influence of the uncertainty factors of the motion errors of each transmission pair on its motion accuracy, the sensitivity analysis method is used to design the robust function, as shown in equation (10):

$$g_2\left(\delta NK\right) = \min \sum_{n=2}^{m-1} \left| \frac{\chi\left[\varepsilon\left(\delta NK\right)\right]}{\chi\left[\varepsilon\left(\delta'_{n-1,n}\right)\right]} \right| \Delta\left[\varepsilon\left(\delta'_{n-1,n}\right)\right] \left|\Delta\left[\varepsilon\left(\delta'_{n-1,n}\right)\right]\right| \tag{10}$$

The optimization model aims at cost and robustness; this is a multi-objective optimization problem. The multi-objective optimization problem is transformed into a single objective optimization problem to reduce the complexity of the problem. The cost and robustness are normalized using the formulas shown in equations (11) and (12):

$$\overline{g}_1\left(\delta NK\right) = \frac{g_1\left(\delta NK\right) - g_1^{\min}\left(\delta NK\right)}{g_1\left(\delta NK\right) - g_1^{\min}\left(\delta NK\right)} \tag{11}$$

$$\overline{g}_2\left(\delta NK\right) = \frac{g_2\left(\delta NK\right) - g_2^{\min}\left(\delta NK\right)}{g_2\left(\delta NK\right) - g_2^{\min}\left(\delta NK\right)} \tag{12}$$

The formula for the optimal allocation model of the integrated motion accuracy of the meta motion chain is shown in equation (13):

$$\min g_{1,2}\left(\delta NK\right) = \eta_1 \overline{g}_1\left(\delta NK\right) + \eta_2 \overline{g}_2\left(\delta NK\right) \tag{13}$$

In the formula, η_1 and η_2 are the weight coefficients, and the distribution value of the motion error of each transmission pair can be obtained.

Optimal Distribution of the Kinematic Accuracy of the Transmission Pair

The parts in the transmission pair belong to different element action units. Thus, the motion accuracy of the transmission pair should be redistributed to obtain the motion error of the power input components and power components of the adjacent element action units.

If the motion error of the transmission pair between the $n-1$ element action unit and the m-th element action unit is $\delta_{n-1,n}$, and the motion error of the matched upstream element action power output and downstream element action power input is δ_{n-1} and δ_n respectively, then through the comprehensive accuracy distribution, the results can be obtained using the formula shown in equation (14):

$$\delta_{n-1,n} = \delta_{n-1} + \delta_n \tag{14}$$

The mean and standard deviation of the motion error of the transmission pair are obtained using the formulas shown in equations (15) and (16):

$$\beta\left(\delta_{n-1,n}\right) = F\left(\delta_{n-1,n}\right) + F\left(\delta_n\right) \tag{15}$$

$$\varepsilon\left(\delta_{n-1,n}\right)=\sqrt{\varepsilon^{2}\left(\delta_{n-1,n}\right)+\varepsilon^{2}\left(\delta_{n}\right)} \tag{16}$$

In the transmission pair, the standard deviation design variable of the motion error of the upstream element action unit and the downstream element action unit is obtained as shown in equation (17):

$$0 \leq \varepsilon\left(\delta'_{n-1,n}\right) \leq \varepsilon\left[\delta_{n-1,n}\right] \tag{17}$$

EVALUATION EFFECT OF MECHANICAL TRANSMISSION ON ML

Experiment Purpose

Two types of mechanical transmission, A and B, were selected as the research objects to study the influence of ML on mechanical transmission. A is the traditional mechanical transmission, and B is the ML mechanical transmission. In recent years, user satisfaction with mechanical transmission, mechanical transmission speed, operation periodicity, mechanical transmission safety, and mechanical transmission efficiency is studied.

Experimental Data

- **Customer Satisfaction with Mechanical Transmission:** The user's satisfaction with mechanical transmission is shown in Table 1.

In Table 1, the satisfaction with mechanical transmission increases and the dissatisfaction decreases over the 4-year period. Among them, user satisfaction with mechanical transmission is approximately 29.77% in 2015 and 38.94% in 2019, showing an increase of approximately 9.17%. Based on ML, machines can better interact with humans. For example, mechanical transmission can execute the driver of the machine and provide feedback through robots. In the ML mechanical transmission system, the machine can be adjusted as required to satisfy the requirements of humans or robots. When traditional mechanical transmission is in operation, the adjustment period of some machines becomes uncertain.

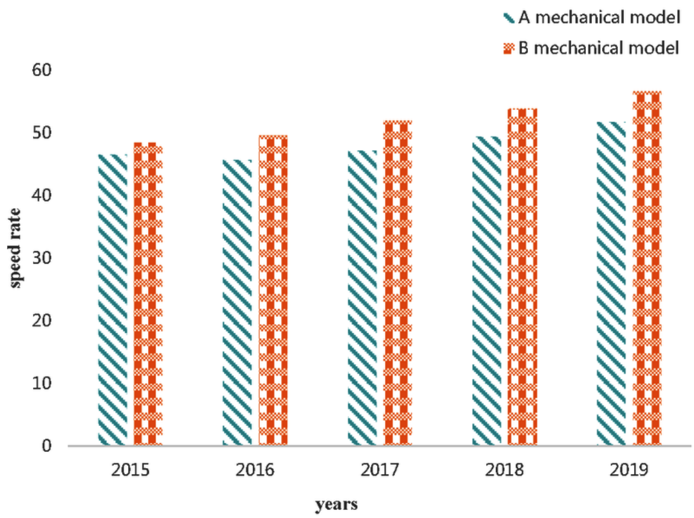
- **Mechanical Transmission Speed:** Mechanical transmission speed is a main research topic, as shown in Figure 5.

In Figure 5, the mechanical transmission speed of B increases, whereas that of A is unstable, and the speed has decreased from 2015 to 2016. In the entire mechanical transmission system based on ML, the shaft is a component that transfers energy from the middle. Thus, the shaft performance is better than that of the motor. In most cases, the ML models are used to predict axes. If the input is constant, then the output is predicted. The larger prediction input indicates smaller prediction error, which is more conducive to improving the transmission speed.

Table 1.
User satisfaction with mechanical drives

	2015	2016	2017	2018	2019
Satisfaction	29.77%	32.65%	35.51%	36.77%	38.94%
General	33.55%	34.36%	36.33%	37.84%	38.66%
Dissatisfaction	36.68%	32.99%	28.16%	25.39%	22.40%

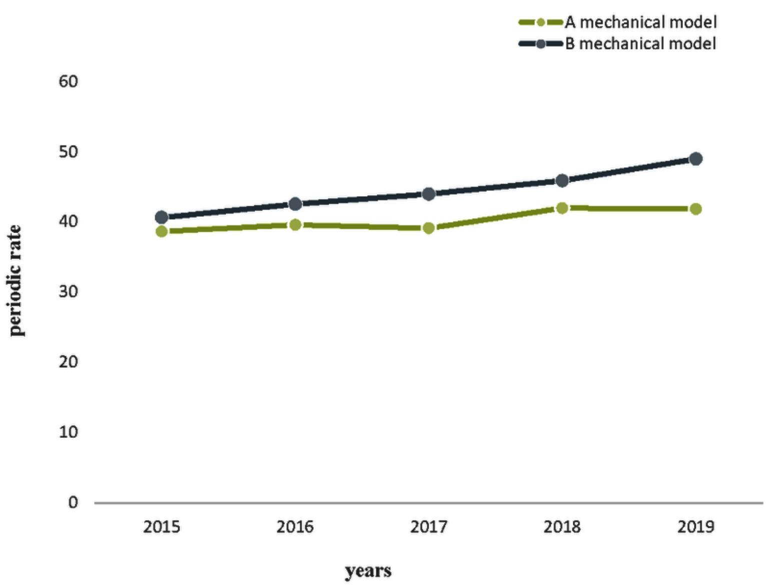
Figure 5.
Mechanical drive speed comparison



- **Operation Periodicity:** The periodicity of mechanical transmission operation reflects the quality of its equipment. The comparison of the periodicity of mechanical transmission operation is shown in Figure 6.

In Figure 6, the mechanical transmission periodicity of B shows an increasing trend, whereas that of A shows an unstable trend. The entire life cycle of the transmission system would be affected by environmental conditions and human behavior. For example, environmental conditions can affect the

Figure 6.
Operational periodicity comparison



motion track, dynamic state, position, and time of the system, and these factors can also affect the entire life cycle. The support of the ML technology on the Internet of Things indicates that if the prediction result of the mechanical transmission system is accurate, then the next stage of operation can be guided according to the prediction results. During the prediction process, the structural parameters of the parts are predicted, and the optimal running state of the machine is obtained. Based on the prediction results, the design is improved to reduce the wear of the machine and reduce its maintenance cost.

- **Mechanical Transmission Safety:** The safety of the mechanical transmission is related to the life and safety of the users. The main research topic is the mechanical transmission safety, as shown in Figure 7.

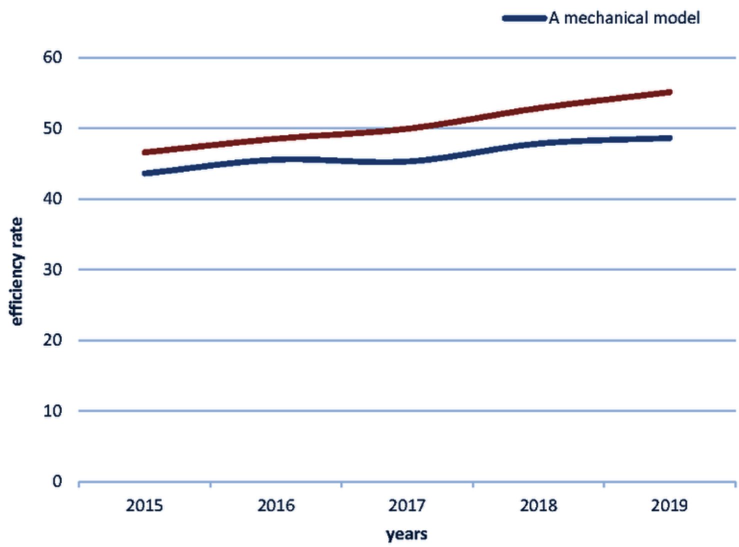
The mechanical transmission safety of A is lower than that of B, which is continuously improved. The ML technology can improve the accuracy and reliability; thus, it can monitor the mechanical parts in the production process in real time. It can also select the appropriate model according to the actual application and predict the movement track and state of the parts to improve the mechanical transmission safety.

- **Mechanical Transmission Efficiency:** The results when the mechanical transmission efficiency is considered as the research object are shown in Figure 8.

Figure 8 shows that the mechanical transmission efficiency of B is always higher than that of A, and the efficiency of A is unstable. The traditional mechanical transmission cannot accurately detect the operation of machinery. Based on the ML background, the sensors can be used to collect data by adding them inside the machinery. Thus, the impact of various factors on transmission efficiency can be evaluated from different dimensions, and the mechanical transmission efficiency can be improved.

Figure 7.
Comparison of mechanical drive safety

Figure 8.
Comparison of mechanical drive efficiency



CONCLUSION

The continuous development of Internet of Things and ML technology was greatly beneficial to the field of mechanical transmission simulation. This study analyzed the structure of the mechanical transmission, the application of ML in mechanical transmission, and the edge computing simulation of the mechanical transmission model under the background of transmission ML. In addition, the ML-based method can simplify the entire analysis process and result in an efficient work to accelerate the product development process and improve the safety and accuracy of the mechanical transmission. When ML is applied to mechanical transmission, it becomes more satisfactory to users.

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