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RESEARCH ARTICLE

# Cooperative Static and Dynamic Correlation-Aware Learning for Vehicle Maintenance Demand Prediction

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**ABSTRACT** Accurate prediction of vehicle maintenance demands is crucial for enhancing service longevity and minimizing costs. However, current methods are limited to predicting maintenance demands for individual vehicle components. They fail to offer a comprehensive prediction that encompasses diverse maintenance demands. Additionally, vehicle maintenance demand prediction must consider the interrelationships among various maintenance projects and maintenance project records. To address these issues, we propose a vehicle maintenance demand prediction method that employs a collaborative approach. This method utilizes both static and dynamic correlation-aware learning techniques. We design a static correlation-aware method for maintenance project representation learning by leveraging prior statistical data from various maintenance projects. To effectively capture the temporal correlations inherent in different maintenance project records, we propose an attention-based dynamic correlation-aware technique. Experiments conducted on real-world datasets demonstrate that the proposed model outperforms existing methods.

**INDEX TERMS** Vehicle maintenance, demand prediction, correlation-aware learning, co-occurrence matrix, attention mechanism.

## I. INTRODUCTION

The worldwide increase in vehicle ownership has amplified the role of vehicles in daily life. Consequently, vehicle maintenance has become an industry essential for sustaining livelihoods and enhancing the quality of life. Regular maintenance is paramount to preventive vehicle management, preventing potential breakdowns, reducing the risk of accidents, and avoiding unwarranted economic costs [1]. Vehicle maintenance demands include all the requirements needed to keep a vehicle operating safely and efficiently throughout its lifecycle. These demands are fulfilled through specific maintenance projects, which are the individual tasks performed during maintenance sessions. For example, replacing a tire, balancing a tire, and aligning a wheel are all maintenance projects. Accurately predicting a vehicle's maintenance demands can significantly reduce operating costs and downtime, increase vehicle safety and lifespan, and streamline maintenance scheduling, thereby greatly enhancing the quality of life associated with vehicle use.

Current methods for predicting vehicle maintenance demands primarily rely on in-vehicle sensor data to diagnose faults in specific parts, indirectly predicting maintenance needs. These predictions mainly utilize time-series methods, such as Convolutional Neural Networks (CNN) [2], and Long Short-Term Memory networks (LSTM) [3]. Due to the lack of sensor data from all parts of the vehicle and the complex correspondence between vehicle faults and maintenance demand, the existing research can only indirectly predict part of the vehicle's maintenance demand, rather than all of it, which may affect the safety and performance of the vehicle.

In the realm of vehicle maintenance, various maintenance projects are interrelated. For instance, In the first vehicle

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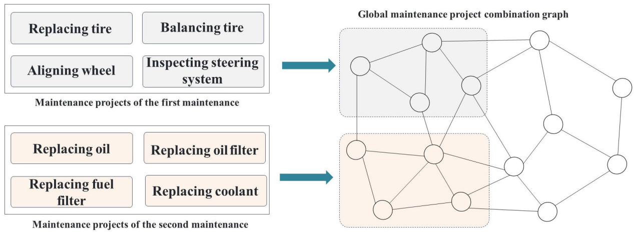



**FIGURE 1.** An example of the correlation of vehicle maintenance projects.

maintenance, four projects are conducted simultaneously to maintain chassis and steering system safety and stability: replacing tire, balancing tire, aligning wheel, and inspecting steering system. The maintenance project combinations that appear in all vehicles' maintenance processes inherently form a global graph structure, as shown in Fig. 1.

Throughout a vehicle's life cycle, there is a clear correlation between maintenance demands at different stages, attributable to the wear and aging of vehicle components over time. As demonstrated by the maintenance project records shown in Fig. 2, the initial phase of brake system maintenance generally involves fundamental inspections and routine replacements. This includes inspecting the overall condition of the brake system and replacing the brake pads, which are crucial for maintaining brake efficiency and safety. As vehicle use increases, it becomes necessary to inspect and replace various brake system components, including brake pads, brake fluid, and brake lines, owing to wear, aging, or corrosion. Early maintenance projects for the engine system typically involve routine tasks such as oil changes and oil filter replacements, which aid in maintaining engine cleanliness and lubrication to avert excessive wear. As the vehicle continues to operate, maintaining the engine system grows more complex and comprehensive. In addition to routine oil and oil filter changes, focus may need to shift to other closely related systems, such as the cooling system.

This study addresses the challenges of predicting vehicle maintenance demands by introducing an innovative framework based on cooperative static and dynamic correlation-aware learning. Our contributions include the following:

- To fully leverage the correlation between different maintenance projects and their records, this paper proposes a static and dynamic correlation-aware cooperative learning method for predicting vehicle maintenance demands.
- By utilizing prior statistical information on various maintenance projects, we design a static correlation-aware method for representing maintenance projects.
- To capture the temporal correlation between maintenance project records, we propose an attention-based dynamic correlation-aware method.
- Extensive experiments were conducted on authentic vehicle maintenance project record data, with results indicating that our model surpasses current state-of-the-art prediction models.

## II. RELATED WORKS

As the vehicle industry expands, predictive methods for vehicle maintenance demands also evolve. These methods have advanced from basic time-based heuristics to sophisticated models that integrate domain expertise and statistical analysis. The increasing availability of vehicle operational data has sparked substantial interest in applying machine learning and deep learning for predicting maintenance demand. This has led to notable improvements in prediction accuracy. Prediction technologies for vehicle maintenance demand can be broadly categorized into three paradigms: traditional approaches, classic machine learning, and deep learning.

### A. PREDICTION OF VEHICLE MAINTENANCE DEMAND BASED ON TRADITIONAL METHODS

Traditional approaches to vehicle maintenance prediction rely heavily on statistical analysis and domain expertise. These methods commonly employ time-based heuristics or basic statistical models, such as the 3-sigma rule and linear regression, to predict potential faults. For instance, Zhao et al. [4] combined the 3-sigma rule with neural networks to enhance fault detection in electric vehicle batteries. Ma et al. [5] employed statistical analysis for early warning of lithium-ion battery faults. Longo et al. [6] emphasized the use of statistical data and predictive models in the automotive industry, demonstrating their effectiveness at FCA plants. Yadav et al. [7] developed an engine fault classification method based on audio signatures using Fourier Transform and correlation techniques to detect faulty conditions amidst noisy data. Kordes et al. [8] investigated vehicle network fault detection using causal rules. Zhou et al. [9] proposed a straightforward fault diagnosis technique aided by neural networks. Shen et al. [10] introduced a method for predicting lithium-ion battery life using an unscented Kalman filter to adapt to discharge currents. Traditional methods are relatively straightforward and easy to implement. However, their lack of adaptability to complex, high-dimensional data or non-linear relationships limits their effectiveness in modern predictive maintenance.

### B. PREDICTION OF VEHICLE MAINTENANCE DEMAND BASED ON CLASSIC MACHINE LEARNING

Classic machine learning methods improve upon traditional approaches by using algorithms capable of learning from data. These methods enhance both prediction accuracy and speed. A variety of algorithms, such as decision trees, support vector machines (SVM), k-nearest neighbors (k-NN), and artificial neural networks (ANN), are used in this paradigm. For example, Wang et al. [11] developed ENN-1, an efficient and fast-training neural network for detecting engine faults. Aye and Heyns [12] utilized GPR for predicting bearing

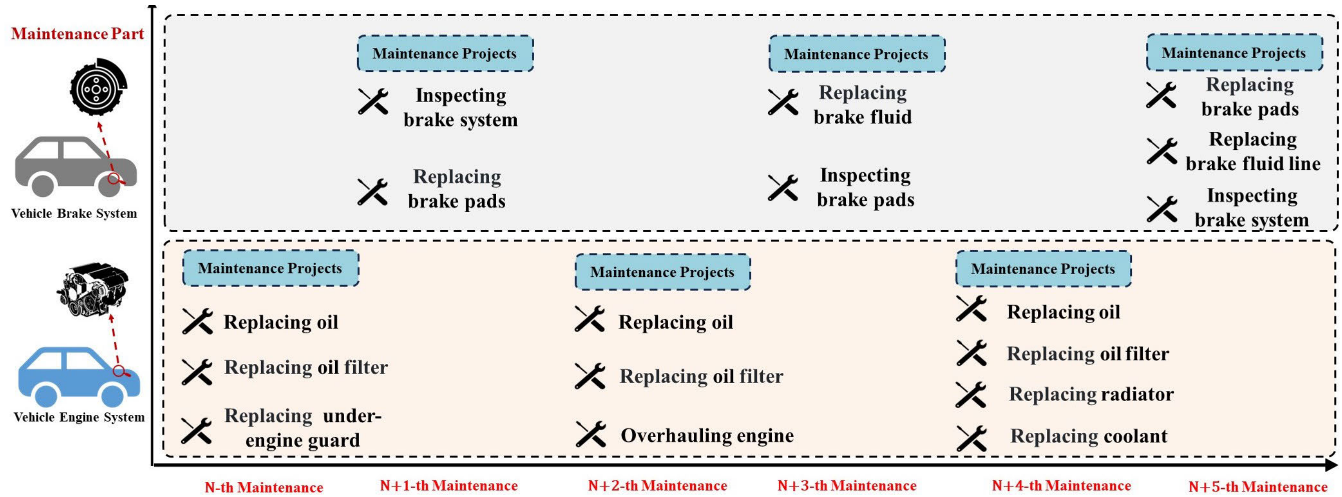



**FIGURE 2.** An example of the correlation between maintenance demands at different stages.

life, while Kong et al. [13] applied MLR to suspension design and coil spring life. Jeong and Choi [14] demonstrated the use of SVM in residual diagnosis, while Vasavi et al. [15] combined ANN and k-NN for monitoring system health. Revanur et al. [16] presented a stack autoencoder for large-scale fault analysis, while Khoshkangini et al. [17] integrated different data types for rapid issue detection. Tessaro et al. [18] and Biddle and Fallah [19] compared various classic machine learning techniques for maintenance prediction and multi-fault diagnostics, highlighting the field's advancement towards automation. However, despite these advancements, classic machine learning models often require extensive feature engineering and domain knowledge, and may struggle with more complex data that necessitates hierarchical feature extraction.

### C. PREDICTION OF VEHICLE MAINTENANCE DEMAND BASED ON DEEP LEARNING

Recent developments in deep learning have revolutionized vehicle maintenance prediction by enabling the automatic extraction of complex patterns and hierarchical representations from large datasets. Deep learning models such as CNN, recurrent neural networks (RNN), and LSTM have shown considerable promise in predictive maintenance tasks. For example, Chen et al. [20] utilized GIS data and AI for robust prediction of automotive component RUL, while Al-Zeyadi et al. [21] demonstrated the efficiency of Deep-SBM in vehicle fault diagnosis within IoT systems. Chen et al. [20] focused on predictive maintenance using maintenance history and sensor data for TBF modeling. Hu et al. [3] validated the use of LSTM for vehicle suspension monitoring, while Guo et al. [22] combined sparse autoencoders with LSTMs for mechanical failure prediction. Safavi et al. [23] revealed that coupling deep learning with data-driven techniques enhances the reliability of autonomous vehicle sensors. Xu et al. [24] employed deep confidence networks and uncertainty mathematics to advance sensor system prognostics.

Although the aforementioned methods predict the maintenance demands of specific vehicle components, they do so indirectly. They fall short in providing a comprehensive prediction of a vehicle's total maintenance needs. In contrast, this paper presents a holistic approach that uses static and dynamic correlations between vehicle maintenance projects and time-based maintenance records to predict overall maintenance demands. This comprehensive methodology can directly and accurately predict the entire spectrum of a vehicle's maintenance demands, significantly enhancing vehicle safety.

## III. NOTATIONS

In order to facilitate the detailed description of the maintenance demand predicting task to be addressed in this paper, some notations are first given in Tab. 1. Throughout the maintenance process of a vehicle, a large number of maintenance projects are required, and all maintenance projects are coded to form a set of project code sets denoted as $P = \{p_1, p_2, \ldots, p_{|P|}\}$, where $|P|$ denotes the number of maintenance project. Each vehicle has multiple maintenance project records, a vehicle's maintenance project records are represented as $\{M_t\}_{t=1,2,\ldots,T}$. The maintenance project record in the $t$-th maintenance are defined as a multi-hot column vector $M_t \in \{0, 1\}^{|P|}$, $M_t^i = 1$ means that the maintenance project $p_i$ was performed on the vehicle in the $t$-th maintenance, $t = 1, 2, \ldots, T$ and $i = 1, 2, \ldots, |P|$, $T$ indicates the number of times the vehicle has been maintained. The maintenance demand prediction task is based on the previous $T$ maintenance projects $M_1, M_2, \ldots, M_T$ to predict the maintenance projects $M_{T+1}$ for the $(T+1)$-th maintenance.

## IV. PROPOSED METHOD

### A. FRAMEWORK

The framework of the proposed **Co**operative **S**tatic and **D**ynamic **C**orrelation-aware (CoSDC) for vehicle

**TABLE 1.** Notations and descriptions.

| Notation | Description |
|---|---|
| $P = \{p_1, p_2, ...., p_{\|P\|}\}$ | Set of all maintenance project codes |
| $\{M_t\}_{t=1,2,...,T}$ | Set of all maintenance project records for a vehicle |
| $M_t \in \{0, 1\}^{\|P\|}$ | The maintenance projects for $t$-th maintenance of a vehicle |
| $A \in \mathbb{R}^{\|P\|\times\|P\|}$ | Co-occurrence matrix for all maintenance projects combination graph |
| $F_1(M_t, A)$ | The project mapping function of $M_t$ |
| $R_t$ | The static correlation-aware mapping result of $M_t$ |
| $O_t$ | The static correlation-aware learning result of $M_t$ |
| $S$ | The static correlation-aware learning result of $\{M_t\}_{t=1,2,...,T}$ |
| $N_t$ | The dynamic temporal modelling results of $M_t$ |
| $E_t$ | The attention weights of $M_t$ |
| $F_2(M_t, E_t, N_t)$ | The dynamic correlation-aware learning function |
| $U_t$ | The dynamic correlation-aware learning result of $M_t$ |
| $D$ | The dynamic correlation-aware learning result of $\{M_t\}_{t=1,2,...,T}$ |
| $Y$ | The fusion result of $S$ and $D$ |
| $M_{T+1}$ | Maintenance projects for the $(T+1)$-th maintenance |

maintenance demand prediction is illustrated in Fig. 3. The framework consists of three key modules:

(1) **Static correlation-aware learning** module constructs a project co-occurrence matrix based on co-occurrence relationships between maintenance projects. This module aims to obtain prior statistical information between different maintenance projects from the co-occurrence graph.

(2) **Dynamic correlation-aware learning** module captures the temporal correlations of vehicle maintenance project records. A dynamic temporal modelling module is proposed to obtain the temporal attention weight of each maintenance project record. Additionally, a dynamic correlation-aware learning function is proposed to enhance the fusion of temporal modelling results and temporal attention weights.

(3) **Cooperative correlation-aware prediction** module employs an attention mechanism to integrate static and dynamic correlation-aware learning results from maintenance project records, obtaining a cooperative correlation-aware result. Utilizing this integrated result, the required maintenance projects are predicted.

### B. STATIC CORRELATION-AWARE LEARNING

In vehicle maintenance, multiple maintenance projects often require attention simultaneously. For example, the replacement of both the oil filter and air filter may appear simultaneously on the maintenance project record, indicating the interrelated nature of different maintenance projects. To effectively utilize the correlation between maintenance projects and enhance predictive accuracy, we propose a static correlation-aware learning framework.

We create a global co-occurrence graph $G$ based on co-occurrence relationships between maintenance projects. In this graph, each node represents a maintenance project $\{p_i\}_{i=1,2,...|P|}$ from the set $P$. Each weighted edge corresponds to the frequency of co-occurrence between two maintenance projects. When a code pair $(p_i, p_j)$ appears in a vehicle's maintenance project record, two equal weights, $\overrightarrow{(i,j)}$ and $\overrightarrow{(j,i)}$, are assigned. These weights are integrated into the graph $G$, reflecting the bidirectional nature of the relationship. Then, we count the total co-occurrence frequency $t_{ij}$ of $(p_i, p_j)$ in the maintenance project records of all vehicles for further computation of edge weights. To identify important and frequent project pairs, we define a threshold $\lambda$ to filter out low frequency combinations and obtain a qualified set $\Delta_i = \left\{p_i \mid \frac{t_{ij}}{\sum_{n=1}^{|P|} t_{ij}} \geq \lambda\right\}$ for $p_i$. We define $q_i = \sum_{p_j \in \Delta_i} t_{ij}$ as the total frequency of qualified projects co-occurring with $p_i$ to quantify their significance. We represent the global co-occurrence graph $G$ using a co-occurrence matrix $A \in \mathbb{R}^{|P|\times|P|}$ as defined in equation 1 to systematically capture the co-occurrence relationships.

$$A_{ij} = \begin{cases} 0 \text{ if } i = j \text{ or } \frac{t_{ij}}{\sum_{j=1}^{|P|} t_{ij}} < \lambda \\ \frac{t_{ij}}{q_i} \text{ otherwise} \end{cases} \tag{1}$$

Note that $A$ is designed to be symmetric, ensuring that the influence of maintenance projects on each other is bidirectional and equally weighted. As a static matrix, $A$ quantifies the global co-occurrence frequencies of maintenance projects. However, the occurrence and non-occurrence of different maintenance projects vary over time. A specific maintenance project might be absent from current records, yet a correlated project could appear later. This highlights the temporal dependencies between maintenance projects. To leverage the prior statistical information between different maintenance projects, we propose a static correlation-aware module based on project mapping to enhance predictive capabilities.

The static correlation-aware mapping result $\{R_t\}_{t=1,2,...,T}$ of each maintenance project record is derived for each vehicle's maintenance project records $\{M_t\}_{t=1,2,...,T}$, using project mapping function $F_1(M_t, A)$. The project mapping function $F_1(M_t, A)$ is defined as shown in equation 2.

$$F_1(M_t, A) = f\left(A^T \times D_t\right)$$
$$D_t = \operatorname{diag}(M_t[1], M_t[2], \ldots, M_t[n]) \tag{2}$$

where $n = |P|$, the function $f$ is employed to filter out the row vectors of the matrix that contain all zeros, ensuring that only relevant project correlations are considered. Once the static correlation-aware mapping results are obtained for successive maintenance project records, $\{R_t\}_{t=1,2,...,T}$ and

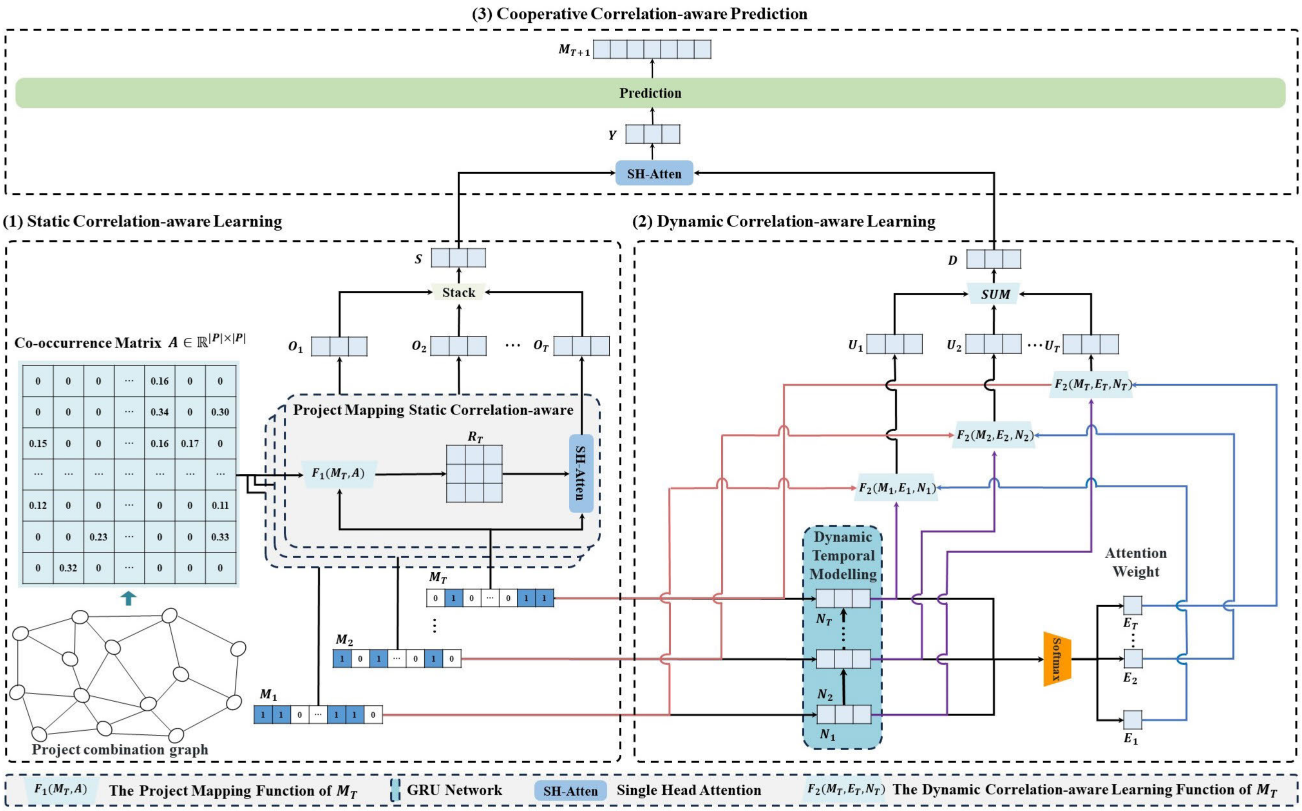



**FIGURE 3.** An overview of the CoSDC model. It is mainly composed of three modules: (1) Static Correlation-aware Learning; (2) Dynamic Correlation-aware Learning; (3) Cooperative Correlation-aware Prediction.

$\{M_t\}_{t=1,2,\ldots,T}$ are input into the attention mechanism [25] item by item. This process yields the static correlation-aware learning results $\{O_t\}_{t=1,2,\ldots,T}$ for each maintenance project record, as shown in equation 3.

$$O_t = \text{Atten}(R_t, M_t, M_t) \tag{3}$$

The attention mechanism in equation 3 is defined as shown in equation 4:

$$\text{Atten}(Q, K, V) = \text{softmax}\left(\frac{QW_q (KW_k)^T}{\sqrt{d}}\right) VW_v \tag{4}$$

where $d$ is the dimension of attention and $W_q, W_k \in \mathbb{R}^{|P|\times d}$, $W_v \in \mathbb{R}^{|P|\times|P|}$ are the attention weights used to compute the relevance scores. The final static correlation-aware learning result $S = [O_1; O_2; \ldots; O_T]$ for all maintenance project records is derived from $\{O_t\}_{t=1,2,\ldots,T}$, providing a comprehensive representation of the correlated maintenance demands.

### C. DYNAMIC CORRELATION-AWARE LEARNING

In the entire vehicle maintenance life cycle, there is a significant correlation not only between different maintenance projects but also between maintenance project records at various stages. Records from early-stage maintenance projects can impact the fault development process of the vehicle, consequently affecting future maintenance demands. To fully leverage the correlation between maintenance project records at different stages, we propose an attention-weighted dynamic correlation-aware learning framework that dynamically models these relationships.

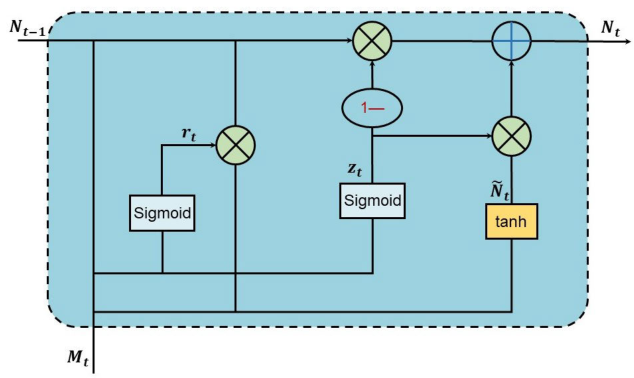



**FIGURE 4.** The architecture diagram of the GRU model used for dynamic temporal modeling.

Firstly, we utilize GRU [26] for the dynamic temporal modeling of maintenance project records, obtaining the results $\{N_t\}_{t=1,2,\ldots,T}$ of the maintenance project records. Each element in $\{N_t\}_{t=1,2,\ldots,T}$ contains both the original maintenance project record information and the cumulative information from all records. The detailed implementation of this dynamic temporal modeling is illustrated in equation 5:

$$N_1, N_2, \ldots, N_T = GRU\left(M_1, M_2, \ldots, M_T\right) \tag{5}$$

The GRU calculation process is detailed in Equation 6. The architecture diagram of GRU is illustrated in Fig. 4.

$$\begin{aligned} r_t &= \text{Sigmoid}\left(W_r^1 M_t + W_r^2 N_{t-1} + b_r\right) \\ \widetilde{N}_t &= \tanh\left(W_c^1 M_t + W_c^2\left(r_t \cdot N_{t-1}\right) + b_h\right) \\ z_t &= \text{Sigmoid}\left(W_z^1 M_t + W_z^2 N_{t-1} + b_z\right) \\ N_t &= \left(1 - z_t\right) \cdot N_{t-1} + z_t \cdot \widetilde{N}_t \end{aligned} \tag{6}$$

Where $W_{\{r,c,z\}}^{\{1,2\}} \in \mathbb{R}^{|P|\times|P|}$ represents the weights and $b_{\{r,c,z\}} \in \mathbb{R}^{|P|}$ denotes the bias.

During vehicle maintenance, personnel review previous maintenance project records to determine the required maintenance projects. To simulate this process, we use $\{N_t\}_{t=1,2,\ldots,T}$, which includes both original and accumulated record information, and apply the Softmax function to compute the attention weights $\{E_t\}_{t=1,2,\ldots,T}$ as shown in equation 7.

$$E_1, E_2, \ldots, E_T = \text{Softmax}\left(N_1, N_2, \ldots, N_T\right) \tag{7}$$

After determining the attention weights for each maintenance project record, we employ the dynamic correlation-aware learning function $F_2\left(M_t, E_t, N_t\right)$ to derive the learning outcome $U_t$ as defined in equation 8.

$$\begin{aligned} F_2\left(M_t, E_t, N_t\right) &= M_t \odot B_t \odot N_t \\ B_t &= E_t \otimes 1_{1\times|P|} \end{aligned} \tag{8}$$

Here, $\odot$ denotes the Kronecker product, and $\otimes$ represents element-wise multiplication (Hadamard product). The results $\{U_t\}_{t=1,2,\ldots,T}$ encompass the original, hidden, and cumulative maintenance project record information, including the weights.The final result $D = \sum_{t=1}^{T} U_t$ is obtained by summing $\{U_t\}_{t=1,2,\ldots,T}$.

### D. COOPERATIVE CORRELATION-AWARE PREDICTION

Static correlation-aware learning leverages prior statistical information among various maintenance projects to learn the global co-occurrence relationships between these projects. Dynamic correlation-aware learning quantifies evolving correlations among maintenance records over different periods from a time-series perspective. To fully leverage both static and dynamic correlations, we propose a collaborative approach that integrates the modeling of these correlations to predict comprehensive vehicle maintenance demands. After performing the static and dynamic correlation-aware learning processes, we obtain the static correlation result $S$ and the dynamic correlation result $D$ for all maintenance project records. To effectively integrate these two learning results, we apply an attention mechanism, as shown in equation 4. This process produces the fused learning result $Y$, detailed in equation 9.

$$Y = \text{Atten}\left(S, D, D\right) \tag{9}$$

The maintenance projects for the $(T+1)$-th maintenance are derived from the correlation-aware fusion result $Y$. The specific implementation of this process is shown in equation 10.

$$\widehat{y} = \text{Sigmoid}(W_Y \text{dropout}(Y) + b_Y) \tag{10}$$

Here, $W_Y \in \mathbb{R}^{|P|\times|d_Y|}$ and $b_Y \in \mathbb{R}^{|P|}$ are parameters, where $d_Y$ is the dimension of $Y$. To enhance the robustness of the model, a dropout operation is performed before $Y$ is used for prediction.

### E. MODEL OPTIMIZATION

We train the CoSDC model to predict the the $(T+1)$-th maintenance project for each vehicle, with a binary cross-entropy loss function for the global objective function, as shown in equation 11:

$$L = -\sum_{i=1}^{|P|}\left(y_i^T \log\left(\widehat{y_i}\right) + \left(1 - y_i\right)^T \log\left(1 - \widehat{y_i}\right)\right) \tag{11}$$

where $\widehat{y_i}$ represents the predicted results of the maintenance project $p_i$ and $y_i$ represents the true label of the maintenance project $p_i$.

## V. EXPERIMENT RESULTS AND ANALYSIS

### A. DATASET DESCRIPTION

To evaluate the performance of our proposed method, we utilize real vehicle maintenance project records from 40 maintenance companies for verification. Records of vehicles with two or more maintenance events were selected after screening. The dataset comprises records of 10,256 vehicles maintained between April 2011 and April 2023. Detailed statistics of the dataset are presented in Table 2.

**TABLE 2.** Experimental dataset statistics.

| Statistic | Value |
|---|---|
| Number of Vehicles | 10,256 |
| Maximum Number of Maintenance | 69 |
| Average Number of Maintenance | 3.92 |
| Number of Maintenance Project Codes | 2,428 |
| Maximum Number of Project Codes at One Maintenance | 51 |
| Average Number of Project Codes per Maintenance | 5.20 |

To enhance the experimental process, we randomly divided the dataset into training and test sets. The training set includes 7,000 vehicles, while the test set consists of 3,256 vehicles. Our approach uses the last maintenance project record as the label, with the remaining records serving as input features. We construct the global project co-occurrence graph $G$ using the maintenance projects from the training set.

**TABLE 3. Maintenance project prediction results using *w-$F_1$* (%) and *R@k* (%).**

| Model | $w$-$F_1$ | $R@5$ | $R@10$ | $R@15$ | $R@20$ | $R@25$ | $R@30$ | $R@35$ |
|---|---|---|---|---|---|---|---|---|
| MLP | 31.67±0.31 | 53.62±0.11 | 60.07±0.18 | 65.23±0.12 | 69.10±0.21 | 72.52±0.20 | 75.73±0.35 | 78.18±0.11 |
| CNN | 40.42±0.37 | 56.79±0.17 | 64.30±0.31 | 69.26±0.18 | 72.87±0.22 | 75.65±0.41 | 77.98±0.28 | 79.88±0.09 |
| Transformer | 31.64±0.19 | 53.61±0.27 | 59.69±0.18 | 64.45±0.35 | 68.61±0.39 | 72.18±0.20 | 74.94±0.29 | 77.48±0.31 |
| RNN | 31.65±0.28 | 53.62±0.13 | 60.11±0.13 | 65.25±0.40 | 69.17±0.24 | 72.68±0.02 | 75.69±0.36 | 78.28±0.17 |
| LSTM | 31.71±0.21 | 53.62±0.27 | 59.99±0.21 | 65.02±0.41 | 69.12±0.24 | 72.79±0.04 | 75.75±0.29 | 78.01±0.38 |
| Dipole | 31.76±0.27 | 53.61±0.13 | 60.06±0.25 | 65.17±0.14 | 69.32±0.92 | 72.63±0.21 | 75.46±0.40 | 77.96±0.38 |
| RETAIN | 40.85±0.35 | 56.96±0.19 | 64.40±0.17 | 69.36±0.32 | 73.04±0.50 | 75.97±0.18 | 78.43±0.17 | 80.48±0.14 |
| Chet | 39.98±0.11 | 56.78±0.21 | 64.26±0.17 | 69.10±0.12 | 72.76±0.21 | 75.72±0.33 | 78.28±0.32 | 80.32±0.23 |
| CoSDC | **41.64±0.10** | **57.35±0.09** | **65.07±0.19** | **70.20±0.10** | **73.88±0.05** | **76.61±0.09** | **79.04±0.12** | **81.07±0.13** |

### B. BASELINE MODELS AND EVALUATION METRICS

The main objective of this experiment is to predict the $(T+1)$-th maintenance project using the vehicle's previous $T$ maintenance records. This task is framed as a multi-label classification problem. For this task, the evaluation metrics are the weighted $F_1$ score ($w$-$F_1$) [27] and $R@k$ [27]. The $w$-$F_1$ score calculates the $F_1$ score for each project code and reports its weighted average. The $R@k$ metric is the average ratio of desired project codes in the top $k$ predictions to the total number of desired project codes in each maintenance, measuring the prediction accuracy. To benchmark our proposed method against state-of-the-art models, we conducted comparative experiments with the following methods.

To validate the performance of our method, it is compared with typical machine learning and deep learning time series prediction methods including multilayer perceptron (MLP) [28], CNN [29], RNN [30], LSTM [31], and Transformer [25]. Additionally, it is compared with typical methods in the field of medical diagnosis prediction, which is similar to maintenance demand prediction, such as RETAIN [32], Dipole [33], and Chet [27].

### C. REALIZATION DETAILS

In our experiment, we randomly initialized the model parameters. Hyperparameters and activation functions were tuned on the validation set. Specifically, we set the threshold $\lambda$ to 0.10 and the batch size to 32. When training our model, we used 100 epochs and the Adam optimizer. The learning rate was set to 0.001. All implementations were done using Python 3.7.0, PyTorch 1.10.0, and CUDA 11.4 on devices with 64GB memory and NVIDIA-SMI 472.39 GPU. To ensure robustness, we repeated the experiment five times with different random seeds.

### D. PREDICTION PERFORMANCE

Table 3 presents the experimental results. Given that the average number of maintenance projects per instance is 5.20, we set $k$=[5, 10, 15, 20, 25, 30, 35] for $R@k$. As illustrated, the performance of our proposed model surpasses all baseline models. In terms of $w$-$F_1$, CoSDC improves by 0.79% compared to the best baseline model, RETAIN. As the $F_1$ score is the harmonic mean of precision and recall, this indicates that CoSDC performs excellently in both metrics, demonstrating the model's capability to accurately predict most maintenance projects while minimizing incorrect predictions. From the perspective of $R@k$, across varying values of $k$, CoSDC consistently maintains its performance advantage. This demonstrates that the CoSDC model can accurately predict the required maintenance projects in both short and long lists, indicating strong generalization ability. In summary, the CoSDC model has demonstrated both innovation and practicality in predicting vehicle maintenance projects. Its performance in accuracy, completeness, and flexibility across different predictive ranges further highlights its effectiveness. These results substantiate CoSDC's superiority and provide a foundation for future research in this domain.

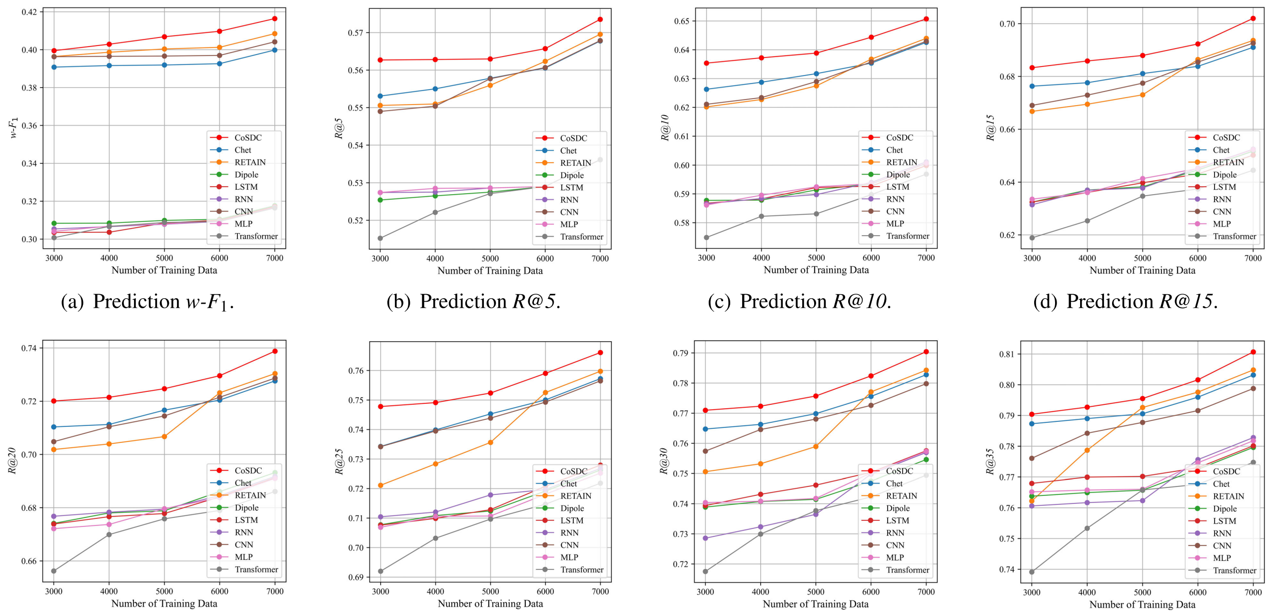
### E. PERFORMANCE ASSESSMENT OF DATA SUFFICIENCY

To evaluate the impact of data sufficiency on prediction accuracy, we keep the size of the validation set fixed at 3256 entries. We vary the size of the training sets to 3,000, 4,000, 5,000, 6000, and 7,000, respectively, and use the remaining data for the test set. The remarkable performance of CoSDC compared to other baseline models, even with limited data, is evident in Fig. 5.

### F. ABLATION STUDY

We analyzed the effectiveness of each module in our proposed approach by comparing three ablation variants of the model. Each variant was designed with distinct settings. The variants are as follows:

- **CoSDC-SCo:** To demonstrate the importance of Static Correlation-aware Learning in Project Mapping for vehicle maintenance project prediction, the Static Correlation Representation Learning process has been removed, resulting in $S = [M_1; M_2; \ldots; M_T]$.
- **CoSDC-GRU:** To illustrate the role of Dynamic Temporal Modelling in Dynamic Correlation-aware Learning, the input $\{N_t\}_{t=1,2,\ldots,T}$ is removed from the dynamic correlation representation function in this model, resulting in $E_1, E_2, \ldots, E_T = \text{Softmax}(M_1, M_2, \ldots, M_T)$.
- **CoSDC-Atten:** To demonstrate the role of attention weighting of successive maintenance project records




(a) Prediction $w$-$F_1$. (b) Prediction $R@5$. (c) Prediction $R@10$. (d) Prediction $R@15$.

(e) Prediction $R@20$. (f) Prediction $R@25$. (g) Prediction $R@30$. (h) Prediction $R@35$.

**FIGURE 5. Accuracy of predictions of CoSDC and baseline with varying of training data.**

**TABLE 4. Ablation study of vehicle maintenance project prediction results using $w$-$F_1$ (%) and $R@k$ (%).**

| Model | $w$-$F_1$ | $R@5$ | $R@10$ | $R@15$ | $R@20$ | $R@25$ | $R@30$ | $R@35$ |
|---|---|---|---|---|---|---|---|---|
| CoSDC-SCo | 41.34±0.31 | 57.42±0.21 | 64.85±0.26 | 70.20±0.15 | 73.79±0.16 | 76.55±0.18 | 79.01±0.11 | 81.07±0.09 |
| CoSDC-GRU | 41.12±0.29 | 57.21±0.08 | 64.79±0.22 | 70.06±0.08 | 73.62±0.21 | 76.29±0.06 | 78.75±0.02 | 80.73±0.15 |
| CoSDC-Atten | 39.22±0.14 | 56.09±0.21 | 63.80±0.28 | 68.91±0.12 | 72.87±0.11 | 75.75±0.18 | 78.30±0.14 | 80.42±0.15 |
| CoSDC | **41.64±0.10** | **57.35±0.09** | **65.07±0.19** | **70.20±0.10** | **73.88±0.05** | **76.61±0.09** | **79.04±0.12** | **81.07±0.13** |

in Dynamic Correlation-aware Learning, the input $\{E_t\}_{t=1,2,\ldots,T}$ was removed from the dynamic correlation representation function in this model, resulting in $U_t = F_2(M_t, N_t) = M_t \odot N_t$.

The experimental results for each variant model are shown in Table 4. The results indicate that the original CoSDC model outperforms the three ablation variants across all performance indices. The findings confirm that each module in the CoSDC model is effective. Each module contributes significantly to the overall performance.The ablation study emphasizes the importance of static correlation representation and GRU unit processing in dynamic correlation representation. It also demonstrates the significant impact of attention weighting on previous maintenance project records, particularly for prediction accuracy.

## G. PREDICT ANALYSIS OF NEW MAINTENANCE PROJECTS

Predicting new maintenance projects in vehicle maintenance holds significant practical value. This study defines new maintenance projects as those absent from the vehicle's maintenance history. This prediction is crucial for identifying potential vehicle problems and expanding the scope of maintenance services. Assuming that different maintenance projects are correlated, our proposed model should perform better in predicting new maintenance projects.

The experimental results for predicting new maintenance projects using each model are shown in Table 5. Our analysis shows that CoSDC surpasses all baseline models in $w$-$F_1$. The closest model, RETAIN, is approximately 0.61% lower.The CoSDC model also outperforms on the recall index $R@k$. This is particularly evident in long list predictions ($R@30$ and $R@35$), where it clearly leads the baseline models.

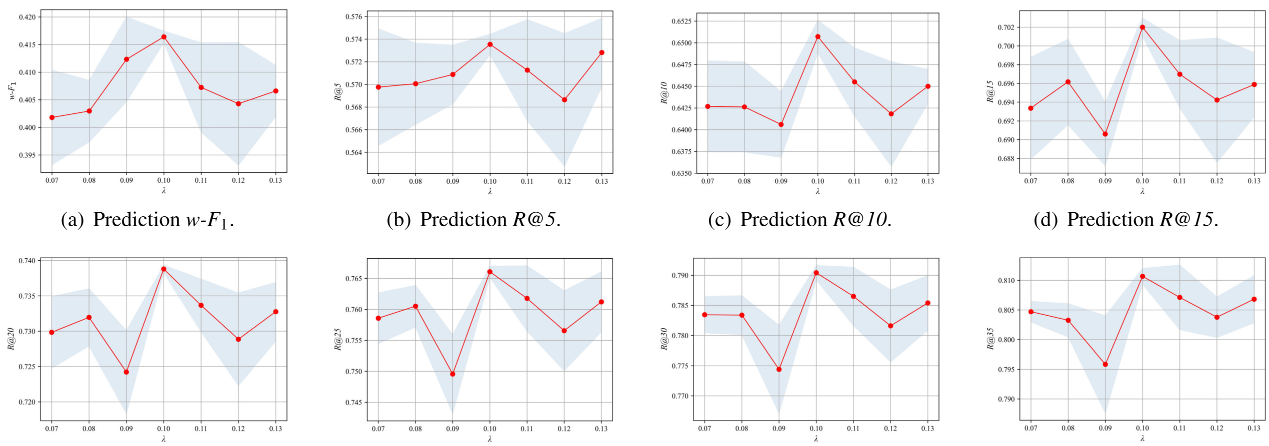
These results strongly support our hypothesis that a prediction model based on the correlation between maintenance projects and maintenance project records can effectively identify new maintenance projects.

## H. PARAMETRIC SENSITIVITY ANALYSIS

To show how the main hyperparameters involved in CoSDC affect the model performance, we check the sensitivity of some hyperparameters, the co-occurrence matrix threshold $\lambda$ the dropout rate in Eq. 10, the dynamic temporal modeling model, and the embedding sizes of $S$ and $D$. We changed $\lambda$ to {0.07, 0.08, 0.09, 0.10, 0.11, 0.12, 0.13}, according to the results in Fig. 6, when $\lambda = 0.10$, the overall performance remains relatively stable and achieves the best performance.

**TABLE 5. New maintenance projects prediction results using $w$-$F_1$ (%) and $R@k$ (%).**

| Model | $w$-$F_1$ | $R@5$ | $R@10$ | $R@15$ | $R@20$ | $R@25$ | $R@30$ | $R@35$ |
|---|---|---|---|---|---|---|---|---|
| MLP | 15.55±0.17 | 23.18±0.18 | 32.38±0.13 | 39.43±0.24 | 45.70±0.21 | 51.39±0.23 | 55.40±0.11 | 58.56±0.26 |
| CNN | 20.38±0.12 | 25.69±0.19 | 35.63±0.73 | 43.12±0.22 | 48.84±0.02 | 53.81±0.26 | 58.31±0.16 | 61.74±0.28 |
| Transformer | 15.43±0.15 | 23.08±0.27 | 32.46±0.37 | 39.44±0.18 | 45.27±0.23 | 50.74±0.21 | 55.09±0.26 | 58.38±0.27 |
| RNN | 15.55±0.17 | 23.27±0.05 | 32.59±0.22 | 39.45±0.28 | 45.95±0.16 | 51.21±0.27 | 55.19±0.23 | 58.84±0.23 |
| LSTM | 15.62±0.16 | 23.37±0.25 | 32.60±0.14 | 39.35±0.26 | 45.83±0.23 | 51.15±0.34 | 55.17±0.12 | 58.57±0.19 |
| Dipole | 15.72±0.22 | 23.10±0.06 | 32.52±0.29 | 39.69±0.17 | 45.71±0.11 | 51.39±0.84 | 55.43±0.24 | 58.68±0.18 |
| RETAIN | 20.68±0.11 | 25.76±0.15 | 35.67±0.25 | 42.62±0.15 | 48.57±0.13 | 53.33±0.14 | 57.62±0.34 | 61.30±0.16 |
| Chet | 20.03±0.14 | 25.94±0.29 | 35.97±0.31 | 43.47±0.26 | 49.21±0.11 | 53.91±0.27 | 58.27±0.13 | 61.76±0.21 |
| CoSDC | **21.29±0.21** | **26.28±0.18** | **36.20±0.12** | **43.78±0.13** | **49.51±0.12** | **54.62±0.22** | **59.24±0.21** | **62.37±0.14** |



(a) Prediction $w$-$F_1$. (b) Prediction $R@5$. (c) Prediction $R@10$. (d) Prediction $R@15$.

(e) Prediction $R@20$. (f) Prediction $R@25$. (g) Prediction $R@30$. (h) Prediction $R@35$.

**FIGURE 6. Parameter sensitivity analysis of λ.**

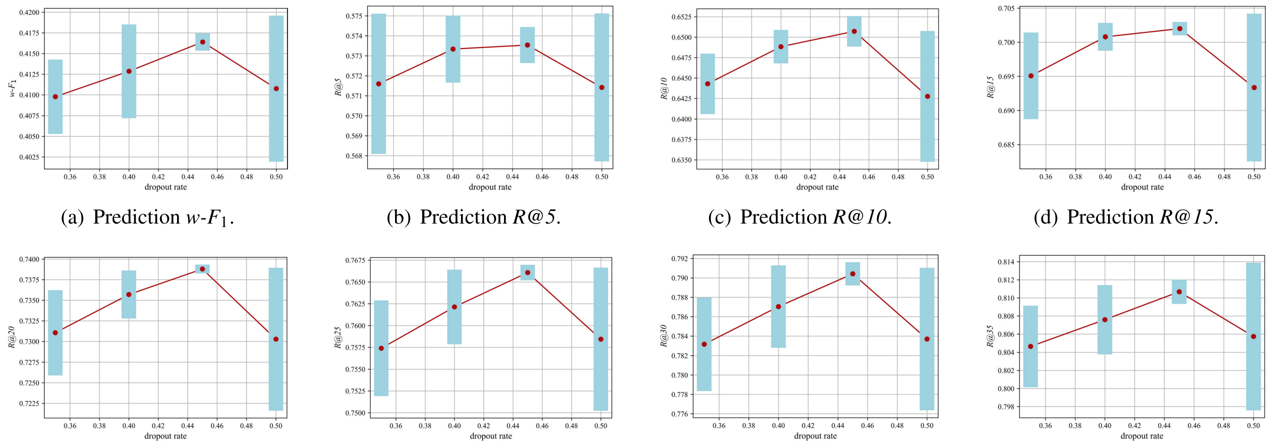
**TABLE 6. Different dynamic temporal modeling of vehicle maintenance project prediction results using $w$-$F_1$ (%) and $R@k$ (%).**

| Model | $w$-$F_1$ | $R@5$ | $R@10$ | $R@15$ | $R@20$ | $R@25$ | $R@30$ | $R@35$ |
|---|---|---|---|---|---|---|---|---|
| RNN | 41.62±0.10 | 57.32±0.07 | 65.03±0.16 | 70.1±0.1 | 73.77±0.02 | 76.57±0.08 | 79.02±0.08 | 81.01±0.07 |
| LSTM | 41.37±0.21 | 57.37±0.10 | 64.79±0.11 | 69.98±0.12 | 73.58±0.13 | 76.41±0.18 | 78.86±0.22 | 80.9±0.17 |
| Transformer | 41.17±0.31 | 57.1±0.24 | 64.53±0.24 | 69.73±0.03 | 73.09±0.15 | 75.97±0.12 | 78.36±0.09 | 80.38±0.08 |
| GRU | **41.64±0.10** | **57.35±0.09** | **65.07±0.19** | **70.20±0.10** | **73.88±0.05** | **76.61±0.09** | **79.04±0.12** | **81.07±0.13** |

To evaluate the effect of dropout rate, we vary it in {0.35, 0.40, 0.45, 0.50}, according to the results in Fig. 7, the overall performance remains relatively stable and achieves the best performance when dropout rate = 0.45. In order to evaluate the impact of dynamic timing modeling on the experimental results, we compared the experimental results of RNN, GRU, LSTM and Transformer used for dynamic timing modeling respectively. Specifically, as shown in Table 6, GRU is the most effective for dynamic temporal modeling. Fig. 8 shows the performance of the proposed CoSDC model over different hyperparameter combinations of embedding sizes of $S$ and $D$. In particular, we found that an optimal balance between efficiency and performance is achieved when the $S$ and $D$ dimensions are set to about 80.

## VI. CASE STUDY

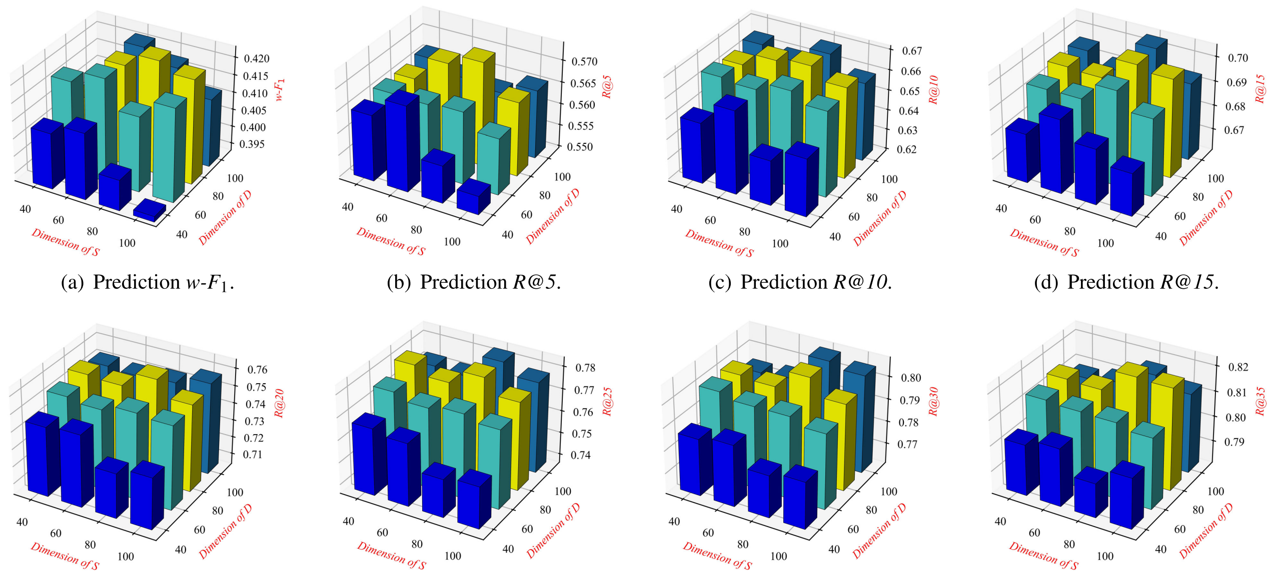
To further demonstrate the model's capability in accurately capturing the temporal correlations among maintenance records, a case study was conducted. Fig. 9 illustrates the maintenance projects carried out across six consecutive maintenance of a vehicle. The sixth maintenance project indicates the need for brake system maintenance. Projects performed during the second and fourth maintenance are closely related to the brake system and significantly influence the sixth maintenance. The CoSDC model proposed in this paper is employed to predict the sixth maintenance projects based on data from the first five recorded projects. Fig. 10 shows the attention weights output by the model for these five records. The weights for the



(a) Prediction $w$-$F_1$. (b) Prediction $R@5$. (c) Prediction $R@10$. (d) Prediction $R@15$.

(e) Prediction $R@20$. (f) Prediction $R@25$. (g) Prediction $R@30$. (h) Prediction $R@35$.

**FIGURE 7.** **Parameter sensitivity analysis of dropout rate.**



(a) Prediction $w$-$F_1$. (b) Prediction $R@5$. (c) Prediction $R@10$. (d) Prediction $R@15$.

(e) Prediction $R@20$. (f) Prediction $R@25$. (g) Prediction $R@30$. (h) Prediction $R@35$.

**FIGURE 8.** **The performance under different dimensions of $S$ and $D$ combinations.**

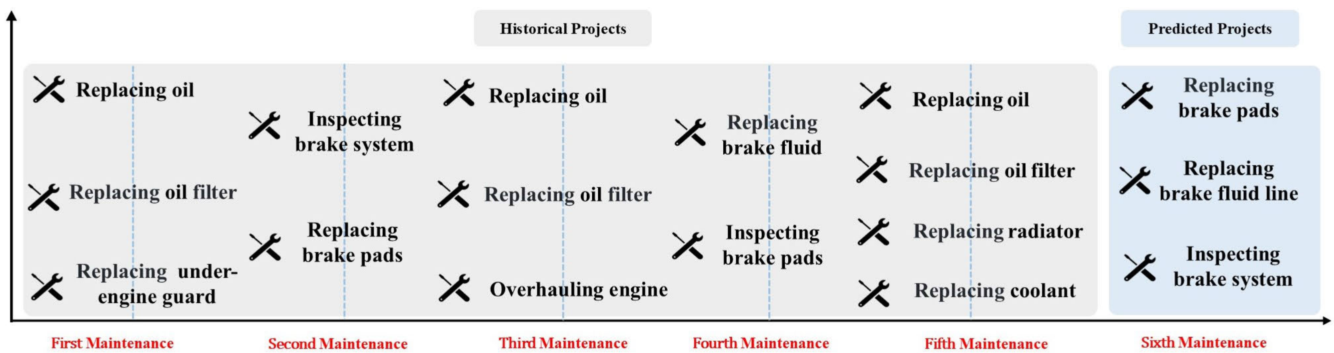



**FIGURE 9.** **Maintenance projects performed in the six maintenance records for a vehicle.**

second and fourth maintenance records are 0.3361 and 0.3409, respectively, which are significantly higher than those for the first, third, and fifth records. This demonstrates that the CoSDC model effectively captures the temporal correlations among maintenance records over different periods.

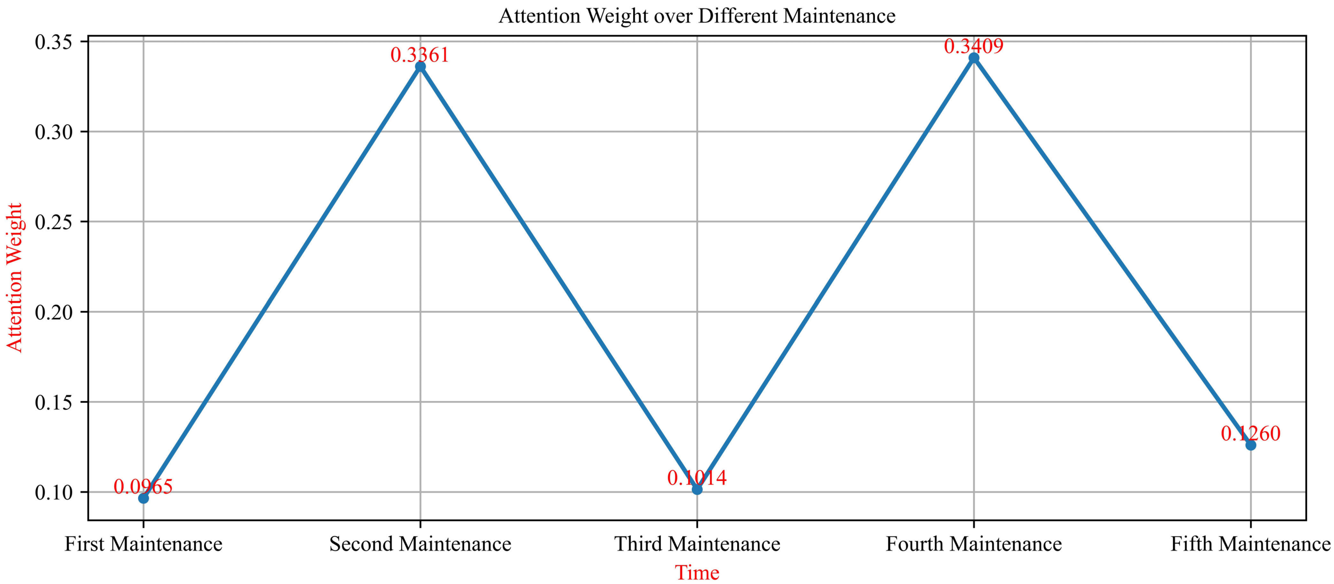



**FIGURE 10.** Attention weight for the first five maintenance records.

## VII. CONCLUSION

To address the limitations of current methods, which only predict part of a vehicle's maintenance demands, this study develops a prediction model based on cooperative static and dynamic correlation-aware learning to predict all maintenance demands of vehicles. Due to the significant static and dynamic correlations between vehicle maintenance projects and different time maintenance project records, we have designed a static correlation perception method based on co-occurrence matrix and a dynamic correlation-aware learning method based on attention weight. By skillfully fusing these two types of correlation perception through the attention mechanism, we can further improve prediction accuracy. The experimental analysis confirms the excellent performance of our model.

Our method deeply exploits the various correlations of the vehicle maintenance process, and can be quickly applied to tasks such as predicting vehicle failures and parts demand due to their strong correspondence. However, the current model only analyzes the correlation between maintenance projects from a statistical perspective, disregarding the underlying semantic links. Future work will explore the semantic correlations between maintenance projects in greater depth. This research direction can enhance the model's interpretability and accuracy, leading to further breakthroughs in the field of vehicle maintenance demand prediction.

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