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An Analytical Study Predicting Future Conditions and Application Strategies of Concrete Bridge Pavement Based on Pavement Management System Database

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Abstract: South Korea is implementing various policies to address the aging of infrastructures and improve road infrastructure management. Moreover, numerous research projects aiming at the development of necessary technologies for the proper implementation of these policies are underway. This study specifically aims to overcome existing problems in bridge pavement maintenance, such as the inaccuracy of future condition predictions and the selection of incorrect evaluation indicators. Our goal is to provide a new approach for the improved management of the bridge pavement management system (BPMS). To address the issues of accuracy in future condition prediction and evaluation indicator selection within the existing maintenance system, we utilized particle filtering, a Kalman filter method among machine learning techniques. This method allows for the prediction of future conditions, based on the nonlinearly collected bridge pavement conditions within BPMS. Furthermore, we proposed a systematic bridge pavement management strategy. This strategy utilizes traffic volume (ESALs; equivalent single axle loadings), a factor that can influence the future condition of bridge pavement, in correlation with the future condition predicted through particle filtering within BPMS.

Keywords: bridge deck concrete pavement; condition index; bridge asset management; Particle Filtering; vehicle type; time series analysis

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1. Introduction

Since 2020, South Korea has enforced the Sustainable Infrastructure Management Basic Act, requiring systematic management of social overhead capital (SOC) like bridges and road pavement surfaces. It mandates the development of advanced asset management strategies as part of the Second Road Management Plan (2021–2025). However, many road management organizations often fail to adequately consider various performance factors when formulating long-term plans. This deficiency is particularly evident due to inaccurate deterioration modeling and performance deduction curves, leading to reduced predictive accuracy and limitations in implementing advanced management through life cycle cost analysis (LCCA).

Among the various components that make up road infrastructure, pavement is a structure that directly bears the brunt of diverse environmental and traffic loads in outdoor conditions. It significantly influences the comfort and safety of road usage. However, compared to other road infrastructure elements, it receives relatively less attention in terms of management budgets and research efforts. Particularly, most of the methods used thus far for predicting the durability or serviceability of road infrastructures have relied more on lab-scale quality tests or simulations rather than on data collected through actual service in the field [1–3]. However, with the recent development of network-level survey technologies, numerous studies are being conducted on life cycle cost analysis based on the service performance survey values of road facilities that are actually in service [4]. Most of these studies target earthwork pavement, and precise management is not being carried out for pavement surfaces, which are managed by different departments and systems compared to general earthwork pavement.

Specifically, bridge deck pavement is typically considered to be only one aspect of safety assessment, and elements considered in pavement management systems (PMS) are not extensively incorporated into bridge management systems (BMS), making systematic management challenging. Furthermore, the pavement surface provides serviceability that is directly sensed by road users, but its importance is relatively lower compared to other bridge components such as abutments, piers, and superstructures.

When conducting safety assessments of bridge deck pavement, the factors considered include crack rate, driving performance, and drainage condition. It is worth noting that, apart from the crack rate, the evaluation of the remaining variables relies on the subjective judgment of inspectors [5]. However, several significant factors that can affect bridge deck pavement have been identified, such as freeze–thaw phenomena due to environmental loads, structural behavior of the pavement substructure, fatigue from traffic loads, corrosion from de-icing agents, long-term durability based on mix design, and drainage capacity [6–11]. Specifically, in conducting a life cycle cost analysis (LCCA) for ultra-high-performance concrete (UHPC) bridge pavement using the anticipated lifespan based on a Monte Carlo simulation, it has been found that the variable with the highest sensitivity over the lifecycle is average daily traffic (ADT) [12]. Therefore, there is a need for a systematic asset management approach that considers these various influencing factors, with particular emphasis on the essential consideration of the following five factors [13].

(1) A statistical model (for each asset type) that predicts the impact level of each treatment type as a function of initial asset condition, treatment intensity, and other variables;
(2) Average (mean) impact level of each treatment type under consideration;
(3) The other statistical parameters of the impact level of each treatment type for each asset type (pavements and bridges): minimum impact, maximum impact, range, and standard deviation;
(4) Sensitivity charts;
(5) Cost-effectiveness values.

Therefore, in this study, we aimed to enhance the systematic asset management of concrete bridge deck pavements with a history of nearly 30 years of long-term use in South Korea. To achieve this, we incorporated additional variables that can be collected within the South Korean Bridge Management System (BMS), namely, surface distress (SD), international roughness index (IRI), age, and cumulative equivalent single-axle loadings (ESALs). In essence, we sought to provide a basis for more advanced BMS operations by considering a broader set of variables for future pavement condition predictions. Additionally, by identifying key vehicle categories using ESALs, we aimed to facilitate the determination of appropriate maintenance timing and the management of heavy vehicle proportions within the road network.

2. Literature Review

2.1. Methodological Research to Predict Bridge Deck Pavement Condition

Methodological research into the accurate prediction of bridge deck pavement condition can be categorized into deterministic and probabilistic models, with state-based probabilistic Markov chain models being widely used in various bridge management systems (BMS) [14]. There are machine learning (physics-based) models and artificial intelligence (AI)-based models, each of which can exhibit either probabilistic or deterministic characteristics. Research has also been conducted to predict bridge performance degradation using various deterministic, probabilistic, and artificial neural network (ANN)-based models, utilizing data from the National Bridge Inventory (NBI).

One representative case using deterministic methods is a study related to the steel deck pavement condition at the Yangtze River Bridge in China [15]. This research involved an analysis of pavement performance under heavy vehicle loads and extreme weather conditions, considering variables such as annual average daily traffic (AADT), climate conditions (temperature, rainfall), and steel deck pavement distresses (e.g., cracks, rutting, potholes).

In the probabilistic–statistical approach, there is research that estimates bridge component deterioration on South Carolina state roads by applying random effect specifications to the ordered probit model [16]. This study utilized variables such as constant, age, waterway indicator, lower country indicator, steel indicator, urban indicator, number of annual precipitation days, and AADT for the development of a superstructure deterioration model. The estimated average marginal effects were categorized based on condition scores for guidance.

Of course, there are prediction modeling studies that consider both of these approaches. Bayesian Markov Hazard (BMH) models have been used to develop deterministic and probabilistic models [5]. In this research, considering the explanatory variable AADT at a 95% confidence level, estimated lifespan ranges were analyzed for asphalt, concrete, and latex-modified concrete (LMC) pavements, in the results being 12.0~13.7 years, 14.7~37.9 years, and 7.8~12.4 years, respectively. The primary goal of this study is to establish a foundation for deterministic and probabilistic life cycle cost analysis of bridge deck pavement. This can have various applications in asset valuation, lifespan extension, and depreciation rate setting, and can also contribute to accounting standardization. However, it is worth noting that there is high uncertainty regarding the expected lifespan range for concrete pavement, and in-depth analysis of variables such as traffic volume's impact on pavement deterioration remains an area that has not been extensively explored.

2.2. Predictive Research on Bridge Deck Pavement Condition Using Various Variables

The majority of distress in bridge deck pavement is primarily attributed to the freeze–thaw mechanism. Freeze–thaw cycles cause rapid changes in internal stress within the pavement as water within voids repeatedly freezes (expands) and thaws (contracts). Furthermore, it has been observed that de-icing agents with high sulfate content, used after freeze–thaw events, can react with cement in the mixture, affecting expansion and internal stress within the composite [8]. This phenomenon, involving changes in internal stress due to reactions between specific components and cement following freeze–thaw events, is believed to accelerate the deterioration rate when subjected to heavy traffic loading. Additionally, various studies have highlighted the effectiveness of different maintenance methods in reducing the rate of condition deterioration for optimal bridge asset management [17].

In the field of road and transportation, the impact of traffic loading is typically evaluated using the annual average daily traffic (AADT). However, in the realm of road pavement, equivalent single-axle load (ESAL) is employed to distinguish the influence of axle characteristics on the pavement. ESAL reflects the phenomenon where pavement damage increases significantly with increasing axle loads, and it is calculated using the equivalent single-axle load factor (ESALf) for various vehicle types [18].

The study of pavement performance using ESAL has been actively pursued for around four decades. For example, research evaluating the durability of pavement based on accumulated ESALs over 30 years has been conducted using design traffic that exceeds the designed traffic volume for target service life as a reference point. ESALf models specific to different pavement types (concrete, asphalt) under varying loads exist, and research analyzing the impact of axle load distribution on pavement durability has been conducted in various countries [19–21].

To calculate ESALs, it is necessary to differentiate ESALf based on the axle configuration of different vehicle types, which should be adjusted according to the traffic patterns of each country and region [22]. In South Korea, which is the focus of this study, the classification system changed in 2006, transitioning from 8 to 12 types. The specifics of this alteration are detailed in Table 1.

Table 1. The classification of vehicle types in South Korea.

Vehicle Type	Axle Configuration	ESALf		8 Types	12 Types
		Before	After	Before	After
Passenger cars	2Axle-4Tire	0.0001	0.0001	1	1
Buses	2Axle-4Tire	0.0007	0.0004	2	-
	2Axle-6Tire	1.043	1.043	3	2
Trucks	2Axle-4Tire	0.015	0.015	4	3
	2Axle-6Tire	0.796	0.795	5	4
	3Axle-10Tire	2.52	2.516	6	5~7
Special purpose trucks		2.948	2.482	7~8	8~12

Thus, factors such as age and traffic volume, which significantly influence the deterioration of bridge deck pavement, can potentially affect the rate of deterioration. In this study, these factors will be utilized as variables to analyze their impact on the deterioration rate of bridge deck pavement conditions.

3. Methodology

Particle filtering is a variation of the Kalman filter, which uses particles and is suited for highly nonlinear prediction models. Furthermore, particle filtering is recognized as a sophisticated method that enhances the predictive precision of Bayesian approaches. Specifically, examining the characteristics of particle filtering grounded in Bayesian probability theory, model variables with high probabilities are weighted and then resampled via an updating procedure that incorporates actual observational data. On the other hand, model variables with lower probabilities are resampled less frequently. This means that through the updating process, model variables with higher probabilities are resampled more often. Therefore, as the reliability of the actual measured data improves, the predictive accuracy of the target data (or model) also increases. Due to these characteristics, particle filtering techniques are also referred to as "Sequential Monte Carlo (SMC)" [23].

In this research, as an initial step towards employing particle filtering, we developed the following formula grounded on the concrete pavement condition index (CPCI), one of many condition indices for concrete pavement.

$$CPCI_k = CPCI_{k-1} + a_k t + b_k \tag{1}$$

$$a_{k+1} = a_k + w_{ak} \tag{2}$$

$$b_{k+1} = b_k + w_{bk} \tag{3}$$

$$y_k = CPCI_k^{measured} - CPCI_k \sim CPCI(0, \sigma_{CPCI}^2) \tag{4}$$

In Equations (1)–(4), a_k, and b_k are regression coefficients derived from the regression line for the parameters *CPCI* and t. This research sets "a" and "b" as uniform distributions, where "a" is the slope of the regression analysis based on the actual measurement data and "b" considers the range of uncertainty of initial *CPCI*. The terms w_{ak}, and w_{bk} represent white noise vectors following a Gaussian distribution, with a mean of zero. $CPCI_k$ is indicative of the future CPCI and is established as the objective function for time variable k. t alludes to the age of the concrete pavement, whereas $CPCI_k^{measured}$ signifies the measured

CPCI. Therefore, y_k can be represented as a CPCI function, like $CPCI(0, \sigma^2_{CPCI})$. As a result, the relative likelihood can be portrayed as demonstrated in Equation (5).

$$q = P(CPCI_k^{measured} - CPCI_k) \sim \frac{1}{\sqrt{2\pi}\sigma_{CPCI}} exp\left\{-\frac{1}{2}\left(\frac{CPCI_k^{measured} - CPCI_k}{\sigma_{CPCI}}\right)^2\right\} \quad (5)$$

At this point, considering the error rate of the pavement surface scanning image analysis data, which is the basis for the CPCI values used in this study, to be between 5~10%, σ_{CPCI} was assumed to be 10% (0.1). Furthermore, by normalizing the relative likelihood, it was depicted as demonstrated in Equation (6).

$$q_i = \frac{q_i}{\sum_{j=1}^{N} q_j} \quad (6)$$

N denotes the count of particles in Equation (6), and the aggregate sum of relative likelihoods must equal one. Based on the relative likelihoods q_i, new particles could be calculated [24]. To avoid any bias towards a specific distribution in the initial CPCI, a random number (r) was configured as a uniform probability distribution ranging between zero and one.

$$\sum_{i=1}^{j-1} q_i < r \leq \sum_{i=1}^{j} q_i \quad (7)$$

Through the process of Equation (7), a_j and b_j were re-selected. q represents the measurement data.

In this case, as the CPCI moved closer to the mean, the probability value escalated, and as it veered toward the tail of the normal distribution, the probability diminished. In essence, by employing this procedure, data with high probability values in a normal distribution were replicated, and these data were preferentially chosen. On the contrary, data with low probabilities were progressively eliminated. Then, in a subsequent step, existing particles were repeated N times. An intuitive explication of this concept is depicted in Figure 1.

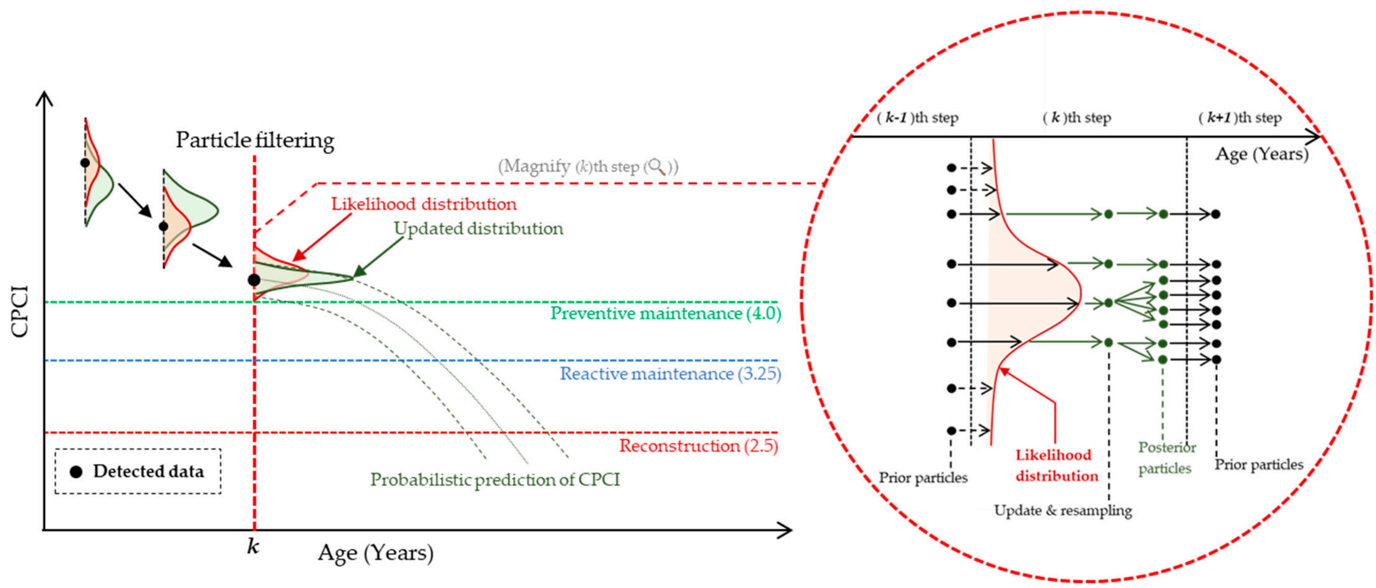

Figure 1. An intuitively comprehensible schematic of the particle filtering process of CPCI [25].

4. Forecasting the Status of Bridge Pavement through Particle Filtering

Recently, the initial step among several to forecast future road pavement condition indices was conducted by utilizing machine learning with PMS DB [25]. While that study predicted future pavement condition indices for roadways, this section aims to develop a CPCI for predicting the future condition of bridge deck pavement and propose a model for more accurate prediction of future conditions.

4.1. Preparation of Data

In this research, the CPCI was derived from the bridge component database within South Korea's PMS DB. It was formulated as per Equation (8) and acted as a function of the amount of surface distress (SD) and the International Roughness Index (IRI).

$$CPCI = f\ (IRI, SD) \tag{8}$$

The data's unit section was structured in 10 m increments, encapsulating information such as route, direction, lane, start and end points, IRI, SD, and CPCI. The same points were gathered biennially. Specifically, to optimize the impact of this study's findings on South Korea's bridge deck pavement—designed and built with a 20-year lifespan in mind—we aimed to compile a dataset focusing on sections where PMS was actively employed, pavement performance varied swiftly, and rehabilitation was regularly implemented. As such, we utilized data collected 19 to 27 years post-construction. The rough distribution of the dataset, based on the number of times the series was collected, is detailed in Section 4.2.

4.2. Pre-processing of Data

Upon the preparation of the dataset, as referenced in Section 4.1, the format was structured in the subsequent sequence:

1. Initiate the matching of start and end points by leveraging GPS values for every 10 m segment, according to the age of the concrete bridge deck pavement;
2. Extract time series sections where more than three consecutive points have been collected for the same start and end points in PMS DB;
3. Organize the data considering four factors—bridge component, type of pavement, initial paving history, and if it pertains to a design lane—then execute the filtering process (229 sections equivalent to 2.29 km);
4. Extract data clusters that lack a maintenance history post-initial paving (comprising 224 sections, which corresponds to 2.24 km);
5. Remove duplicate history data to improve the reliability (prediction accuracy) of data (188 sections = 1.88 km);
6. Categorize the dataset into two clusters according to time series data points consistently gathered within the identical start and end point segments (5 points accounting for 146 sections and 4 points for 42 sections, amounting to a total of 188 sections).

4.3. CPCI Prognosis Using Particle Filtering

Based on the DB derived through the data preprocessing process of the six stages introduced in Section 4.2, we calculated a basic model that can intuitively check the time series changes of bridge deck pavement. Through this basic model, it is possible to check the approximate status changes by age in the analysis target section, and the results are shown in Figure 2 below. In Figure 2, for the same section out of 1.88 km, which is an analysis target section, trend lines for each section's basic model were differentiated according to the amount of existing time series data (five for section A and four for section B), excluding the initial CPCI. In the case of a basic model, since outlier removal was performed through the process in Section 4.2 above, although there were no cases where the status index increased over time, it was confirmed that it did not show a decreasing trend in continuous form like general regression models do, and, thus, it was judged that the particle filtering application was necessary. In addition, particle filtering techniques were considered suitable for road pavements that included overall pavement conditions at various levels distributed over long networks, because they can secure higher-level prediction accuracy through continuous updates to time series regression analysis models.

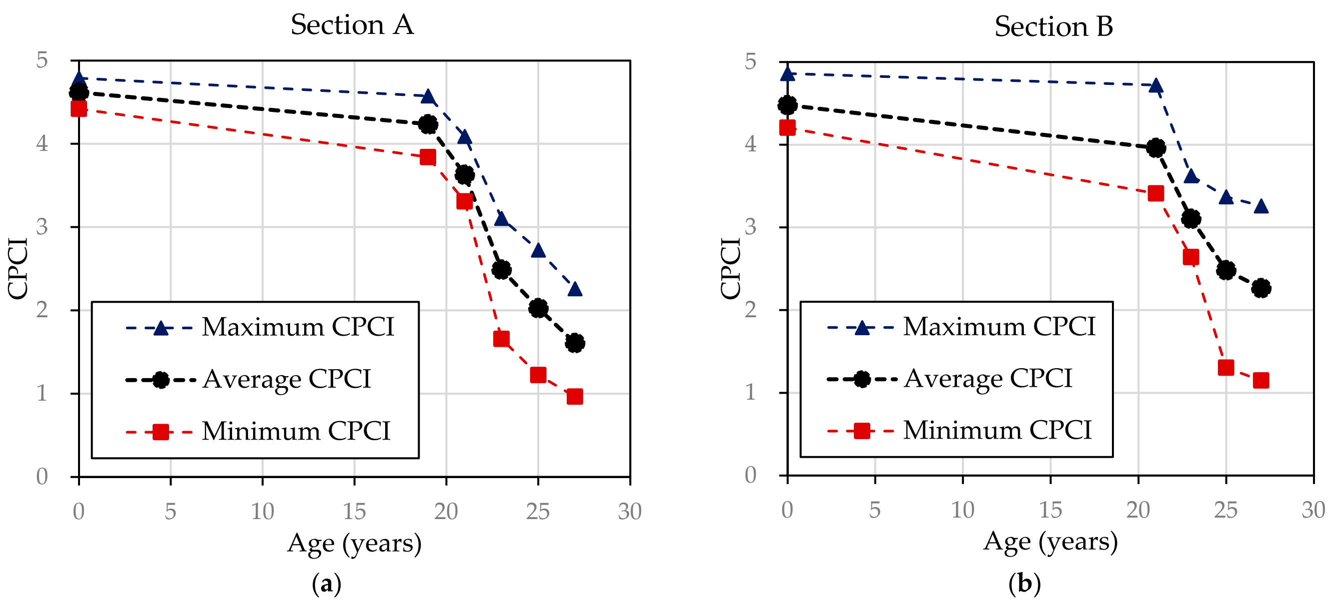

Figure 2. Establishing a basic prediction curve based on the condition history of concrete pavement. (**a**) Section A (using 5 points); (**b**) Section B (using 4 points).

On one hand, securing status indices for all ages is important for high-accuracy future state prediction. This is because trends (or slopes) are determined depending on the location's initial values, playing an important role in predicting the future. However, since this study was constructed during the 1980s, initial condition surveys were not conducted. Therefore, in this study, we assumed the initial values of various cases and the selected case, which was able to predict the current pavement condition with the highest accuracy, as described below in Section 5.1.

5. Results of Predicting Future Pavement Condition with Particle Filtering

5.1. Application of Particle Filtering

Figure 3 below shows one case with the highest prediction power among the results, assuming the initial CPCI of sections A and B to be 4.3, 4.4, 4.5, 4.6, and 4.7; all results for all cases are shown in Table 2 below. In Figure 3, to clarify the meaning of the predicted CPCI curve, maintenance application baselines were also expressed (preventive maintenance (4.0), reactive maintenance (3.25), and reconstruction (2.5)). As a result of the analysis, at the age of 27 years, the accuracy of the pavement condition prediction was analyzed to be highest when the initial CPCI was at 4.4 for section A, with accuracy rates of approximately 99.69%, and approximately 97.37% for section B. On the other hand, according to previous analyses on roadway sections [25], when considering five consecutive time series points as targets, the prediction accuracy was highest at approximately 96.6% when the initial CPCI was assumed to have been approximately estimated and calculated. This means that even though bridge deck pavement and roadway pavement had identical five-point time series data sets, they exhibited different characteristics in terms of the optimal initial CPCI values that would yield maximum predictive accuracy. This discrepancy can be attributed to differences in key variables constituting CPCI, such as roughness (IRI), which results in slightly lower status indices for bridge deck pavements compared to roadway pavements, despite them having been constructed using identical materials and methods during the same period.

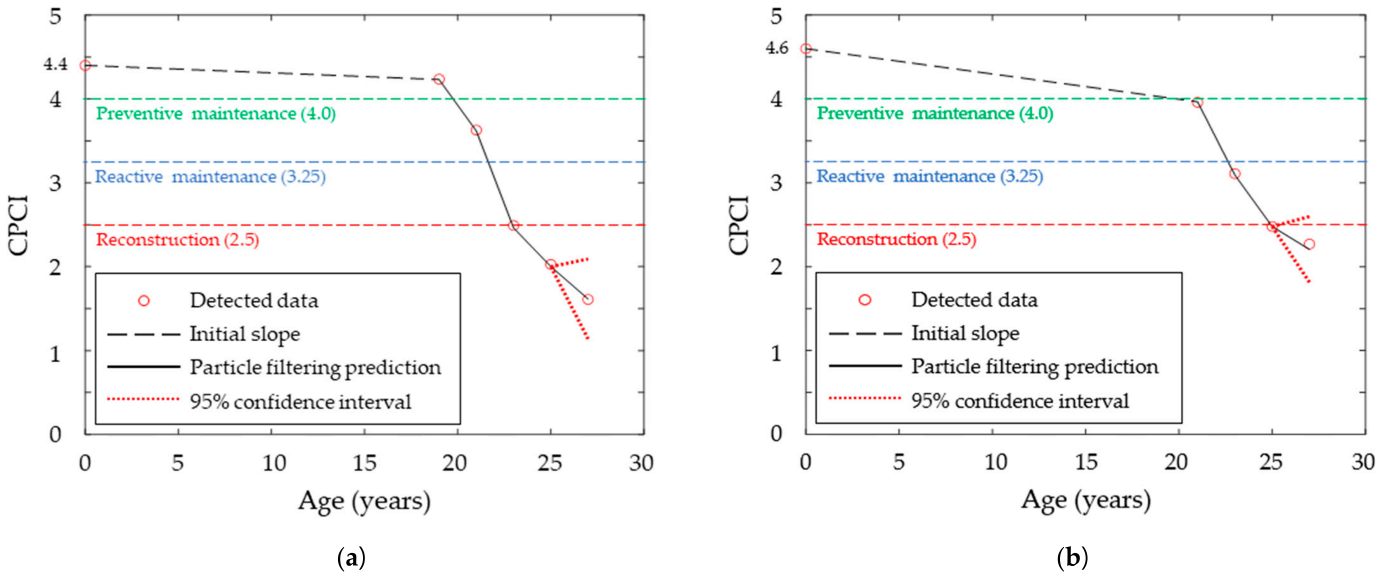

Figure 3. Contrasting the observed data with the predictions from particle filtering. (**a**) Initial CPCI 4.4 in Section A (5 points of time series condition); (**b**) initial CPCI 4.6 in Section B (4 points of time series condition).

Table 2. Assessing the changes in prediction accuracy for each section based on the variations in initial CPCI (4.3, 4.4, 4.5, 4.6, and 4.7).

Division	Section A (in 27 Years)					Section B (in 27 Years)				
	Detected CPCI	Particle Filtering		Multinomial Regression		Detected CPCI	Particle Filtering		Multinomial Regression	
		Predicted CPCI	Prediction Accuracy (%)	Predicted CPCI	Prediction Accuracy (%)		Predicted CPCI	Prediction Accuracy (%)	Predicted CPCI	Prediction Accuracy (%)
4.3	1.609	1.663	96.69	1.698	94.47	2.266	2.036	89.85	2.282	92.61
4.4		1.614	99.69	1.696	94.59		2.066	91.16	2.281	92.66
4.5		1.659	96.95	1.693	94.78		2.102	92.77	2.279	92.75
4.6		1.726	92.74	1.691	94.90		2.207	97.37	2.278	92.80
4.7		1.710	93.77	1.689	95.03		2.125	93.75	2.277	92.85

Additionally, declining performance trends were found to differ between roadways and bridge deck pavements, with bridge deck pavements exhibiting larger decreases compared to roadways. This suggests that degradation occurs more rapidly within bridge deck pavements than within roadways, indicating the importance of selecting appropriate maintenance timing in order to ensure more pleasant drivability for road users.

The prediction accuracy shown in Table 2 uses the concept of relative error, and the formula is as follows (Equation (9)). $\varepsilon_{R.E}$ represents the relative error rate between the actual data and the predicted data, while $CPCI_{predicted}$ and $CPCI_{detected}$, respectively, represent the CPCI predicted through particle filtering and the actual CPCI.

$$Predictionaccuracy\ (\%) = 1 - \varepsilon_{R.E} \quad \frac{\left|CPCI_{predicted} - CPCI_{detected}\right|}{CPCI_{detected}} \tag{9}$$

In particular, Table 2 allowed us to assess the applicability of particle filtering by directly comparing the CPCI predicted through the traditional method of multinomial regression and that predicted through particle filtering for future state prediction. As a result, we found that Section A, which had one more time-series point, had higher prediction accuracy in both methods compared to Section B. However, while the multinomial regression showed a relatively constant ratio and trend as the initial CPCI changed, particle filtering yielded high prediction accuracy only at a specific initial CPCI. This characteristic was perceived as a well-reflected advantage of particle filtering, which can derive more fit results by increasing particles, especially for a network with a narrow range like the target section of this study.

Through Table 2, we examined the difference in prediction accuracy between the traditional method of multinomial regression and particle filtering. However, multinomial regression was unable to undergo direct comparative analysis due to its limitations when compared to the extensibility of the particle filtering method, such as resampling (determining the number of particles) and determining the appropriate number of time-series points.

5.2. Verification of the CPCI Prediction Model

Particle filtering can change the prediction accuracy depending on the number of particles, so in this section, we calculated the prediction accuracy of sections A and B for the actual data (age 27 years) by changing the number of particles. The results are shown in Table 3.

Table 3. Analysis and validation of the prediction precision by unit section in relation to the variation in the number of particles.

Num. of Particles	Section A (In 27 Years)			Section B (In 27 Years)		
	95% Confidential Interval		Prediction Accuracy (%)	95% Confidential Interval		Prediction Accuracy (%)
	Included (Not Included)	Validation Accuracy (%)		Included (Not Included)	Validation Accuracy (%)	
1000	135 (11)	92.47	87.54	41 (1)	97.62	88.42
5000	137 (9)	93.84	88.07	42 (0)	100.00	89.54
10,000	136 (10)	93.15	87.98	41 (1)	97.62	89.47
15,000	133 (13)	91.10	88.03	41 (1)	97.62	89.35
20,000	134 (12)	91.78	88.04	41 (1)	97.62	89.32

As a result of the analysis, as shown in the shaded area of Table 3, it was analyzed that the prediction accuracy was highest when both sections A and B used 5000 particles. The results are shown in Figure 4 below. Among the 188 sections analyzed, for the 1.46 km section (section A), predicting an age of 27 years, data falling within the 95% confidence interval accounted for about 93.84% of the total (137 out of 146 sections), with only nine points (6.16%) not included in this range. On the other hand, for a section of a length of 42 km (section B), data included in the 95% confidence interval accounted for all of them (42 out of 42 sections or 100%), and additional calculation results regarding prediction accuracy resulted in an accuracy rate of approximately 89.54%.

In addition, this study aimed to verify the minimum amount of time series data required for predicting the future condition of bridge deck pavement in general by calculating the prediction accuracy according to the amount of consecutive time series data for the same section.

Therefore, excluding the initial CPCI, we analyzed the trend of prediction accuracy by increasing the number of data points accordingly for Section A (2, 3, and 4 points) and Section B (2 and 3 points). Tables 4 and 5 below contain the results for Section A and Section B. The result values predicted through measured data are indicated in blue shading. As a result of learning from measured data, the prediction accuracy was analyzed to ensure at least 98.69% accuracy, which was judged to represent sufficient confidence in the learning materials. Also, as a result of analyzing prediction accuracy according to changes in the number of time series points in sections A and B, it was analyzed that there must be three consecutive time series points to secure at least 95% prediction accuracy.

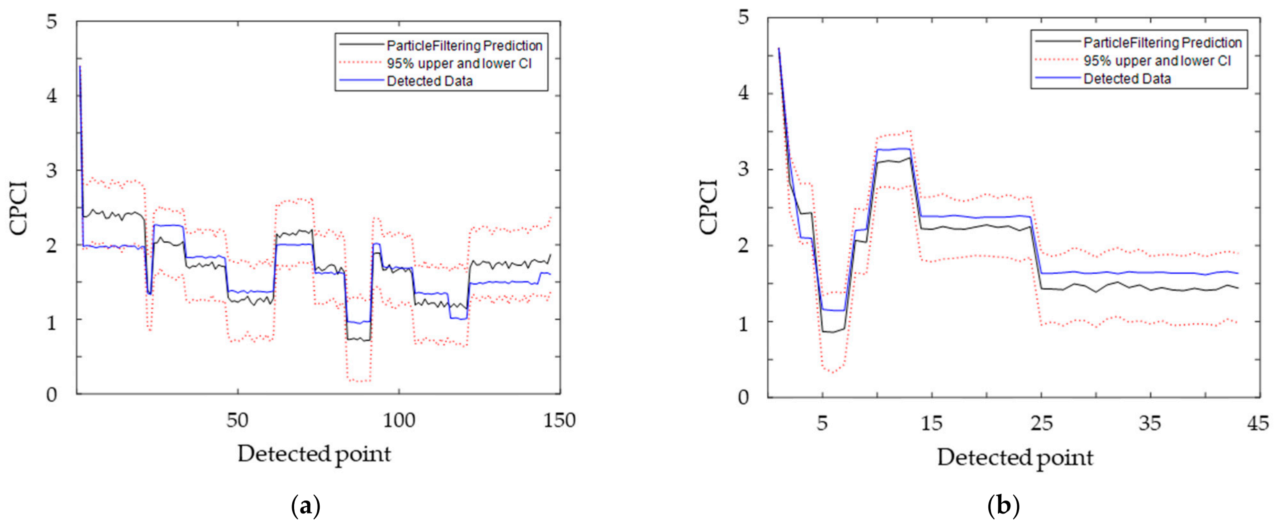

Figure 4. CPCI's particle filtering prediction and its 95% confidence interval using 5000 particles. (**a**) 146, Section A (1.46 km); (**b**) 42, Section B (0.42 km).

In terms of prediction time, we analyzed that, as the number of time series points was short and the required prediction period lengthened, the prediction accuracy would gradually decrease. The results are shown in Figure 5a,b. Also, the relative error for each number of time series points for the same section showed a decrease as more points appeared. The results are shown in Figure 5c,d.

Table 4. Assessing the prediction precision in response to variations in the number of time-series points in Section A.

Age (Year)	Actual CPCI	2 Data		3 Data		4 Data	
		PF * CPCI	Prediction Accuracy (%)	PF * CPCI	Prediction Accuracy (%)	PF * CPCI	Prediction Accuracy (%)
19	4.236	4.234	99.97	4.240	99.90	4.232	99.90
21	3.629	3.620	99.77	3.652	99.35	3.618	99.71
23	2.491	3.303	67.40	2.500	99.63	2.462	98.83
25	2.027	2.986	52.71	2.077	97.52	2.001	98.69
27	1.609	2.669	34.19	1.655	97.20	1.614	99.69

* Note: PF: particle filtering.

Table 5. Assessing the prediction precision in response to variations in the number of time-series points in Section B.

Age (Year)	Actual CPCI	2 Data		3 Data	
		PF * CPCI	Prediction Accuracy (%)	PF * CPCI	Prediction Accuracy (%)
21	3.961	3.957	99.91	3.967	99.86
23	3.106	3.086	99.38	3.093	99.60
25	2.483	2.781	87.98	2.478	99.82
27	2.266	2.476	90.73	2.207	97.37

* Note: PF: particle filtering.

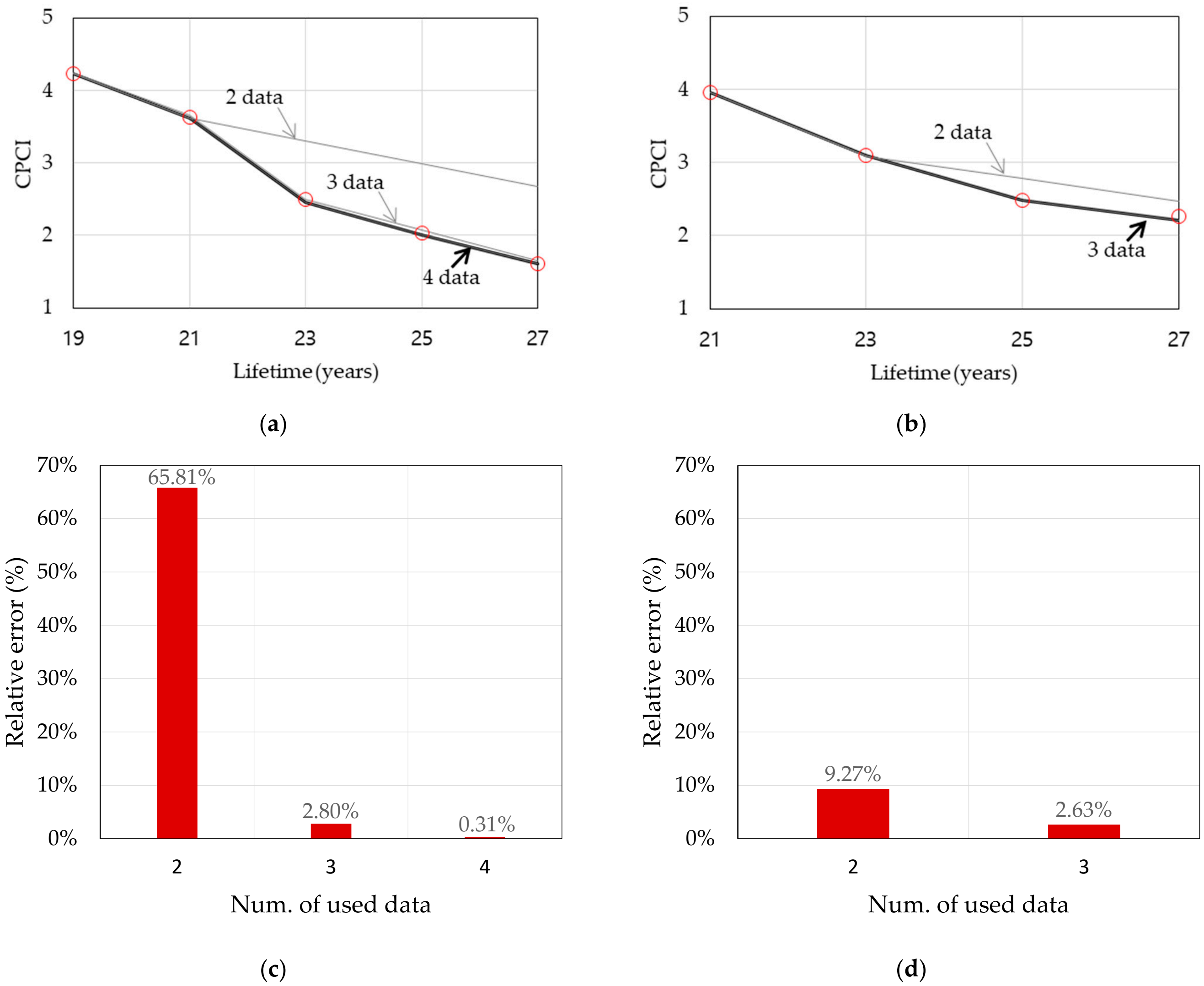

Figure 5. Results of prediction precision in relation to variation in the quantity of time-series points per section. The impact of the amount of real data used to update the CPCI prediction via particle filtering; the lines represent the average values. (**a**) Section A; (**b**) Section B. Relative errors according to the amount of data used for updating. (**c**) Section A; (**d**) Section B.

6. Discussion on the Utilization of Predicted CPCI

This study proposes a method that utilizes the particle filtering method to attain higher future prediction accuracy for concrete bridge pavement and to work as a basis for decision making regarding maintenance from various perspectives.

For the first, the influence of the initial CPCI on prediction accuracy was found to be significant (refer to Table 2). Specifically, by determining the initial CPCI immediately after completion, not only could we secure more accurate prediction accuracy for future conditions, but we also presented deterioration models for each performance index range immediately after the pavement's construction. This could help the practical workforce responsible for future bridge pavement maintenance to make decisions based on various scenarios. Also, this could be a solution with which to overcome the common limitation of most road networks currently in public use, which is the inability to predict accurate future performance during decision making regarding maintenance due to the lack of application of BPMS to secure the initial CPCI immediately after the actual pavement construction.

Based on the final determined initial CPCI values of sections A and B, conditions for ensuring over 90% prediction accuracy for concrete bridge pavement were derived by identifying the time-series conditions of at least three consecutive identical sections and the appropriate number of particles (5000 particles). Such findings are believed to be usable as a basis for comparisons when utilizing particle filtering or other prediction methods based on the PMS database.

As mentioned in the introduction and literature review, there are a variety of factors that can influence future bridge pavement conditions. However, the only variable that can be systematically collected for each unit section and used for management at the network level is the BPMS (bridge pavement management system). Therefore, this study aimed to identify a direct relationship between the results of CPCI prediction based on particle filtering derived so far and AADT (annual average daily traffic volume), a major variable affecting future bridge pavement condition according to the literature survey [5,12], among the variables that can be collected within the BPMS.

Thus, in this section, we aim to provide a basis for more advanced BPMS operations that allow for appropriate management time and heavy vehicle ratio management by specifying important vehicle groups that can affect the deterioration of bridge pavement conditions, considering vehicle type-specific ESALs through distinguishing AADT, which can be collected within BPMS, by vehicle type.

Based on the 12 vehicle classifications (Table 1) classified in South Korea, the results of individual calculation of ESALs by vehicle classification showed the cumulative ESAL traffic volume up to the age of 27 years in sections A and B, which is provided in Figure 6. In the analysis of cumulative ESAL traffic volume, vehicle types 5, 6, 7, and 8 accounted for the highest proportions, with percentages of 23.4%, 15.36%, 13.98%, and 21.65% in section A and 21.14%, 15.16%, 16.64%, and 18.54% in section B, respectively.

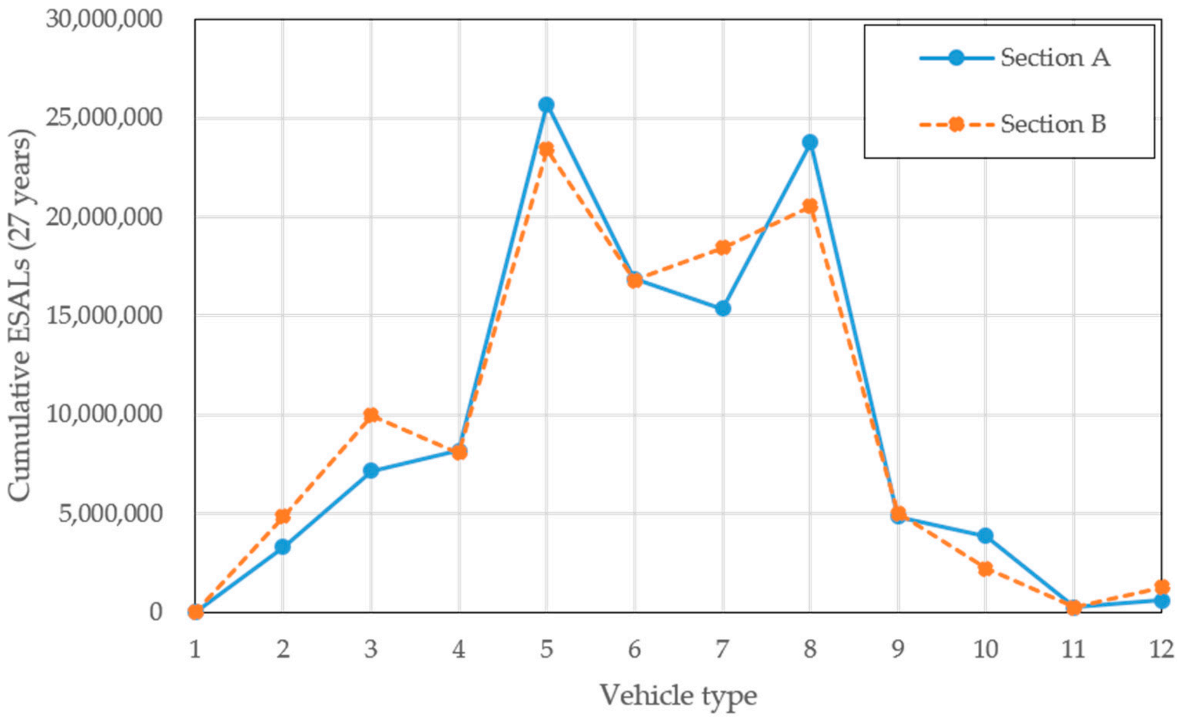

Figure 6. Cumulative ESAL traffic volume for Sections A and B.

Based on the results in Figure 6, the cumulative ESAL traffic volume rankings by vehicle type were considered, and their correlations with the predicted CPCI were analyzed (Table 6). Three groups with the highest correlations were identified among all cases. These groups consisted of: group 1, composed of vehicle types 3, 4, 5, 6, 7, and 8; group 2, composed of vehicle types 4, 5, 6, 7, and 8; and group 3, composed of vehicle types 5, 6, 7, and 8. While all three groups showed significant correlation and significance levels with CPCI, group 3, comprising vehicle types 5, 6, 7, and 8, demonstrated the highest significance.

Table 6. Ranking of cumulative ESAL traffic volume by vehicle type (at the age of 27 years). Total refers to a range or interval that includes both sections A and B.

Type	Total	Section A	Section B
1	12	12	12
2	8	9	8
3	5	6	5
4	6	5	6
5	1	1	1
6	3	3	4
7	4	4	3
8	2	2	2
9	7	7	7
10	9	8	9
11	11	11	11
12	10	10	10

Using Group 3 as a reference, vehicle types 5, 6, 7, and 8 were categorized as group 3-1, while the remaining eight vehicle types were categorized as group 3-2. The correlation between each group and CPCI was analyzed to evaluate their impact on the pavement condition. Consequently, groups 3-1, comprising vehicle types 5, 6, 7, and 8, exhibited a high correlation with CPCI and had correlation coefficients of 0.97 and 0.99, respectively. However, groups 3-2 showed relatively lower correlation with CPCI, with correlation coefficients of 0.97 and 0.03, respectively. Based on these results, it was analyzed that vehicle types 5, 6, 7, and 8 in group 3-1 were associated with pavement deterioration, while groups 3-2, while still showing a correlation with age, had less significant relationships with other vehicle types.

Furthermore, regression analysis was performed for groups 3-1 and 3-2 (dependent variable: CPCI; independent variables: age, ESAL traffic volume by group). The F-values of both models were deemed appropriate—0.002 for groups 3-1 and 0.064 for groups 3-2—securing a significant level. Thus, we categorized vehicle types into 5, 6, 7, and 8, and the remaining types were considered appropriate. However, this regression analysis utilized only age and ESAL traffic volume as data beyond the PMS (pavement management system) road pavement condition information. Other variables, such as climate (temperature, humidity, temperature fluctuation) and de-icing agent usage, were not considered. Therefore, the results of this study are considered preliminary information for predicting pavement deterioration. Subsequent research that considers various external factors affecting pavement deterioration, in addition to ESAL traffic volume, is expected to improve the accuracy of future condition predictions.

7. Conclusions

This study was conducted to predict the future conditions of concrete bridge deck pavement using the particle filtering technique based on time series data, aiming for more accurate predictions compared to conventional regression analysis. Instead of using evaluation factors such as crack rate (quantitative), driving performance (qualitative), and drainage condition (quantitative), which have limitations in terms of accurately assessing the pavement condition, this study focused only on quantitative variables, including surface distress amount, roughness (IRI), age, and ESALs, to predict the future condition of concrete bridge deck pavement. The results obtained from this study are as follows:

1. In this study, a predictive model for the future condition of bridge deck pavement using particle filtering was proposed, considering initial CPCI, an appropriate number of particles, and a minimum number of time series data points.
2. By presenting the deterioration model in a categorical form based on performance indicators acquired during the future construction of actual new sections, bridge maintenance practitioners made decisions more easily. Particularly, in future research, it is anticipated that the model will present a more specific performance measure, such as initial CPCI values of 4.3, 4.4, 4.5, 4.6, and 4.7, to facilitate practical use.
3. The operation principle of particle filtering suggests that, as the number of particles increases, the predicted accuracy for the analyzed section improves, but the accuracy of identifying that specific section may decrease. Therefore, the analysis of prediction accuracy for all cases, using 1000, 5000, 10,000, 15,000, and 20,000 particles, revealed that using 5000 particles was the most efficient approach.
4. It was observed that the number of time series data points within the analyzed section had a significant impact on prediction accuracy, rather than the number of sections. Specifically, when utilizing sections with four data points (146 sections), the prediction accuracy was 99.69%, while it was 97.37% for sections with three data points (42 sections) (using 5000 particles).
5. To predict the initial CPCI at the age of 27 years, for sections with four data points, the accuracy values were 34.19%, 97.20%, and 99.69% when sequentially adding two, three, and four data points. Therefore, it is crucial to select sections with a minimum of three consecutive data points to ensure the reliability of the data and results when predicting the pavement condition index.
6. By validating the correlation and significance between the CPCI prediction results based on particle filtering and the cumulative ESAL traffic volume by vehicle type over 27 years, it was concluded that the cumulative ESAL traffic volume of vehicle types 5, 6, 7, and 8 directly affected pavement deterioration. Therefore, for sections where these vehicle types are prevalent, various traffic management strategies, including direct maintenance (e.g., partial depth repair, overlay, etc.) and alternative route planning considering the specific vehicle types, can be considered effective alternatives to ensure appropriate road performance.

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Nomenclature

a_k	coefficient of the regression line for two parameters *CPCI* and *t* (regression model slope)
b_k	coefficient of the regression line for two parameters *CPCI* and *t* (initial *CPCI* when *t* is zero)
CPCI	concrete pavement condition index
$CPCI_k$	measurement function of *CPCI*
$CPCI_k^{measured}$	measured *CPCI*
$CPCI_{predicted}$	random variable of the predicted *CPCI*
$CPCI_{detected}$	random variable of the detected *CPCI*
$\varepsilon_{R.E}$	the rate of relative error between the predicted data and the actual data
w_{ak}	zero-mean Gaussian white noise sequences about a_k
w_{bk}	zero-mean Gaussian white noise sequences about b_k
σ^2_{CPCI}	variance for zero-mean Gaussian measurement function $CPCI_k^{measured}$
y_k	measurement function
SD	surface distress
IRI	international roughness index
K	time index
N	number of particles
q	relative likelihood
r	random number
t	time

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