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Machine Learning Based Asset Risk Management for Highway Sign Support Systems

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Abstract: Road sign support systems are not usually well managed because bridges and pavement have budget and maintenance priority while the sign boards and sign supports are considered as miscellaneous items. The authors of this paper suggested the implementation of simplified machine learning algorithms for asset risk management in highway sign support systems. By harnessing historical and real-time data, machine learning models can forecast potential vulnerabilities, enabling early intervention and proactive maintenance protocols. The raw data were collected from the Connecticut Department of Transportation (CTDOT) asset management database that includes asset ages, repair history, installation and repair costs, and other administrative information. While there are many advanced and complicated structural deterioration prediction models, a simple deterioration curve is assumed, and prediction model has been developed using machine learning algorithm to determine the risk assessment and prediction. The integration of simplified machine learning in asset risk management for highway sign support systems not only enables predictive maintenance but also optimizes resource allocation. This approach ensures that decision-makers are not inundated with excessive detailed information, making it particularly practical for industry application.

Key words: Sign support; asset management; Deterioration modeling; Preventive maintenance; Machine Learning; AI

1. INTRODUCTION

Sign support systems (Figure 1) are essential structures in the Connecticut Department of Transportation (CT DOT) bridge management system, and they are often neglected until they are in critical condition and fail. Periodic inspections and maintenance activities are needed as a long-term, cost-effective preventive maintenance strategy. Sign support systems are included in the Bridge Management System (BMS). The data collected from the BMS were analyzed using predictive deterioration curves with educated estimates from the literature review. This research developed the asset maintenance strategy using the deterioration prediction model and risk management for sign support systems.

Figure 1. Sign support 21311 on I-84, Hartford, Connecticut

2. METHODOLOGIES

In the methodology, authors implemented the Weibull function for modeling deterioration processes, capitalizing on its robustness in predicting the aging and wear of components. Concurrently, machine learning techniques were employed to conduct risk analysis and determine maintenance priorities. This dual approach allows for a comprehensive understanding of system health and optimal allocation of maintenance resources.

Weibull Function for Deterioration Prediction Model

Usually, when machines or structures are newly built, during the operation's initial status, there is a high chance of failure or breakdown due to defective parts and installation. Once the initial status is settled, it goes into a stable service period until it reaches the end of its service life (Figure 2).

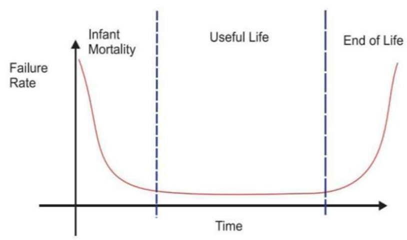

Figure 2. Bathtub curve for infrastructure failure rate

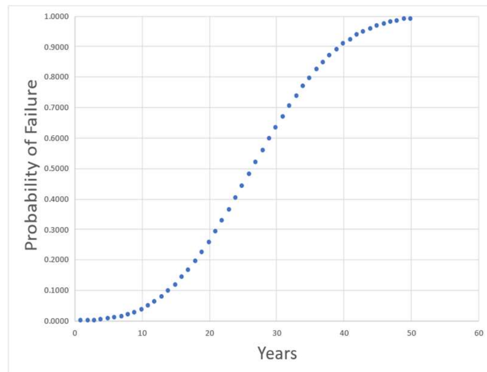

Figure 3. Weibull function when MTTF β = 30 and shape factor γ = 3

Table 1. Average daily traffic adjustment

Average Daily Traffic (ADT)	Adjustment Value	No. of Lanes under Structure	Adjustment Value
0–10,000	35	1	35
10,001–25,000	27	2	33
25,001–45,000	25	3	31
45,001–75,000	23	4	30
75,001–100,000	21	5	28
100,001–140,000	18	6	26
140,000 +	16	7	24
		8	22
		10	20
		12	18

The Weibull distribution is perhaps the most widely used of all the failure time distributions (Zhang, 2021), and it is noted for its flexibility as a failure prediction model. Reliability deals with reducing the frequency of failures over a time interval and is a measure of the probability of failure-free operation during a given interval, i.e., it is a measure of success for a failure-free operation. Reliability is quantified as *MTBF* (Mean Time Between Failures) for repairable products and *MTTF* (Mean Time to Failure) for the non-repairable product. In reliability theory, the Weibull function is widely used for its simplicity without losing too much accuracy. Figure 3 shows the typical failure rate over time by the Weibull function, where x is usage time and β and γ are the graph shape parameters. The shape parameters, γ and β, are assumed in this case to be 3 and 30, respectively, where β is the scale parameter that directly relates to the spread of the distribution curve. In reliability theory, β is either *MTBF* or *MTTF*. The cumulative distribution curve plots the cumulative probability of occurrence over time for a specific action. In this case, it plots the probability of failure over time.

$$f(x) = 1 — e^{-(\frac{x}{\beta})^{\gamma}} \qquad (1)$$

Development of Deterioration Prediction Model

MTTF (Mean-time-to-Failure) is calculated as an average of different adjustment factors relevant to each sign. The adjustment factors are as follows: (1) average daily traffic, (2) lanes under the structure, (3) material type, and (4) structure type. These four factors are chosen as they most accurately represent the structures' average wear and tear from reviewing existing sign support literature. The factors of the sign support system failures were previously studied by Kipp et al. (1987), Barle et al. (2011), and Shboul et al. (2021).

All the factors below contain a variable that begins with an "s". These variables represent the years a structure would take to fail when no other influence is considered. For example, an adjustment value of 36 for a support constructed of A-36 steel is because the structure is made of A-36 steel where it is defined by ASTM (2018). The shape, location, and average daily traffic are not considered when assigning these scores, as they are all brought back together when averaging out.

This methodology of estimating *MTTF* would be to average these scores and then find the average number of years for a structural failure. Each structure is unique; therefore, coming up with an *MTTF* for each individual would take an incalculable amount of time and is beyond the scope of this paper. By assigning scores based on each factor's relative durability, we can assign a normalized *MTTF* score to each structure based on an average. These scores are assigned based on prior research, and each factor is present in at least one of each in any given sign support.

Material types of yield strength (*sMAT*) accurately represent how a sign support structure's material type plays into the general deterioration of the support over time. According to the ASTM 2018 standards reference documents, assuming all else are constant, the different materials and their yield strengths are shown in Table 1.

The formula to calculate the *MTTF* for any given structure is as follows:

$$MTTF = (sADT + sMAT + sTYP + sLNE)/4 \tag{1}$$

The *MTTF* score can be inserted into a probability distribution function to model the probability of failure. The Weibull function (Equation 1) used to model this is as follows:

$$p(f) = 1 - e^{\left(-\left(\frac{Age\ of\ Structure}{MTTF}\right)^{\gamma}\right)} \tag{2}$$

where γ is the shape factor of the Weibull function. A shape factor of 3 is used to calculate *p(f)* because this shape factor relates to the failure rate behavior (increasing over time). This is known as a "wear-out failure", or a failure rate that increases over time. This is shown in Figure 3.

The reliability factor *(r(f))* can be found simultaneously alongside the *p(f)*. The *r(f)* is a measurement to identify the measure of failures over a time interval. It measures the probability of failure-free operation during a given interval. *r(f)* is calculated using the following equation:

$$r(f) = e^{\left(-\left(\frac{Age\ of\ Structure}{MTTF}\right)^{\gamma}\right)} \tag{3}$$

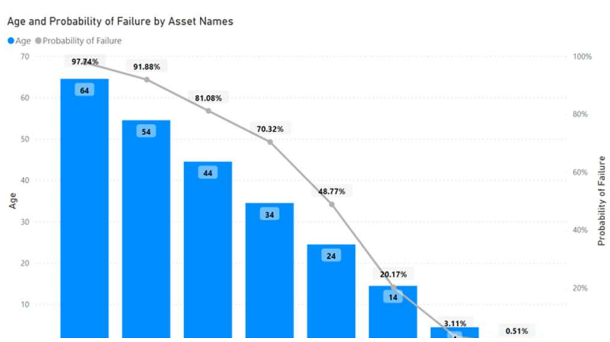

Figure 4 Age and probability of failure by assets

The result is shown in Figure 4. The graph shows the assets, ages, and probability of failure. It shows only a few assets out of thousands in the database. Note that the numbers on the x-axis are the asset names. For example, the name of the first asset is "21231B", the second one is "20574", etc. As expected, and by the Weibull function's definition, age and probability of failure have a strong direct relationship.

Because the Mean-time-to-failure (MTTF) is defined by four variables such as (1) average daily traffic, (2) lanes under the structure, (3) material type, and (4) structure type, each sign support system has different MTTFs; however, the age of the structure is the main factor in estimating the probability of failure.

Maintenance Prioritization

As risk is typically portrayed on a dollar basis, converting the impacted commuters to a dollar value requires using the same census data. An impact cost per commuter can be calculated using the average individual income and the average commuters above. The assumption is that commuters to the city contribute to the average income of that city.

$$iCMT\$ = \frac{iCMT}{Per\ Capita\ Income} \tag{5}$$

Table 2 specifies the commuter impact can be found below, along with the intermediate steps required to calculate the values. Finally, a risk factor can be calculated by multiplying the impact in dollars by the probability of failure.

$$Risk = iCMT\$ * p(f) \tag{6}$$

Table 2. Component repair cost breakdown (showing only selected data)

Asset Name	Sign and Illumination	Structure Overall	Foundation Overall	Traffic Safety	Structure Overall	Member Alignment	Anchor Bolt	Attachments	Base Plates	Bolts & Fasteners	Bulbs/Electrical	Coating	Collision Damage	Concrete
21311	$ 12,934.68	$15,521.68	$12,934.68	$ 12,934.68	$12,934.68	$7,760.68	$ 5,173.68	$ 5,173.68	$ 5,173.68	$5,173.68	$ 7,760.68	$6,467.18	$7,760.68	$7,760.68
21671	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
20292	$ 2,249.82	$ 2,699.82	$ 2,249.82	$ 2,249.82	$ 2,249.82	$1,349.82	$ 899.82	$ 899.82	$ 899.82	$ 899.82	$ 1,349.82	$1,124.82	$1,349.82	$1,349.82
20519	$ 12,934.96	$15,521.96	$12,934.96	$ 12,934.96	$12,934.96	$7,760.96	$ 5,173.96	$ 5,173.96	$ 5,173.96	$5,173.96	$ 7,760.96	$6,467.46	$7,760.96	$7,760.96
20516	$ 12,934.96	$15,521.96	$12,934.96	$ 12,934.96	$12,934.96	$7,760.96	$ 5,173.96	$ 5,173.96	$ 5,173.96	$5,173.96	$ 7,760.96	$6,467.46	$7,760.96	$7,760.96
21595	$ 12,934.78	$15,521.78	$12,934.78	$ 12,934.78	$12,934.78	$7,760.78	$ 5,173.78	$ 5,173.78	$ 5,173.78	$5,173.78	$ 7,760.78	$6,467.28	$7,760.78	$7,760.78
20017A	$ 2,249.75	$ 2,699.75	$ 2,249.75	$ 2,249.75	$ 2,249.75	$1,349.75	$ 899.75	$ 899.75	$ 899.75	$ 899.75	$ 1,349.75	$1,124.75	$1,349.75	$1,349.75
20317	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
20290	$ 7,508.90	$ 9,010.72	$ 7,508.90	$ 7,508.90	$ 7,508.90	$4,505.27	$ 3,003.45	$ 3,003.45	$ 3,003.45	$3,003.45	$ 4,505.27	$3,754.36	$4,505.27	$4,505.27
20611	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
21593	$ 12,934.75	$15,521.75	$12,934.75	$ 12,934.75	$12,934.75	$7,760.75	$ 5,173.75	$ 5,173.75	$ 5,173.75	$5,173.75	$ 7,760.75	$6,467.25	$7,760.75	$7,760.75
20435A	$ 2,249.90	$ 2,699.90	$ 2,249.90	$ 2,249.90	$ 2,249.90	$1,349.90	$ 899.90	$ 899.90	$ 899.90	$ 899.90	$ 1,349.90	$1,124.90	$1,349.90	$1,349.90
20615B	$ 2,249.88	$ 2,699.88	$ 2,249.88	$ 2,249.88	$ 2,249.88	$1,349.88	$ 899.88	$ 899.88	$ 899.88	$ 899.88	$ 1,349.88	$1,124.88	$1,349.88	$1,349.88
20022	$ 7,508.81	$ 9,010.63	$ 7,508.81	$ 7,508.81	$ 7,508.81	$4,505.17	$ 3,003.36	$ 3,003.36	$ 3,003.36	$3,003.36	$ 4,505.17	$3,754.26	$4,505.17	$4,505.17
20413	$ 2,249.98	$ 2,699.98	$ 2,249.98	$ 2,249.98	$ 2,249.98	$1,349.98	$ 899.98	$ 899.98	$ 899.98	$ 899.98	$ 1,349.98	$1,124.98	$1,349.98	$1,349.98
21589	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
20515	$ 12,934.94	$15,521.94	$12,934.94	$ 12,934.94	$12,934.94	$7,760.94	$ 5,173.94	$ 5,173.94	$ 5,173.94	$5,173.94	$ 7,760.94	$6,467.44	$7,760.94	$7,760.94
20419	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
20573	$ 12,934.97	$15,521.97	$12,934.97	$ 12,934.97	$12,934.97	$7,760.97	$ 5,173.97	$ 5,173.97	$ 5,173.97	$5,173.97	$ 7,760.97	$6,467.47	$7,760.97	$7,760.97
20435B	$ 2,249.84	$ 2,699.84	$ 2,249.84	$ 2,249.84	$ 2,249.84	$1,349.84	$ 899.84	$ 899.84	$ 899.84	$ 899.84	$ 1,349.84	$1,124.84	$1,349.84	$1,349.84
20320	$ 7,508.77	$ 9,010.59	$ 7,508.77	$ 7,508.77	$ 7,508.77	$4,505.13	$ 3,003.32	$ 3,003.32	$ 3,003.32	$3,003.32	$ 4,505.13	$3,754.23	$4,505.13	$4,505.13
20615A	$ 2,249.97	$ 2,699.97	$ 2,249.97	$ 2,249.97	$ 2,249.97	$1,349.97	$ 899.97	$ 899.97	$ 899.97	$ 899.97	$ 1,349.97	$1,124.97	$1,349.97	$1,349.97
20574	$ 12,934.95	$15,521.95	$12,934.95	$ 12,934.95	$12,934.95	$7,760.95	$ 5,173.95	$ 5,173.95	$ 5,173.95	$5,173.95	$ 7,760.95	$6,467.45	$7,760.95	$7,760.95
20515	$ 12,934.90	$15,521.90	$12,934.90	$ 12,934.90	$12,934.90	$7,760.90	$ 5,173.90	$ 5,173.90	$ 5,173.90	$5,173.90	$ 7,760.90	$6,467.40	$7,760.90	$7,760.90
20416	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
21310	$ 12,934.64	$15,521.64	$12,934.64	$ 12,934.64	$12,934.64	$7,760.64	$ 5,173.64	$ 5,173.64	$ 5,173.64	$5,173.64	$ 7,760.64	$6,467.14	$7,760.64	$7,760.64
20012	$ 2,249.89	$ 2,699.89	$ 2,249.89	$ 2,249.89	$ 2,249.89	$1,349.89	$ 899.89	$ 899.89	$ 899.89	$ 899.89	$ 1,349.89	$1,124.89	$1,349.89	$1,349.89
20417	$ 12,934.80	$15,521.80	$12,934.80	$ 12,934.80	$12,934.80	$7,760.80	$ 5,173.80	$ 5,173.80	$ 5,173.80	$5,173.80	$ 7,760.80	$6,467.30	$7,760.80	$7,760.80
20013	$ 7,509.00	$ 9,010.81	$ 7,509.00	$ 7,509.00	$ 7,509.00	$4,505.36	$ 3,003.54	$ 3,003.54	$ 3,003.54	$3,003.54	$ 4,505.36	$3,754.45	$4,505.36	$4,505.36
20613	$ 12,934.73	$15,521.73	$12,934.73	$ 12,934.73	$12,934.73	$7,760.73	$ 5,173.73	$ 5,173.73	$ 5,173.73	$5,173.73	$ 7,760.73	$6,467.23	$7,760.73	$7,760.73
20517	$ 12,934.94	$15,521.94	$12,934.94	$ 12,934.94	$12,934.94	$7,760.94	$ 5,173.94	$ 5,173.94	$ 5,173.94	$5,173.94	$ 7,760.94	$6,467.44	$7,760.94	$7,760.94
20770	$ 12,934.83	$15,521.83	$12,934.83	$ 12,934.83	$12,934.83	$7,760.83	$ 5,173.83	$ 5,173.83	$ 5,173.83	$5,173.83	$ 7,760.83	$6,467.33	$7,760.83	$7,760.83
21600E	$ 2,249.59	$ 2,699.59	$ 2,249.59	$ 2,249.59	$ 2,249.59	$1,349.59	$ 899.59	$ 899.59	$ 899.59	$ 899.59	$ 1,349.59	$1,124.59	$1,349.59	$1,349.59
20576	$ 12,934.96	$15,521.96	$12,934.96	$ 12,934.96	$12,934.96	$7,760.96	$ 5,173.96	$ 5,173.96	$ 5,173.96	$5,173.96	$ 7,760.96	$6,467.46	$7,760.96	$7,760.96
20268	$ 12,934.83	$15,521.83	$12,934.83	$ 12,934.83	$12,934.83	$7,760.83	$ 5,173.83	$ 5,173.83	$ 5,173.83	$5,173.83	$ 7,760.83	$6,467.33	$7,760.83	$7,760.83
20384	$ 7,508.71	$ 9,010.52	$ 7,508.71	$ 7,508.71	$ 7,508.71	$4,505.07	$ 3,003.25	$ 3,003.25	$ 3,003.25	$3,003.25	$ 4,505.07	$3,754.16	$4,505.07	$4,505.07
21613E	$ 2,249.62	$ 2,699.62	$ 2,249.62	$ 2,249.62	$ 2,249.62	$1,349.62	$ 899.62	$ 899.62	$ 899.62	$ 899.62	$ 1,349.62	$1,124.62	$1,349.62	$1,349.62
21309	$ 12,934.58	$15,521.58	$12,934.58	$ 12,934.58	$12,934.58	$7,760.58	$ 5,173.58	$ 5,173.58	$ 5,173.58	$5,173.58	$ 7,760.58	$6,467.08	$7,760.58	$7,760.58
20298	$ 7,508.90	$ 9,010.72	$ 7,508.90	$ 7,508.90	$ 7,508.90	$4,505.26	$ 3,003.44	$ 3,003.44	$ 3,003.44	$3,003.44	$ 4,505.26	$3,754.35	$4,505.26	$4,505.26
20510	$ 7,508.76	$ 9,010.58	$ 7,508.76	$ 7,508.76	$ 7,508.76	$4,505.12	$ 3,003.30	$ 3,003.30	$ 3,003.30	$3,003.30	$ 4,505.12	$3,754.21	$4,505.12	$4,505.12
20421A	$ 2,249.86	$ 2,699.86	$ 2,249.86	$ 2,249.86	$ 2,249.86	$1,349.86	$ 899.86	$ 899.86	$ 899.86	$ 899.86	$ 1,349.86	$1,124.86	$1,349.86	$1,349.86
20415	$ 12,934.78	$15,521.78	$12,934.78	$ 12,934.78	$12,934.78	$7,760.78	$ 5,173.78	$ 5,173.78	$ 5,173.78	$5,173.78	$ 7,760.78	$6,467.28	$7,760.78	$7,760.78
20017B	$ 2,249.54	$ 2,699.54	$ 2,249.54	$ 2,249.54	$ 2,249.54	$1,349.54	$ 899.54	$ 899.54	$ 899.54	$ 899.54	$ 1,349.54	$1,124.54	$1,349.54	$1,349.54

The chart below shows a 3D representation of the impact on commuters in dollars. There is a normalized distribution trending towards an increase in the commuter impact in dollars as the age of the structure rises—the risk increases as the structures age and p(f) trends toward the limit of 1. The increase in risk is shown by the color of the cubes going from green to red. This chart shows that each factor affecting the outcome (commuter impact) is relative to the support factors and not a linear curve. When utilizing charts and maintenance schedules, it is vital to look at the entire picture.

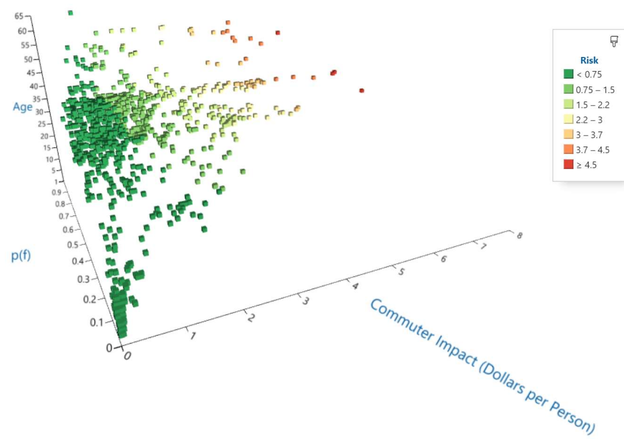

Figure 5. Scatter plot of commuter impact (Dollars per person) by p(f) by Age, and colored by the risk

Neural Network Training and Prediction Model

There have been numerous studies on predicting the condition of civil infrastructure using neural networks (Hassan et al. (2022), Hallaji et al. (2022), Mohamed et al. (2021), and Ni et al. (2012)). While academically, this approach is not particularly novel, the significance of this research lies in its ability to create a simple failure prediction model solely based on the data available in the sign support system's database.

This process consists of (1) Preparation of the data, (2) Creation of the neural network, (3) Configuration of the neural network, (4) Training of the neural network, and (5) Evaluation of the neural network.

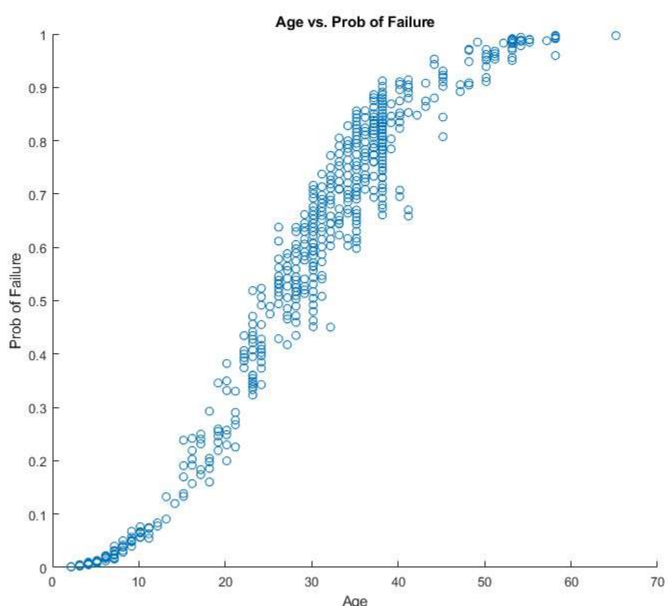

Figure 6. Asset Age and Probability of Failure

(1) Preparation of the data: Numerical values such as the age of the asset and daily traffic must first be normalized. Since the material type is not a numerical value, it was converted into binary to differentiate between types. The output of the data is defined as the probability of failure.

(2) Creation of the neural network: The authors of this paper coded the neural network using Matlab and trained it using the Levenberg-Marquardt algorithm.

(3) Configuration of the neural network: The training was performed over 1000 epochs, with two-thirds of the total data used for training and one-third for verification.

(4) Training of the neural network and (5) Evaluation of the neural network: After training, the neural network was used to perform scatter plotting, as shown in Figure 6. The graph only shows the relationship between the asset age and the probability of failure. While the two variables appear

to be generally related, the presence of other variables means that not only one output is derived as a result.

In conclusion, by inputting variables used in this study (Age, Material, Structure Type, Number of Lanes, and Daily Traffic), it is possible to derive the probability of failure directly using the neural network, which can then be combined with commuter impact to derive a risk value, thereby creating a priority for maintenance.

3. SUMMARY AND CONCLUSION

This study conducted research on the selection of maintenance priorities for the sign support system, a very common but often ignored aspect in terms of its importance. A model was developed to predict the probability of failure, taking into account factors such as the material and structural type of the sign support system, daily traffic, and asset age. The relationship between age and useful life was assumed using the Weibull function, and additional variables such as daily traffic were used to adjust the mean-time-to-failure (MTTF). Furthermore, an artificial neural network was trained to correlate the probability of failure with variables, enabling the development of a system that can predict the probability of failure simply based on asset information stored in a database.

Significant effort was not devoted to developing a deterioration prediction model in this research. While many studies related to asset management focus on the development of deterioration models, such efforts can sometimes be excessive compared to the importance of the facility and the impact of failure. In the case of sign support systems, the impact of failure on commuters is substantial, but the direct costs are not significant, and the direct harm to human life is presumed to be minimal. Therefore, this study focused on developing a simple predictive model using straightforward formulas and AI, and determining maintenance priorities through risk assessment, rather than relying on complex calculations required by precise deterioration prediction modeling.

The significance of this research lies in the fact that the probability of failure produced by the predictive model was calculated considering commuter impact to assess asset risk. This derived asset risk was then utilized as a criterion for determining maintenance priorities, thereby enabling the achievement of effective strategic asset management.

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