# Integrating BMS Economic Evaluation with Random Forest Algorithm for Bridge Maintenance Intelligent Prioritization

**Ismail Wahyudi, Akhmad Aminullah, Suprapto Siswosukarto**

Department of Civil and Environmental Engineering, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, INDONESIA

E-mail: akhmadaminullah@ugm.ac.id

**| Submitted: May 11, 2026 | Revised: June 01, 2026 | Accepted: August 29, 2026 |**

**| Published: October 26, 2026 |**

## ABSTRACT

Bridges have a long design life, but over time, their function and quality decline due to material degradation and other factors. Therefore, a bridge management system (BMS) is crucial for making appropriate maintenance decisions. This study developed a model to determine bridge maintenance priorities on the Solo-Ngawi Toll Road, which includes 70 bridges by integrating an economic feasibility evaluation (BMS) method with machine learning using the Random Forest algorithm. The bridge condition was conducted in accordance with the 2022 Bridge Inspection Guidelines, while the economic evaluation was based on the 1993 IBMS guidelines, using Net Present Value per square meter (NPV/m²) and Internal Rate of Return (IRR) indicators. The results of the economic evaluation in the form of bridge maintenance priority rankings, were used as the primary target variables for the machine learning model, enabling Random Forest to predict the order of economic priority for maintenance directly. Input variables include 13 bridge element Condition Scores summarized through the Weighted Condition Score (WCS), as well as five economic variables such as remaining service life, floor area, AADT, diversion distance, and maintenance costs. The Random Forest model produces an $R^2$ on the test data of 0.8744. Comparison of ranking results between the BMS and Random Forest methods shows good consistency in high-priority bridges and the Random Forest model is able to identify bridges with critical structural conditions that are less accommodated by the conventional BMS method, resulting in more holistic treatment recommendations.

**Keywords:** BMS, random forest, condition score, economic evaluation, priority ranking.

## INTRODUCTION

Toll roads are a crucial infrastructure used to connect regions in the distribution of goods and services. The existence of toll roads can stimulate economic growth in the regions they traverse, thereby reducing disparities between regions. Given the significant impact, the Indonesian government has undertaken various toll road projects. One such project is the Trans Java Toll Road megaproject which stretches over 1,000 km and crosses five provinces on the island of Java those are Banten, DKI Jakarta, West Java, Central Java, and East Java.[1]. The diverse geographical conditions of the various regions traversed by the Trans Java Toll Road ranging from lowlands to hills, necessitate the construction of bridges to connect roads that traverse obstacles such as rivers or extreme elevation differences. Furthermore, bridges on toll roads also serve as vehicle infrastructure to cross other road sections without disrupting traffic through interchanges. According to the Ministry of Public Works and Public Housing [2], bridges have a design life of 75 years, except for temporary bridges, which are planned for a life of 20 years, and bridges with strategic functions, which have a design life of 100 years. However, as time passes during its service life, the bridge experiences a decline in function due to a decline in the quality of the materials used to make it or other factors.

Given the crucial role of bridges in maintaining smooth mobility, inspection and maintenance are necessary to determine and maintain bridge performance to ensure it remains in service within its intended lifespan. Therefore, the government through the Directorate General of Highways, created a Bridge Management System (BMS) that was first developed in 1993 and updated in 2022 as outlined in Bridge Inspection Guidelines No. 01/P/BM/2022. The BMS is used for decision-making in prioritizing bridge maintenance. Decisions are based on field surveys categorized by bridge

pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
DOI: http://dx.doi.org/10.32832/astonjadro.v15i4.23672 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

condition scores (CS) ranging from 0 to 5. The lower of CS, the better of bridge's performance and the higher the CS, the worse the bridge's performance. In determining priority decisions for maintenance, the bridge's economic value is also assessed based on its Net Present Value (NPV) and Internal Rate of Return (IRR). NPV is the present value of profits minus the present value of the total maintenance costs required for a bridge. IRR, on the other hand represents the cost savings/benefits obtained from bridge maintenance. Bridges are recommended for repair if they have a positive NPV and an IRR greater than or equal to the interest rate in the year of repair. Bridges can still be repaired if they have a negative NPV, but the costs will be greater than the benefits received when the bridge is completed [3].

Economic evaluation in BMS is considered less representative if it relies solely on NPV and IRR to determine bridge maintenance priorities because various other aspects need to be considered, such as vehicle growth, maintenance costs, and others [4]. Furthermore, the Indonesian BMS has shortcomings in determining the priority order of element conditions due to the absence of bridge element priority weights [5]. These various shortcomings can certainly hinder or even lead to errors in the decision-making process for bridge maintenance priorities. Consequently, the allocation of limited resources and budgets becomes suboptimal because urgent bridge maintenance can be delayed. This has the potential to increase long-term maintenance costs and reduce the performance and reliability of bridge functions. Therefore, this study presents the use of the Random Forest algorithm to improve the accuracy of bridge maintenance prioritization. The Random Forest algorithm is an ensemble learning method that develops multiple decision trees trained on random samples with replacement to capture underlying patterns in the data, providing a final prediction through majority voting [6]. Previous studies have shown that this method produces highly accurate predictions for assessing bridge deck conditions and monitoring structural damage[7], [8], [9]. Furthermore, other studies have highlighted that Random Forest maintains high prediction accuracy due to its advantage in handling complex and non-linear relationships among many bridge condition variables without requiring strict data distribution assumptions [6], [10]. In addition to its robustness to overfitting and data noise, the algorithm provides transparent feature importance metrics which enable decision-makers to objectively identify the most critical bridge elements and allocate maintenance budgets more effectively [11].

## RESEARCH METHODS

### Location and Data

The research location is on the Solo-Ngawi Toll Road. This toll road was inaugurated in 2018 as part of the Trans Java Toll Road network. The Solo-Ngawi Toll Road crosses several areas, namely Boyolali Regency, Surakarta City, Karanganyar Regency, Sragen Regency, and Ngawi Regency. The research was conducted on 70 bridges consisting of river bridges, overpasses, and interchanges. The locations of the studied bridges can be seen in **Figure 1**.

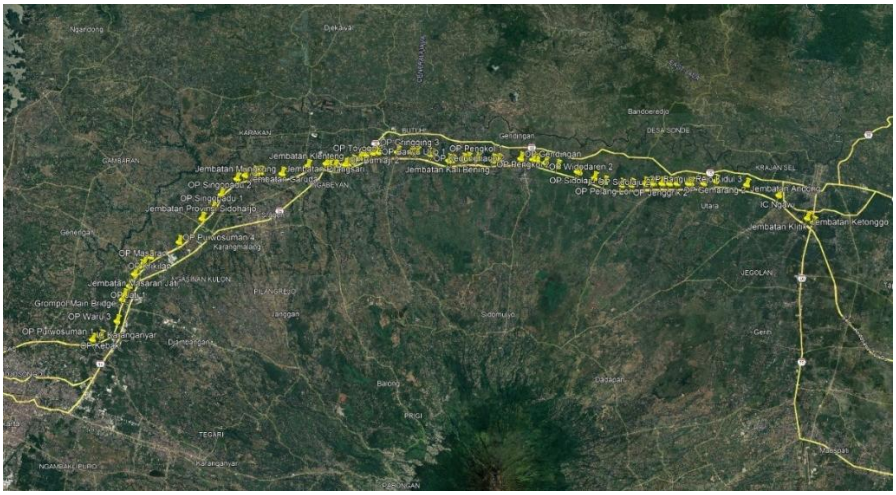



**Figure 1**. Research Location

The data used in this study are entirely secondary. The secondary data consists of bridge inventory data, detailed bridge inspection results, bridge damage documentation, annual average daily traffic (AADT) data, and as-built drawings obtained from the Solo-Ngawi Toll Road operator, PT Jasamarga Solo Ngawi.

**Research Procedures**

All stages carried out in this research can be seen in **Figure 2**.

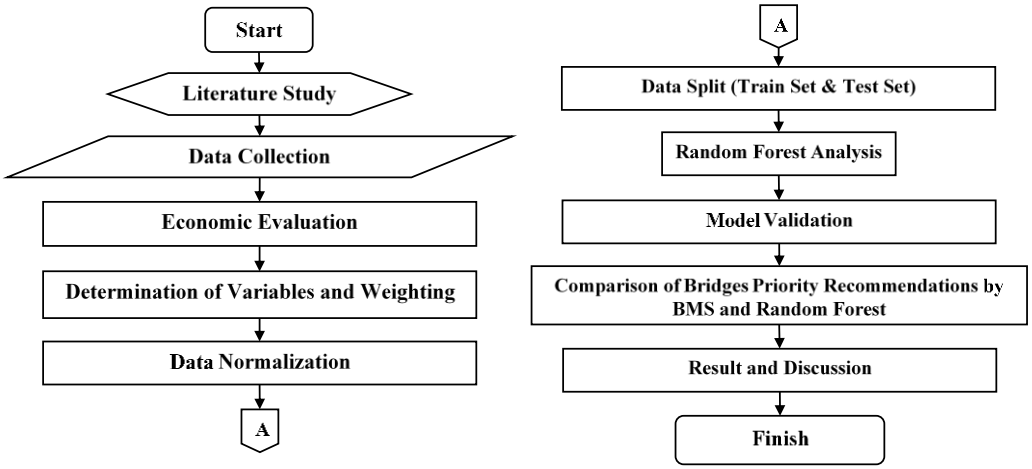



**Figure 2**. Research Flowchart

An explanation of the research flow chart above is as follows.

a. This research begins by establishing objectives, problem formulation, and the scope of the research to be studied so that the direction of the research is clear and structured from the start.
b. The literature study was carried out by reviewing various scientific sources such as journals, reference books, and official guidelines relating to the Bridge Management System (BMS), the IBMS 1993 economic evaluation method, as well as the machine learning algorithm namely Random Forest as the theoretical basis for the research.
c. Research data collection is carried out by collecting bridge data from related agencies which includes important parameters such as data on bridge inspection results, annual average daily traffic (AADT), as-built drawings, and data on vehicle operational costs required.
d. The economic evaluation analysis was carried out using the IBMS 1993 method by considering various aspects of handling costs and the economic benefits obtained, to provide an overview of the economic feasibility in determining bridge handling priorities. This analysis produces a priority ranking for bridge handling based on Net Present Value (NPV) and Internal Rate of Return (IRR).
e. Determining variables and weighting is done by identifying variables that influence bridge handling priorities, then giving weight to each variable according to its level of importance.
f. Data normalization is carried out to equalize the scale between variables that have different units, so that the analysis process can run objectively and avoid the dominance of certain variables in the final results.
g. The data is divided into 80% training data and 20% test data to ensure that the model built can be trained well and its accuracy level is tested.
h. Modeling using the Random Forest algorithm is carried out by applying a regression approach to predict priority score values for bridge handling.
i. Model evaluation is carried out using appropriate performance metrics such as $R^2$, RMSE, and MAE to assess the extent to which the model can produce correct predictions.
j. A comparison of the results was carried out between the BMS and Random Forest methods to analyze the differences in the results of priority recommendations for handling bridges and to see the level of consistency and superiority of each method.
k. Results and discussion are presented by interpreting the analysis results obtained, including reviewing the advantages and disadvantages of each method and their implications for decision-making in bridge management.

pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
DOI: http://dx.doi.org/10.32832/astonjadro.v15i4.23672 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

l. The research ends with a conclusion that summarizes all the research findings and provides recommendations that can be used as consideration in determining priorities for handling bridges in the future.

## Methods

### Bridge Condition Assessment and Economic Evaluation

The BMS method condition assessment refers to the 2022 Bridge Inspection Guidelines. The assessment is based on the results of a visual inspection of the damage that occurred on each bridge element. 5 assessment levels represent the level of detail of the elements being assessed by taking into account the criteria of Structure (S), Damage (R), Quantity (K), Function (F), and Influence (P). The results of condition assessment using the BMS method produce CS with a range of 0 to 5 which defines the level of damage that occurs on a bridge.

Economic evaluation of bridges has the main objective of calculating the cost-effectiveness of treatment and ranking the priority order of bridge treatment. The ranking index is based on Net Present Value (NPV) and Internal Rate of Return (IRR). NPV states the present value of profits minus the present value of total handling costs. Meanwhile, IRR is a value that states the cost savings/benefits obtained in handling a bridge. Bridges will be ranked based on the results of the economic evaluation with NPV/m for replacement and IRR for rehabilitation. Bridges with high economic benefits will receive a higher treatment priority and bridges with low economic benefits will receive a lower treatment priority [3], [12].

Before calculating NPV and IRR, it needed to pay attention to several parameters such as Discount Rate (DR) and Present Value (PV). DR is the economic opportunity cost of capital or the best rate of return that will be received from using funds for certain activities. DR is also considered to be the same as the interest rate for deposits which has been reduced by the inflation rate. The discount rate varies based on time and is determined by the Central Bank, namely Bank Indonesia. The discount rate for 2026 is 4.75%. Meanwhile, PV states the current value of a future value based on a certain discount rate. Equation (1) is used to determine the magnitude of PV [3].

$$\text{Present Value (PV)} = \frac{\text{Future Value (FV)}}{(1+r)^n} \quad (1)$$

With,
FV : Value in year n
n : Number of years counted from now
r : Deduction rate per year

Meanwhile, equations (2) and (3) can be used to calculate the NPV and IRR for the bridge being evaluated [3].

$$NPV = PV(b) - PV(c) \quad (2)$$

Where:
NPV : Net Present Value
PV (b) : Present value gain
PV (c) : Present value cost

$$IRR = \left(\left(\frac{\text{Future Value (FV)}^{\frac{1}{n}}}{\text{PV (c)}}\right) - 1\right) \quad (3)$$

Where:
FV : Value in year n
PV (c) : Present value cost
n : Number of years counted from now

### Random Forest

Random Forest is an ensemble learning method used in predictive analysis because of its ability to combine many simple models (decision trees) into one more powerful model. In general, Random Forest works by building several decision trees using bootstrap sampling data, then combining the prediction results from all trees through an average process. This approach has been proven to be able to increase accuracy while reducing overfitting and is effective in capturing nonlinear and complex relationships between variables. Apart from that, Random Forest is also relatively robust against noise and does not require certain data distribution assumptions, so it is widely used in various research fields [13].

In this research, data were collected from 70 bridges consisting of two main groups of variables, namely physical condition and economic variables. Physical condition is represented through the condition score (CS) of each structural element at level 3 on a scale of 0–5 according to applicable guidelines, while economic variables include remaining life, AADT, diversion distance, maintenance costs, and floor area. All of this data is the basis for the analysis of determining bridge handling priorities using Random Forest. The condition score of each element is then summarized into one composite indicator using a weighted condition score (WCS). Each element is given a weight according to its level of importance which refers to the Bridge Inventory Manual by NYSDOT and related study, resulting in a WCS value in the range of 1 to 5. A value close to 5 indicates the condition of the bridge is increasingly critical, while a value close to 1 indicates the condition is still good.

Economic variables are then normalized using the Min-Max method so that all variables are on the same scale, namely 0 to 1. This process aims to avoid domination of certain variables due to differences in units or value ranges, so that each variable can contribute proportionally to the analysis. The dataset is then divided into 80% training data and 20% testing data using the stratified split method. This division maintains the proportion of each category in both data subsets, so that the model can be trained and tested more representatively.

The Random Forest model is used to predict priority ranking values in continuous form. This model builds many decision trees using the CART algorithm with MSE reduction criteria, equipped with bootstrap bagging techniques to increase the variation of the training data. The final prediction results are obtained from the average of all trees, thereby increasing accuracy and reducing overfitting. Model performance was evaluated using $R^2$, MAE, RMSE metrics, and a feature importance analysis was carried out to determine the influence of each variable.

## RESULT AND DISCUSSION

### Bridge Condition Score

The condition score (CS) of the bridges shows that there are 2 bridges with CS 1 and 64 with CS 2, indicating that, in general, the bridges are still functioning but require routine maintenance and periodic monitoring to prevent further deterioration in condition. Apart from that, 4 bridges with CS 3 require more serious attention and handling due to damage that can affect performance and safety. This results in a condition score at level 1 shown in **Figure 3**.

pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
DOI: http://dx.doi.org/10.32832/astonjadro.v15i4.23672 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

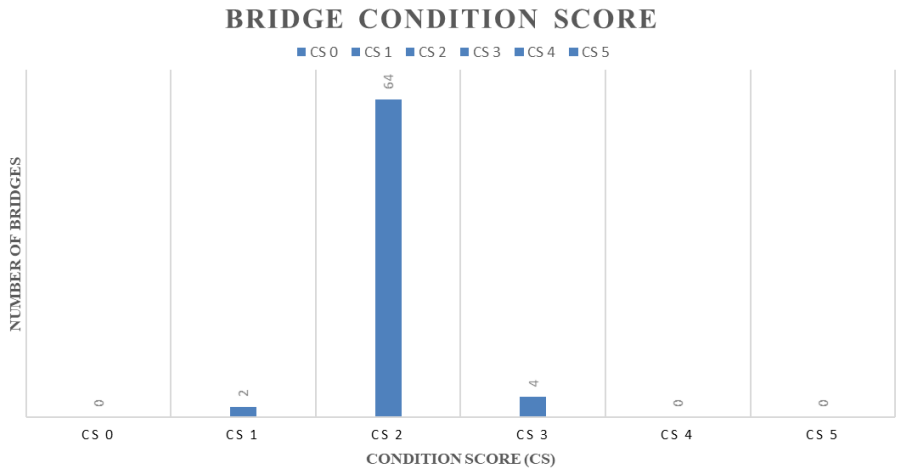



**Figure 3.** Bridge Condition Score

**Economic Evaluation of Bridges**

Economic evaluation is carried out as an instrument to determine the priority order for handling bridges in a measurable manner, so that the available budget allocation can be utilized effectively and efficiently. The economic feasibility assessment in this research refers to the 1993 IBMS guidelines using two main indicators, namely Net Present Value (NPV) per unit area and Internal Rate of Return (IRR). Bridges that have higher NPV/m² and IRR values are prioritized earlier because they reflect greater potential economic benefits relative to the costs incurred.

The basic parameters used in the economic evaluation in this research are as follows:

- Vehicle speed for VOC calculations is determined based on Law no. 22 of 2009, namely a minimum of 60 km/hour on toll roads.
- The inflation rate for the East Java region is 3.29%.
- The discount rate (r) of 4.75% refers to the Bank Indonesia in February 2026 benchmark interest rate.
- The traffic growth rate is 5.85% using East Java gross regional domestic product (GRDP) data for Quarter IV 2025.
- The unit price for bridge replacement is set at IDR 28,290,432.17/m² referring to previous research.
- Basic Annual Average Daily Traffic (AADT) data ($AADT_0$) in 2024 is 68,300 vehicles/day based on PT Jasa Marga Tol Solo–Ngawi entrance data.

The following describes the systematic stages of economic evaluation calculations applied to all bridges, taking the Kedung Prau Bridge as an illustrative example of the calculation.

a. Bridge Inventory

Kedung Prau Bridge located at KM 558+140 in the Ngawi region, has a total length of 40.8 meters and a width of 11.2 meters, resulting in a floor area of 456.96 m². Currently, the bridge has a condition score (CS) of 3, indicating a moderate level of deterioration and it is projected to reach a critical condition (CS = 5) by the year 2042. The bridge has an equivalent age of 82.55 years with a remaining service life of approximately 17.45 years. In terms of traffic demand, the projected LHRT at the end of its service life is 184,230 vehicles per day and the diversion distance in case of closure is 36.5 km. Using a discount rate of 4.75%, the estimated replacement cost is IDR 28,290,432.17 per square meter.

b. Bridge Replacement Costs (BRC)

Bridge Replacement Costs in the survey year ($BPJ_0$) are calculated based on multiplying the price of replacement area (PRA) by the bridge floor area (A):

$BRC_0 = PRA \times A$

$BRC_0$ = IDR 28,290,432.17 × 456.96 m² = IDR 12,927,595,884
Next, BRC in the year of handling ($BRC_n$) is obtained by calculating price escalation using the discount rate (r) for the remaining service life (n = 17.45 years):
$BRC_n = BRC_0 \times (1 + r)^n$
$BRC_n$ = IDR 12,927,595,884 × $(1 + 4.75\%)^{17.45}$ = IDR 29,058,461,726

c. Vehicle Operating Costs
Basic Vehicle Operating Costs (VOC) are calculated using the PCI method which divides cost components into Fixed Costs (FC) and Non-Fixed Costs (NFC). The basic aggregate VOC value ($VOC_0$) for all vehicle classes obtained is IDR 15,581.51/km. To calculate costs for the handling year, the basic VOC value must be projected (escalated) to the $n^{th}$ year VOC ($VOC_n$) using the local regional inflation rate (3.29%).

$VOC_n = VOC_0 \times (1 + \text{inflation})^n$
$VOC_n$ = IDR 15,581.51 × $(1 + 3.29\%)^{17.45}$ = IDR 27,414.05

d. Traffic Diversion Costs (TDC)
Traffic Diversion Costs (TDC) reflect the financial losses of road users due to using alternative routes when bridges are closed. Calculations use $VOC_n$ and handling year traffic volume ($AADT_n$) as well as diversion distance. The TDC value is immediately discounted to present value using the discount rate (r).

$TDC = (VOC_n \times AADT_n \times \text{Diversion Distance}) / (1 + r)^n$
TDC = (Rp 27,414.05 × 184,230 × 36.5) / $(1 + 4.75\%)^{17.45}$
TDC = IDR 184,343,456,877 / 2.2478 = IDR 82,011,119,535

e. Speed Reduction Costs (SRC)
During the maintenance work period, passing vehicles must reduce speed, thereby incurring additional operational costs (SRC). The assumed duration of the speed reduction is 180 working days. As with TDC, the SRC value is also immediately discounted.

$SRC = (VOC_n \times \text{Bridge Length} \times 180) / (1 + r)^n$
SRC = (Rp 27,414.05 × 40.8 × 180) / $(1 + 4.75\%)^{17.45}$
SRC = IDR 201,328,783 / 2.2478 = IDR 89,567,609

f. Engineering Costs (Repairs and Maintenance)
Engineering costs are the real costs incurred by toll managers to deal with physical damage to the bridge. This cost consists of two main components namely Element Repair Costs and Routine Maintenance Costs.

- Element Repair Costs calculated specifically based on the type of element that experienced dominant damage (on the Kedung Prau Bridge it was the Floor element with a condition score of 3). This calculation considers the area of damage and severity ($CS^2$).

  Repair Cost = 0.25 × Element Unit Price × Length × Width × $CS^2$
  Repair Costs = IDR 4,101,279,794

- Routine Maintenance Costs, set at a fixed percentage (2%) of the Basic Bridge Replacement Cost ($BPJ_0$).

  Maintenance Fee = 2% × $BRC_0$
  Maintenance Fee = 2% × IDR 12,927,595,884 = IDR 258,551,917

g. Future Value, NPV, and IRR
After all cost components are obtained, the economic feasibility value of the bridge is calculated in stages. In accordance with the rules of economic evaluation, total benefit (Future Value) is the sum of $BRC_n$, as well as the TDC and SRC values.

Future Value (FV) = $BRC_n$ + TDC + SRC

FV = IDR 29,058,461,726 + IDR 82,011,119,535 + IDR 89,567,609 = IDR 111,159,148,870

PV Benefit [PV(m)] = $FV / (1 + r)^n$

pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
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PV(m) = IDR 111,159,148,870 / (1 + 4.75%)$^{17.45}$ = IDR 49,452,740,099

Present Value Costs [PV(b)] is the total of all expenses (Engineering Costs) and losses (SRC) during the maintenance period:
Cost PV [PV(b)] = Repair Cost + Routine Maintenance Cost + SRC
PV(b) = IDR 4,101,279,794 + IDR 258,551,917 + IDR 89,567,609 = IDR 4,449,399,320

Net Present Value (NPV) = PV(m) − PV(b)
NPV = IDR 49,452,740,099 − IDR 4,449,399,320 = IDR 45,003,340,779

NPV/m² = NPV / Bridge Floor Area
NPV/m² = IDR 45,003,340,779 / 456.96 m² = IDR 98,484,202

Internal Rate of Return (IRR) = (FV / PV(b)$^{(1/n)}$) − 1
IRR = (Rp. 111,159,148,870 / Rp. 4,449,399,320)$^{(1/17.45)}$) − 1 = 20.25 %
The IRR value obtained was 20.25% exceeding the specified discount rate (4.75%), so that handling the Kedung Prau Bridge was declared economically feasible.
The economic evaluation procedure described above was applied consistently to all 70 bridges that were the object of research on the Solo–Ngawi toll road section. All bridges producing an IRR above the discount rate of 4.75% also had positive NPV. The treatment priority ranking is determined based on two criteria, namely the highest NPV/m² value for the bridge replacement category and the highest IRR value for the rehabilitation category. The rank of each bridge can be seen in **Figure 4**.

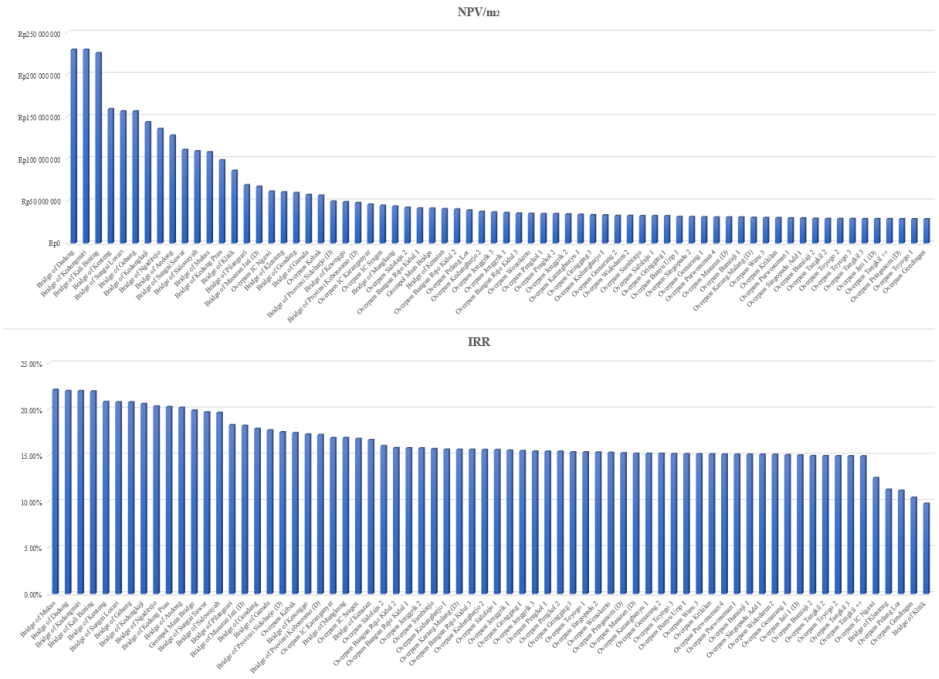



**Figure 4**. NPV/m$^2$ and IRR

## Random Forest

Analysis using the Random Forest algorithm was applied to predict and rank bridge handling priorities on the Solo–Ngawi toll road in a data-driven manner. This approach utilizes data on the physical condition of bridge elements as a result of BMS inspections as well as economic variables that have been calculated previously as model input.

a. Input Variables and Data Preparation

The input variables used in Random Forest modeling consist of two large groups, namely economic variables and Condition Score (CS) variables for bridge elements. Economic variables include remaining service life, bridge floor area, AADT in the year of handling, traffic diversion distance, and element maintenance costs. Meanwhile, the CS variable was obtained from the results of a detailed BMS inspection at level 3, which includes the condition of the thirteen bridge elements, namely river flow, approach road pavement, safety buildings, embankment land, approach road soil retaining structures, foundations, bridge heads/pillars, girder systems, plates, floor systems, floor connections, back rest, and equipment. All economic variables are normalized to the range [0,1] to equalize the data scale.

b. Calculation of Weighted Condition Scores (WCS)

The Condition Scores of bridge elements are integrated into one single indicator called the weighted condition score (WCS). Element weighting refers to the 2004 Bridge Inventory Manual by NYSDOT and experts which reflects the level of importance of each element to the overall structural integrity of the bridge. Elements with a critical role in the load transfer path receive a higher weight.

The WCS calculation formula is as follows.

$$WCS = \Sigma (CS_i \times w_i) / \Sigma w_i \quad (4)$$

With:
$CS_i$ = Condition Score of the $i^{th}$ element
$w_i$ = Weight of the $i^{th}$ element

The weight value of each element used is presented in **Table 1**.

**Table 1**. Weight of Bridge Elements [14], [15]

| No | Bridge Elements | Weight (w) |
|---|---|---|
| 1 | Bridge Head / Pillar | 0.2222 |
| 2 | Girder System | 0.2083 |
| 3 | Plate | 0.1111 |
| 4 | Approach Road Soil Retaining Structures | 0.0656 |
| 5 | Approach Road Pavement | 0.0556 |
| 6 | Floor Connection | 0.0556 |
| 7 | Floor System | 0.0417 |
| 8 | River flow | 0 (no weight) |
| 9 | Safety Building | 0.0400 |
| 10 | Landfill | 0.400 |
| 11 | Foundation | 0.1600 |
| 12 | Backrest | 0 (no weight) |
| 13 | Equipment | 0 (no weight) |

c. Determining Variable Target

This model uses priority ranking (the results of the economic evaluation) as the absolute variable target. In the regression model, the target is the ranking number (1, 2, 3, ...). The smaller the ranking number, the higher the priority for handling the bridge.

d. Data Diversion (Train-Test Split)

Data from 70 bridge samples were divided into training data (train set) and test data (test set) using the stratified random sampling method with a proportion of 80%: 20% and random state = 42. Stratification was carried out based on priority categories to ensure proportional representation of each class in both data subsets. With this proportion, 56 bridges were obtained as training data and 14 bridges as test data. This data separation aims to evaluate the model's generalization ability to data that has never been seen during training, so that the model's reported performance reflects its actual performance in real conditions.

e. Random Forest Modelling

Random Forest Regression is used to predict priority ranking values continuously. The model was built using the Random Forest Regressor algorithm from the scikit-learn library with parameters n

**ASTONJADRO**
pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
DOI: http://dx.doi.org/10.32832/astonjadro.v15i4.23672 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

estimators = 1000 (1000 decision trees) and random states = 42 to utilize all available processor cores. Training is performed exclusively on training data (56 bridges).

Each tree in the ensemble is trained using a random subset of the training data (bootstrap sampling) and at each node split, only a subset of features is randomly selected (a total of $\sqrt{18} \approx 4$ features out of a total of 18 features) for consideration. This double randomness mechanism produces diverse trees, so that the aggregation of predictions through averaging is able to reduce variance and increase the generalization ability of the model. The final prediction of the regression model is the average of the predictions of all trees as in the following equation.

$$\text{Priority Rank Pred} = (1/T) \times \Sigma\, h_t(x),\ t = 1, 2, ..., T \quad (5)$$

With,
T = number of trees (1000)
h_t(x) = predicted $t^{th}$ tree for sample x

f. Validation and Result

The Random Forest model trained on 56 bridges shows excellent performance in priority-ranking prediction, with an $R^2$ of 0.8744. This shows that the model can generalize and explain almost 87% of the variance from test data that has never been seen before. Apart from that, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values were 5.0305 and 7.2120 respectively.

The results of the Feature Importance analysis in the model show that diversion distance is the most dominant feature with an importance value of 0.6595, followed by approach road pavement (0.1228), AADT (0.0447), remaining life (0.0324), and maintenance costs (0.0323). Structural elements such as foundations, equipment, and embankments have very little importance (< 0.002), indicating that economic and accessibility factors dominate in predicting continuous priority scores as seen in **Figure 5**.

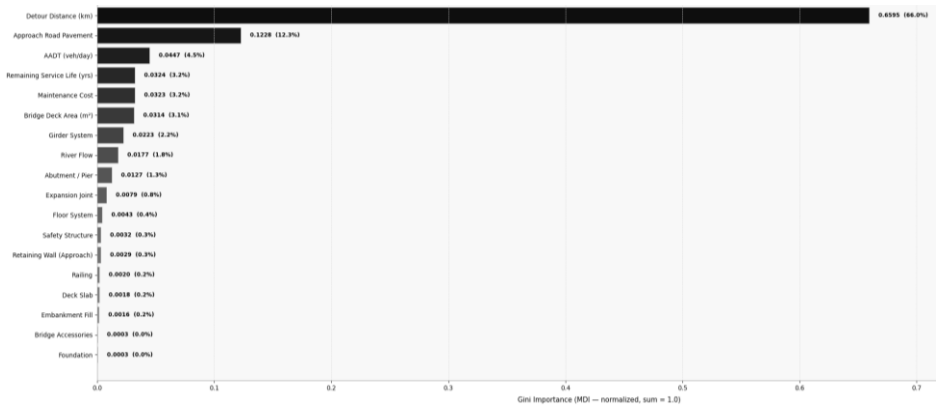



**Figure 5**. Feature Importance

**Comparison of Bridge Handling Priority Ranking Results with BMS and Random Forest Methods**

The two methods used to determine the priority ranking for bridge handling, both BMS and Random Forest, showed very good results with an $R^2$ of 0.8744, which means the model was able to explain 87% of the existing variance. Comparison of the rankings in the figure shows a consistent pattern in each bridge handling category as seen in **Figure 6**. There are several bridges that have experienced a shift in ranking. The Ketonggo Bridge is an example of a bridge that gets a much higher priority in the Random Forest model compared to the BMS method. This is because the Random Forest model recognizes a high WCS value (critical structural condition) as a signal for urgent treatment, even though the pure economic impact is not as big as that of other bridges that have a higher AADT. In contrast, several overpass bridges experienced a downgrade in Random Forest because even though the economic loss due to traffic diversion was large (long diversion distance), their structural condition was still relatively good, so the model assessed them as less urgent.

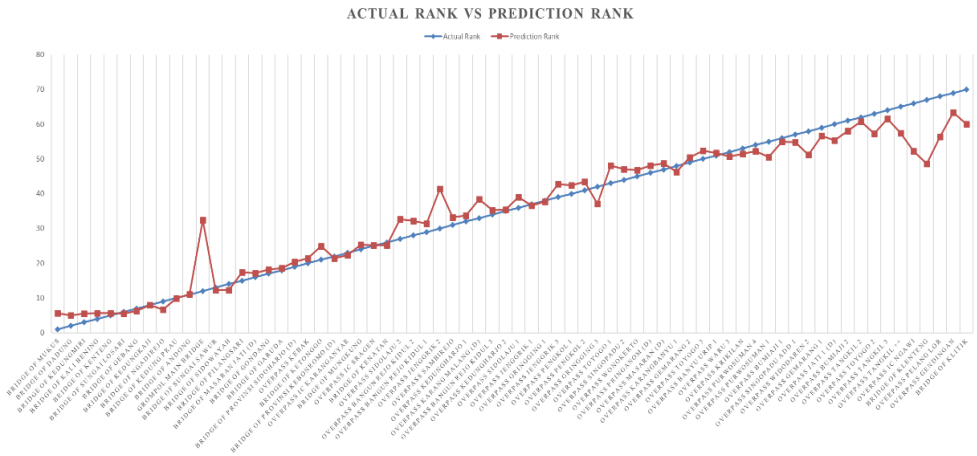



**Figure 6**. Actual Rank Vs Prediction Rank

This ranking shift characteristic proves the superiority of the Random Forest machine learning approach in bridge management systems. The model is able to integrate the dimensions of structural safety and economic efficiency simultaneously in one modeling framework. In contrast to the traditional BMS method which tends to be dominated by one economic factor (NPV/IRR), Random Forest gives more proportional weight to the physical condition of the bridge as an indicator of the risk of structural failure.

Overall, this comparison confirms that the use of machine learning as a complement to conventional BMS systems can improve the quality of decision-making. BMS provides a standardized and measurable basis for economic evaluation, while Random Forest adds a holistic, data-based dimension that accommodates the complexity of relationships between bridge physical and economic condition variables simultaneously.

## CONCLUSION

Evaluation of the economic feasibility using the BMS method on 70 bridges on the Solo–Ngawi toll road section produced varying IRR values, with all bridges producing an IRR above the discount rate of 4.75%. The priority ranking based on IRR is dominated by bridges with a combination of high AADT and long diversion distances, which result in large traffic diversion costs (TDC) thereby increasing the economic benefits of handling. The Random Forest model, which was trained using priority rankings based on economic evaluation results as the target variable, was able to predict bridge handling priorities with $R^2 = 0.8744$ indicating adequate generalization ability on a dataset of 70 samples. Feature importance analysis shows that diversion distance is the most dominant feature (0.6595), followed by approach road pavement, maintenance costs, and bridge floor area. This finding is consistent with the dominance of economic factors in the formation of priority ranking targets for bridge management. Comparison of BMS and Random Forest rankings shows good consistency for high category bridges, but there are differences for medium category bridges. The use of the Random Forest machine learning algorithm as a complement to the conventional BMS system has been proven to produce more holistic treatment priority recommendations by considering physical structural conditions and economic factors simultaneously. This approach has the potential to increase the effectiveness of the bridge infrastructure maintenance budget allocation on the toll road network.

## ACKNOWLEDGEMENT

This study could not have been conducted without crucial data support from the industry. Therefore, the author wishes to express sincere gratitude to PT Jasamarga Solo Ngawi (JSN) for facilitating access to historical maintenance data of the toll bridges. The collaboration and seamless access to empirical data provided by the institution represent a significant contribution to bridging the gap between machine-learning-based academic theories and the practical evaluation of bridge infrastructure in Indonesia.

pISSN 2302-4240
eISSN 2655-2086
Volume 15, Issue 4, December 2026, pp.01194-01205
DOI: http://dx.doi.org/10.32832/astonjadro.v15i4.23672 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

## REFERENCES

[1] F. salam Ahmad, "Dampak Pembangunan Jalan Tol Trans Jawa terhadap Pertumbuhan Ekonomi di Jawa Tengah," *Jurnal Ekonomi dan Kebijakan Pembangunan*, vol. 11, no. 1, pp. 1–18, Jul. 2022, doi: 10.29244/jekp.11.1.2022.1-18.

[2] Kementerian PUPR, *Pedoman Persyaratan Umum Perencanaan Jembatan*. Jakarta, 2015.

[3] Kementerian PUPR, "Panduan dan Rencana Program IBMS," 1993.

[4] R. A. Dananjoyo, A. Aminullah, and A. S. Budi Nugroho, "Penerapan Metode Life-Cycle Cost dalam Perhitungan Evaluasi Ekonomi Jembatan untuk Penentuan Prioritas Penanganan Jembatan," *Jurnal Teknosains*, vol. 9, no. 2, p. 165, Jul. 2020, doi: 10.22146/teknosains.39052.

[5] O. Wahyudhi, A. Aminullah, and A. Triwiyono, "Modifikasi Penilaian pada Sistem Manajemen Jembatan di Indonesia (Interurban Bridge Management System) dengan Mengimplementasikan Condition States dari Metode Bridge Health Index," 2018.

[6] N. Chawla, "Predicting Bridge Condition Ratings Using Machine Learning and Public Inspection Data," Nov. 25, 2025. doi: 10.20944/preprints202511.1826.v1.

[7] F. Fard and F. Sadeghi Naieni Fard, "Development and Utilization of Bridge Data of the United States for Predicting Deck Condition Rating Using Random Forest, XGBoost, and Artificial Neural Network," *Remote Sens. (Basel).*, vol. 16, no. 2, Jan. 2024, doi: 10.3390/rs16020367.

[8] Y. Wei, R. Ji, Q. Li, and Z. Song, "A Condition Assessment Tool for Steel Bridge Deck Pavement Systems Based on Data Balancing Methods and Machine Learning Algorithms," *Buildings*, vol. 14, no. 9, Sep. 2024, doi: 10.3390/buildings14092959.

[9] I. Afriyie, S. N. Joshua, and M. N. Abuanor, "Utilizing Several Machine Learning Techniques to Investigate the Bridge Deck Condition," *Journal of Studies in Civil Engineering*, vol. 2, no. 2, pp. 35–53, Dec. 2025, doi: 10.53898/jsce2025223.

[10] B. Wulan Sari and D. Prabowo, "Analisis Perbandingan Prediksi Harga Rumah Dengan Random Forest, Gradient Boosting, dan XGBoost," *Intellect : Indonesian Journal of Learning and Technological Innovation*, vol. 4, no. 1, pp. 42–51, Jun. 2025, doi: 10.57255/intellect.v4i1.1385.

[11] M. Lu and S. I. Guler, "Comparison of Random Survival Forest with Accelerated Failure Time-Weibull Model for Bridge Deck Deterioration," *Transp. Res. Rec.*, vol. 2676, no. 7, pp. 296–311, Jul. 2022, doi: 10.1177/03611981221078281.

[12] F. Hariman, H. H. Christady, A. Triwiyono, B. Kota Sawahlunto, J. Sukarno-Hatta Sawahlunto, and J. Teknik Sipil dan Lingkungan, "Evaluasi dan Program Pemeliharaan Jembatan dengan Metode Bridge Management System (BMS) (Studi Kasus : Empat Jembatan Propinsi D.I. Yogyakarta)," *Forum Teknik Sipil No.XVII*, 2007.

[13] D. Zindani and S. Singh, "Leveraging Random Forest Regression for Informed and Risk-aware Material Selection in Supercapacitor Fabrication," *Journal of Engineering and Applied Science*, vol. 72, no. 1, Dec. 2025, doi: 10.1186/s44147-025-00789-4.

[14] G. E. Pataki and J. H. Boardman, "Bridge Inventory Manual," New York, 2004.

[15] H. Vaza, R. Sastrawiria, H. Halim, and Septinurriandiani, *Identifikasi Kerusakan & Penentuan Nilai Kondisi Jembatan untuk Mendukung Manajemen Aset Jembatan*, 1st ed. Jakarta: Pusat Litbang Jalan dan Jembatan Kementerian PUPR, 2017.