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Prediction Model of Rigid Runway Pavement Performance Using Nonlinear Autoregressive with Exogenous Input Neural Network

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Abstract— *Research and development of runway pavement have been investigated in several airports globally. The damage pavement prediction is vital for preventing accidents during landing and take-off flights. This study carried out the prediction of the performance of rigid runway pavement correlated with damage index. Non-linear autoregressive with exogenous input neural network (NARXNN) was implemented to construct model prediction using the Levenberg-Marquardt algorithm. The NARXNN model has been constructed based on input variables that affect the structural performance of rigid runway pavement, such as air traffic, temperature, thickness, humidity, service life, maximum deflection on rigid runway pavement centre and edge. The results indicate that the performance of runway pavement reduces in a linear (non-linear) way. The external parameter significant to the prediction model is air traffic and temperature. The performance of rigid runway pavement is categorized into three levels good, poor, and critical. It is feasible to guide airport agencies to accomplish appropriate decisions on rigid runway pavement maintenance and reconstruction. It concluded that NARXNN is a powerful and effective method in predicting the performance of rigid runway pavement.*

Keywords— *Rigid runway pavement, runway performance, damage index, prediction model, NARXNN.*

I. INTRODUCTION

An airport is a facility where aircraft take off and land. The simplest airports have at least one runway, but large airports are usually provided with various other facilities for flight service operators and users. The function of the airport is like a terminal that serves aircraft passengers as a place to stop, depart, or just an aircraft stopover [1]. According to Annex 14 of ICAO (International Civil Aviation Organization), an airport is a particular area on land or water (including buildings, installations and equipment) intended either in whole or in part for the arrival, departure and movement of aircraft. The main factor that needs to be maintained at the airport in safety and in-flight the safety of airport runway operations is essential [2]

The safety of runway operations must be ensured for safety and to understand well the mechanisms of damage to runway pavements, periodic check and maintenance or emergency repairs are accomplished by authorized officers at the airport [3]. In addition, periodic assessment of rigid runway pavement performance is also a significant factor of runway operation. In Indonesia, airport authorities have made great efforts to assess rigid runway pavement performance and inspect runway pavement damage at each airport. During the assessment, performance prediction is an essential aspect for operator runways—the achievement rate is based on the built model. A good predictive model has affected the evaluation results of rigid runway pavements and has a significant effect on the process of design, construction, maintenance, and rehabilitation [4].

Presently, empirical-mechanistic models are widely applied simultaneously with the improvement of computer technology. A pavement management system (PMS) is a simple predictive model to execute statistical regression analysis with a theoretical basis and simple assumptions [5]. Furthermore, the results from original data and laboratory experiments are used together to build predictive models of runway pavement performance, such as the Markov model and expert decision models [6]. Thus far, empirical-mechanistic models have been advanced for PMS, such as the popular artificial Neural Network (ANN) [7]– [10].

ANN is usually applied with the method as the human brain by mapping input to output to simulate the working process to get the results, which has been widely used in modelling and estimation of classification, grouping, functions, and identification of systems [11]. The results obtained by the ANN method do not depend on the causal relationship between input and output. ANNs with modified architectures have been applied to predict pile settlement, subgrade strength, voids, pavement serviceability and modulus of resistance for rigid/flexible pavements [12], [13]. The ANN model was constructed to determine the modulus of flexible non-linear pavement layers on the runway pavement at the National Airport Pavement Test Facility (NAPTF) using the heavyweight deflectometer (HWD) test [14]. In addition, significant effort has been established with the study to identify possible correlations between severe runway pavement damage and roughness, difficulty and surface profile [8], [15]. Furthermore, the approach using Nonlinear Autoregressive with Exogenous Input Neural Network (NARXNN) as implemented in previous researchers has much better accuracy than conventional ANN networks when predicting time series data [16]. Therefore, NARXNN is more suitable for dynamic modelling [17].

Therefore, a new method is needed to make a prediction model of rigid runway pavement damage with better accuracy

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and show the correlation between external and target parameters so that it can be one way to prevent accidents caused by damaged runways.

II. METHODOLOGY

The estimation of pavement service lifetime according to deviations from the original and target data as the rigid pavement damage index (Δ) [18]. The load cycles number is an essential factor to build a rigid runway pavement failure by calculating a crack in the surface as shown by expression of N_p [18], as shown in Equation (1).

$$N_p = \int_{co}^{d} \frac{dc}{A \Delta K^n} \quad (1)$$

Where the initial crack's length is represented as co, the rigid runway pavement thickness is shown as d, the material fracture parameters as shown by A and n, then the change in the stress intensity factor at the crack tip was ΔK.

The rigid runway pavement service life due to departures was predicted based on target data by constructing the rigid runway pavement damage index (Δ). Further, the model has been

The Δ was built to evaluate the predicted change in the pavement service life due to departures from the target profile, which have been confirmed in the design stage and targeted model, as shown in Equation (2)

$$\Delta = \frac{N_{pl} - N_{po}}{N_{po}} \quad (2)$$

where the rigid runway pavement service life is based on the predicted values as shown by N_{po}, and the rigid runway pavement service life is based on targeted values represented by N_{pl} (1). Therefore, FAA advises to analyze the rigid runway pavement performance based on the dynamic displacement of rigid runway pavement by HWD test [19] and recommends an empirical method of calculating Δ without calculating N_p, as shown in Equation (3).

$$\Delta = \frac{D_E - D_C}{D_C} = \frac{D_E}{D_C} - 1 \quad (3)$$

where DC and edge by DE present the maximum deflection of the rigid runway pavement on the centre . Equation (3) was shown the simplified and powerful method to analyze the rigid runway pavement damage index. Furthermore, it is simplified, as shown by Equation (4).

$$\Delta = 2\left(\frac{D_E}{2D_C}\right) - 1 = 2 \times \tau - 1 \quad (4)$$

where

$$\tau = \frac{D_E}{2D_C} \quad (5)$$

The NARXNN was a suitable method for calculating a new and simplified rigid runway pavement damage index (τ) as shown in Equation (5) based on the predicted value of the life-cycle performance of rigid runway pavement. The evaluation of rigid runway pavement performance was widely approved as a positive value. Further, the rigid runway pavement was in good status when the Δ = 0 and the danger status when Δ = 1 as represented by Equation (3). Equation (4), rigid runway pavement damage index perchance is harmful in several conditions. Further, Equation (5) was represented physical meanings compared to Equation (4).

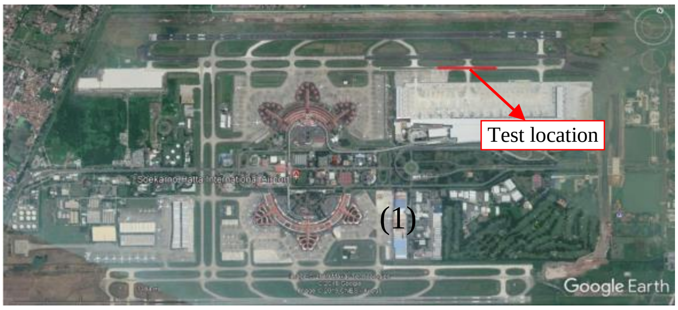

Fig. 1. Soekarno-Hatta Airport locations for rigid runway pavement performance prediction by HWD test.

Data HWD measurements are needed to achieve this objective. Thus, the HWD data in 2019 of Soekarno-Hatta International airports were chosen as a steady data source represented by Figure 1. The red line shows the location of the HWD test for rigid runway pavement performance prediction. The data of D_E and D_C and comparable analysis results of rigid runway pavement performance at each test location were first selected from the database. The deflections data and calculated τ as input were implemented into the NARXNN model.

Examples of input variables are shown in Table I.

TABLE I. Examples of inputs and output variables.

inputs							output
Deflection							
D_C (μm)	D_E (μm)	T (°C)	H (%)	TH (cm)	S (months)	A	τ
358.4	338.4	29.4	59	30	12	447,490	0.47

A NARX is an essential non-linear class of discrete-time non-linear systems that can be mathematically represented in Equation (6) [20].

$$y(k+1) = F[(y(k), y(k-1), \ldots, y(k-d_y+1); u(k), u(k-1), \ldots, u(k-d_u+1))] \quad (6)$$

Where $y(k) \in \mathbb{R}$ and ( )UK $\in \mathbb{R}$ denote, respectively, k was represented as the time step of the input and output, the input and output memory shown as $d_u \geq 1$ and $d_y \geq 1$, and finally, the non-linear function as shown by $F[.]$. NARXNN was a recurrent dynamic network with feedback connections with tapped delay time around the layer. The multi-layered perceptron, a feedforward and a recurrent network have been combined. The input, output, and hidden layers were used to construct the model. Further, the input layer consists of the current and previous inputs and outputs.

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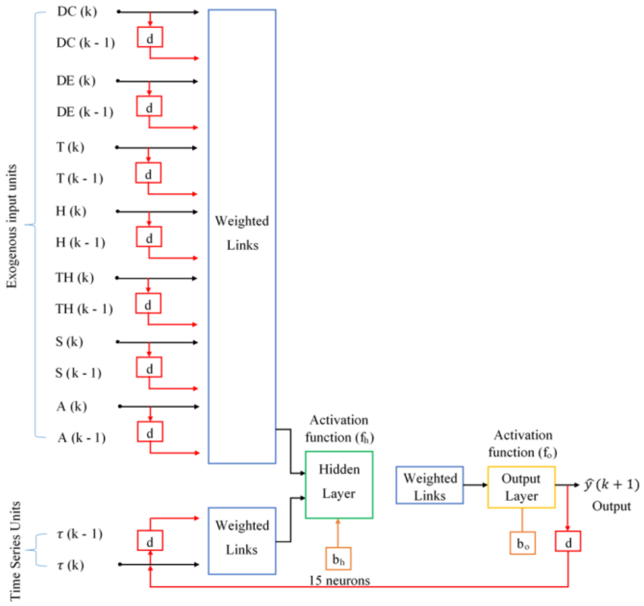

Fig. 2. The model prediction of pavement damage index using NARXNN architecture.

The output from the input layer was fed to the hidden layer and processed by neurons in a non-linear mapping of an affine weighted combination—furthermore, the output layer represented an affine combination of the values from the hidden layer.

The NARXNN exogenous inputs (u) were deflection of pavement centre (DC), deflection of pavement edge (DE), temperature (T), humidity (H), thickness (TH), service life (S), and air traffic (A) have been applied using Levenberg Marquardt Neural Network (LMANN) Algorithm [21]. The pavement damage index (τ) was implemented as the output (y). The 2-months before was applied as a memory of the inputs and output. The NARXNN consisted of 15 neurons in the hidden layer. The NARXNN model of rigid runway pavement performance for one-step-ahead prediction has been diagrammatically shown in Figure 2.

The NARXNN model for rigid runway pavement performance prediction as represented by equation (7)

$$\tau(k+1) = F[(\tau(k), \tau(k-1); DC(k), DC(k-1); DE(k), DE(k-1); T(k), T(k-1); H(k), H(k-1); TH(k), TH(k-1); S(k), S(k-1); A(k), A(k-1);)] \quad (7)$$

where F[.] denotes a non-linear function.

III. Results and Discussion

The MATLAB software built the NARXNN model using LMANN training algorithms. The training data set was selected from 70% of the data in 2019 fed into the model. Thus, the validation and test data set to have 30% of the data. The data set of the NARXNN model was implemented to establish the network's performance, and the weights and biases of the network will update, while the data set of the validation process was implemented to supervise the error during the training process. Furthermore, the test data set error was implemented to assess the training process and the certainty of the prediction model. The early stopping technique used in this study involves simultaneous training, validation, and testing. The lowest root means square error (RMSE) indicated the training process stops when it is reached. The overfitting was increased the RMSE value for the validation set after the minimum value reached.

The NARXNN inputs parameters (*DC*, *DE*, *T*, *H*, *TH*, *S*, *A*) and an output parameter (τ) weighted values were calculated based on Equation (7). Further, the 15 neurons in the hidden layer and 2-months input memory using the LMANN algorithms were implemented for the model in Equation (7) and produced the NARX NN model structure as shown by equation (8).

$$\tau(k+1) = F[(1.547\tau(k) + 0.817\tau(k-1) + 1.176DC(k) - 0.953DC(k-1) + 1.215DE(k) - 0.864DE(k-1) + 0.864T(k), +1.974T(k-1) - 0.487H(k) + 0.922\,H(k-1) + 0.631TH(k) - 0.782TH(k-1) + 0.617S(k) - 0.921\,S(k-1) + 1.129A(k), +2.128A(k-1);)] \quad (8)$$

where *F*[.] is a non-linear function.

TABLE II. Performance of rigid runway pavement by NARXNN.

	τ	**Performance**	**Suggestions for maintenance**
Condition 1	$0<\tau<0.2$	Excellent	Routing inspection and repair
Condition 2	$0.2<\tau<0.5$	Good	Preventive repair
Condition 3	$0.5<\tau<0.8$	Poor	Major repair
Condition 4	$0.8<\tau<1$	Dangerous	Rehabilitation or reconstruction

The most significant parameter is the air traffic one month before with a weight coefficient of 2.128. The second significant parameter is the temperature one month before, as indicated by the weight coefficient of 1.974. The rigid runway pavement performance of the present time becomes the third significant, informed by the weight coefficient of 1.547. Temperature and air traffic is significant parameter that affects the rigid runway pavement damage index [22].

The architecture of NARXNN was constructed, the data set of training and test was the beginning of the learning process. The Soekarno-Hatta International Airport HWD test data were implemented to analyze the NARXNN prediction results. Tangential hyperbolic fit was applied to produce the accuracy of the model prediction. A higher Pearson correlation coefficient (*r*) determined a higher prediction accuracy. Figure 3 shows the predicted and the original value of τ equally distributed among the regression curve, and r is 0.91. It demonstrates that the prediction accuracy is good, and the suggested NARXNN is highly effective in estimating τ.

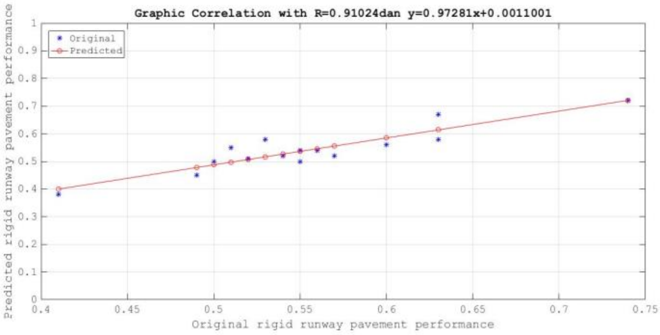

Fig. 3. The correlation coefficient of rigid runway pavement performance prediction.

NARXNN model shows a novelty prediction model of rigid runway pavement performance. The rigid runway pavement performance consists of 4-regions, starting from excellent to dangerous conditions, as shown in Table II. They consider Soekarno-Hatta International Airport, mainly the rigid runway pavement performance curve in Figure 4. As shown in Figure 4, the RMSE of the predicted value is 0.035.

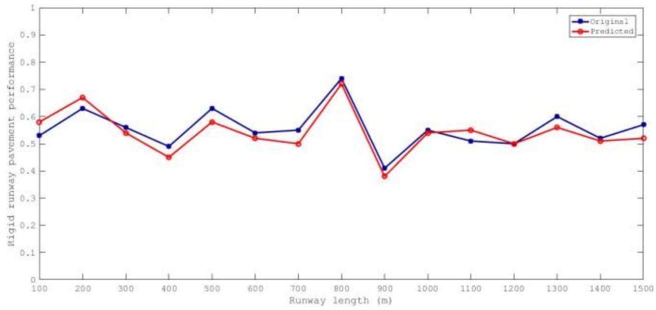

Fig. 4. The prediction of rigid runway pavement performance of September 2019 (original data: blue solid; the prediction: red line).

IV. CONCLUSIONS

NARXNN model prediction using Levenberg-Marquardt is successful in predicting rigid runway pavement performance. The building model indicates that air traffic and temperature one month before have the most significant contribution to rigid runway pavement performance. The one month predicted rigid runway pavement performance agrees with the original valuer of 0.91 and RMSE of 0.035. Therefore, the rigid runway pavement performance using NARXNN model prediction will have an exciting future. According to other factors associated with pavement damage, the characterization of rigid runway pavement performance is still unknown.

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