

AN OPTIMIZATION OF FLIGHT SCHEDULING USING A DEEP LEARNING APPROACH UTILIZING ROOT MEAN SQUARE PROPAGATION IN ADJUSTING ROUTES AND TIME FOR OPERATIONAL EFFICIENCY

Donna Nm Sirait ^{a*)}, M. Amril ^{a)}, Ivana Wardani ^{a)}, Darmeli Nasution ^{a)},
Yosei Ht Simanjuntak ^{a)}, Fahri Septiadi ^{a)}

^{a)} Polytechnic Aviation Medan, Medan, Indonesia

^{*)}Corresponding Author: donnanur@poltekbangmedan.ac.id

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Abstract. This research explores the application of a Deep Learning approach by utilizing the Root Mean Square Propagation (RMSprop) algorithm to increase efficiency in flight scheduling. The main focus of the research is on adjusting routes and times to achieve higher operational efficiency in the aviation industry. Aviation is an important aspect of transportation that requires accurate and efficient scheduling to achieve punctuality, operational efficiency and a better passenger experience. This research aims to improve flight scheduling by applying Deep Learning techniques, specifically using the RMSprop algorithm. The research method includes the use of historical flight data to train the model, adjusting routes and times based on the analysis carried out by the RMSprop algorithm. The research results are expected to provide new insights into the application of Deep Learning technology in the aviation industry, with the aim of improving punctuality, reducing flight delays, and increasing the overall efficiency of airline operations. Thus, this research is expected to provide a valuable contribution in the development of a scheduling system that is more adaptive and responsive to the dynamics that occur in flight operations.

Keywords: Aviation, Optimization, Algorithms, Deep Learning, RMSprop.

I. INTRODUCTION

Aviation is an increasingly advanced industry and depends on parameters such as efficiency, safety and punctuality. In aviation there is scheduling which is the most crucial aspect in the aviation industry [1][2]. Scheduling will ensure that aircraft fly and operate efficiently on time and effectively, which is the goal of all airlines in the aviation industry [3]. In the aviation industry, it is closely related to scheduling which involves complex variables such as flight routes and departure times [4]. Flight scheduling usually uses conventional technology, although it provides a framework, but in analysis conventional technology is less able to make adjustments because it is more dominant and tends to rely on static rules that are not flexible enough to deal with sudden changes in flight operations. In its development, many researchers use deep learning to overcome complex prediction and decision-making problems. Deep learning is able to overcome complex matters as proven in managing air traffic, but several studies have carried out air traffic management using deep learning or machine learning. However, the use of the root mean square propagation algorithm has never been carried out, so this research will apply a Deep Learning approach and root mean square propagation which is expected to provide a more adaptive and responsive solution to dynamic changes that occur in flight route scheduling. The main objective of this research is to

apply a Deep Learning approach by utilizing the RMSprop algorithm to improve predictions of flight routes and departure times. Thus, the hope is to increase the operational efficiency of airlines. Through this approach, it is hoped that it can reduce flight delays, increase the efficiency of resource use, and increase overall customer satisfaction.

II. RESEARCH METHODS

The research evaluation process includes the implementation process from start to finish as follows.

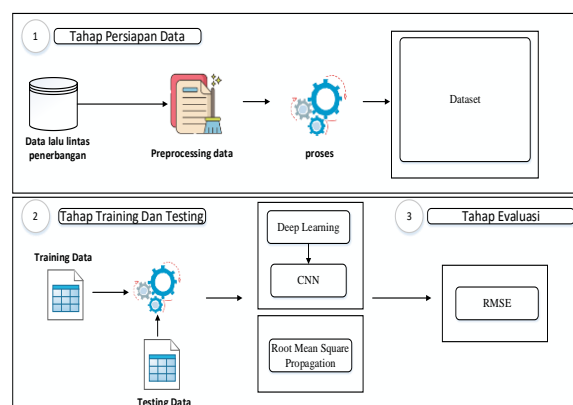


Figure 1. Research Stages

In this research there will be research stages as in Figure 1. with the following explanation:

1. The data preparation stage aims to find out what must be done regarding data collection, cleaning the data so that it becomes a data set. The data collection stage will be obtained from the airnav website.
2. Model training: This stage involves training the model with a deep learning approach using the CNN algorithm and using the optimization architecture of CNN, namely root means square propagation
3. This evaluation stage will involve evaluating the error value calculation using RMSE

The research was carried out in the Medan Aviation Polytechnic environment which is located on Jalanl. Flight No.85, Sempakata, Kec. Medan Selayang, Medan City, North Sumatra 20131.

III. RESULTS AND DISCUSSION

In this phase, the output of the research that has been carried out in accordance with the steps described in the research methodology will be discussed. In this section, the research will review the results of research that has been carried out. Initially, this research will provide a general overview of the data analysis that has been carried out by applying data preprocessing techniques. After that, training will be carried out using a deep learning approach using the CNN algorithm and adopting the CNN optimization architecture, namely root mean square propagation. Subsequently, the testing process will be carried out on the test data. The next step is Phase Evaluation by calculating error values using the RMSE method with the aim of assessing model performance in the context of flight scheduling.

Data analysis

The data used in this research is scheduling data which will be used to schedule flights using a deep learning approach using the root mean square propagation algorithm. This data will be preprocessed for the data preparation and cleaning process before being analyzed or modeled.

Table 1. Flight Data

No	Airline	Home airport	Destina-tion Airport	Depart-ure time	Time of arrival
1	Garuda	BTJ	SRG	08.00	10.00
2	Wings	MES	BDO	09.00	10.00
3	Sea lion	BTH	BPN	11.00	13.00
4	Srivijaya	TNJ	PNK	14.00	16.00
5	Name water	PKU	TRK	09.00	11.00
6	Water batik	PDG	DPS	10.00	11.00
7	Citilink	PLM	AMI	18.00	20.00
8	Trigana water	BKS	COE	19.00	21.00
9	Air Asia	TKG	BPN	20.00	21.00
10	Wings	CKG	PNK	12.00	14.00
11	Sea lion	HLP	AMQ	14.00	16.00
700	Srivijaya	SUB	BIK	10.00	12.00
800	Citilink	SOC	TEAM	07.00	10.00
999	Garuda	JOG	SRG	17.00	19.00
1000	Srivijaya	SRG	BDO	08.00	10.00

The goal of data preprocessing is to improve data quality to ensure that the data used in analysis or modeling has adequate characteristics and can be relied upon and used. After preprocessing the data, the dataset will be processed using a deep learning model using the root mean square propagation algorithm for flight scheduling optimization. The following is table 1. data for use in flight scheduling.

Data Visualization

Data visualization is a display that will display the distribution of fake and non-fake account data. The purpose of data visualization is to see the character of the data that will be used. The following is a visualization of the data contained in the model for optimizing flight scheduling using the CNN algorithm and using the CNN optimization architecture, namely root means square propagation:

1. Flight Data Visualization

Flight data visualization will display the entire flight data so that it can be seen in a visualization of the data used. In the flight visualization there are percent values and day data as in the following image:

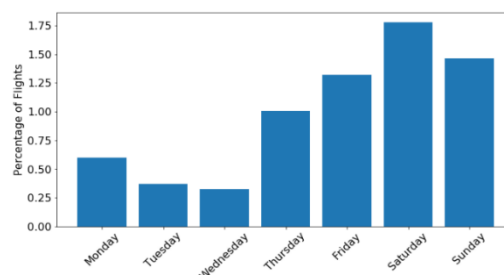


Figure 2. Visualization of flight data

2. Departure Time Visualization

Departure time visualization will display a graph of departure time data on flight data as in Figure 3 below:

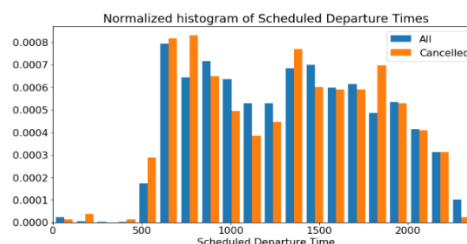


Figure 3.

Visualization of departure time data

3. Flight Distance Visualization

Flight distance visualization will display a graph of flight distance on flight data as in Figure 4 below:

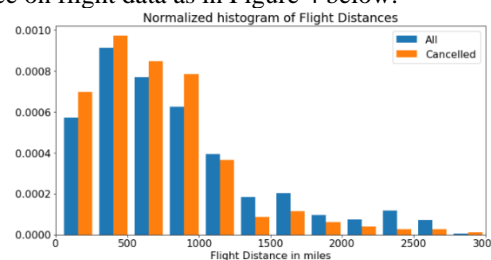


Figure 4. Visualization of flight distance data

4. Flight Scheduling Optimization Data Visualization
 Flight scheduling optimization data visualization will display graphs on flight data with weather, security, scheduling, delay and operator variables as in Figure 5. the following:

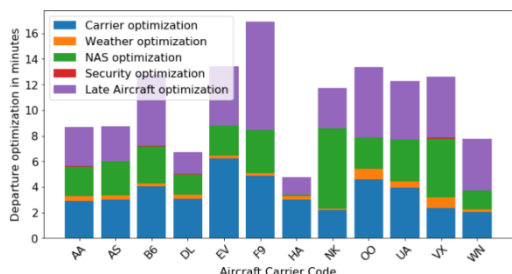


Figure 5. Visualization of flight distance data

The description in Figure 5 explains as follows:

- On Carrier optimization in minutes: carrier optimization is within the control of the airline. Examples of events that can determine the optimization of flight scheduling are: aircraft cleaning, aircraft breakdown, waiting for the arrival of connecting passengers or crew, baggage, bird strikes, cargo loading, catering, computers, stopping of transport equipment, crew legality (pilot or flight attendant rest), damage due to dangerous goods, engineering inspection, refueling, handling disabled passengers, late crew, toilet servicing, maintenance, overselling, drinking water servicing, transfer of unruly passengers, slow boarding or seating, carry-on baggage storage, delays weight and balance.
- NAS optimization in minutes: Optimizations that are within the control of the National Airspace System (NAS) can include: non-extreme weather conditions, airport operations, heavy traffic volumes, air traffic control, etc.
- Weather Optimization in minutes: weather optimization can be avoided by looking at weather conditions and forecasting at the point of departure, en route, or at the point of arrival.
- Security Optimization in minutes: security optimization can be carried out by accelerated evacuation of the terminal or waiting room, reboarding of the aircraft due to security violations, functioning of screening equipment and/or long queues not exceeding 29 minutes in the screening area.
- Optimization in minutes: optimization of arrivals at an airport due to the arrival of the same aircraft at the previous airport.

R-square visualization

R-square (R-squared), also known as the coefficient of determination, is a statistical metric used to measure how well a linear regression model fits the observed data. R-square provides an idea of how much variability in the dependent variable can be explained by the regression model. The higher the R-square value, the better the linear regression model is at explaining variations in the data. However, R-square also has weaknesses, especially if it is used in complex models or does

not comply with certain assumptions. The following are the R-square results on the data:

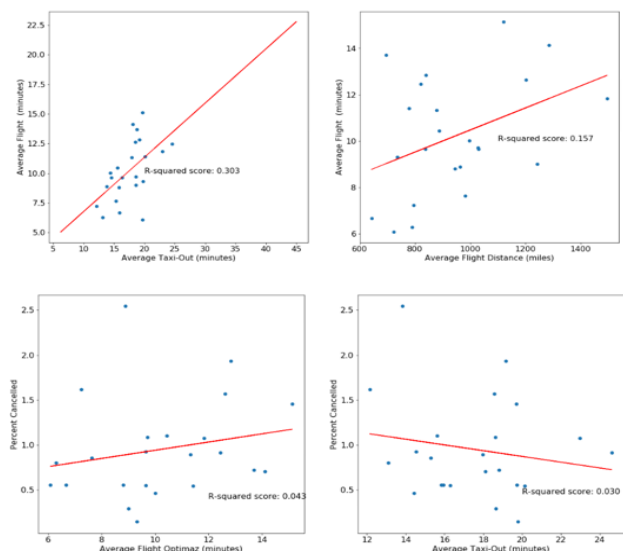


Figure 6. R-square visualization

Visualization of Correlation Between Variables

Visualizing correlation between variables is an effective way to understand the statistical relationship between two or more variables in a dataset. Correlation graphs help identify patterns, trends, or dependencies between variables, which can provide insight into how those variables interact. One of the most common ways to visualize correlation is to use a scatter plot. A scatter plot places points on a graph with the x and y axes representing the values of two different variables. If the points on the graph form a pattern or trend line, it indicates a correlation between these variables. The following are the results of the correlation with the scatter plot in Figure 7:

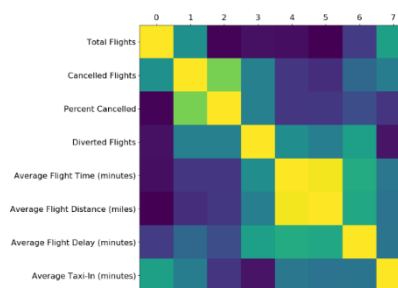


Figure 7. Correlation Visualization

By using correlation visualization, understanding of the structure and dynamics in a dataset can be improved, enabling more informed and informed decisions.

Evaluation of Deep Learning Models

After the training process, a model evaluation will be carried out with test data for the deep learning model using the CNN algorithm utilizing root mean square propagation in scheduling flights. In this research we will use the ROC (Receiver Operating Characteristic) curve graph which is an evaluation technique that is often used for models in make

predictions. The ROC curve displays the relationship between the True Positive Rate (TPR) level and the False Positive Rate (FPR) level at various threshold values. The following are the results of the evaluation with the ROC curve in Figure 8:

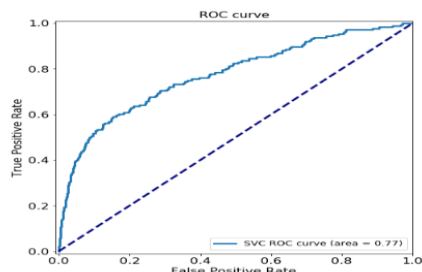


Figure 8. Evaluation of the ROC curve

Based on Figure 8, there is a red curve which is the result of the deep learning model. From a recall of about 80% and from a rate of false positives and ineffective scheduling predictions of approx. 20%, barely deviating from the ideal. So, the model generally looks very good because it follows the gray ideal rather than the blue price line. The model with the CNN algorithm for scheduling flights has an accuracy of 0.85.

Evaluate deep learning models with root mean square propagation

Evaluation of deep learning models using Root Mean Square Propagation (RMSprop) is an important stage in measuring the effectiveness and consistency of model performance. During the training process, the model is given feedback regarding its performance on the training data, and the use of RMSprop ensures that changes in model parameters are adapted to an adaptively adjusted learning rate. Monitoring model performance during training involves monitoring evaluation metrics such as loss function or accuracy to understand the extent to which the model is able to understand patterns present in the training data. Once training is complete, the model is tested using validation data to ensure its ability to generalize on data not used during training. RMSprop is then applied to adjust the learning rate for each model parameter, preventing problems with exploding or vanishing gradients. The final evaluation is carried out by analyzing performance metrics such as Root Mean Square Error (RMSE), which provides an idea of the extent to which the model can accurately predict numerical values. The following are the results of the ROC curve in the model by applying RMSprop as shown in Figure 9:

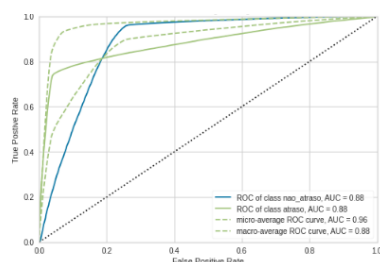


Figure 9. Evaluation of the ROC curve of the CNN model with RMSprop

Based on Figure 9, the accuracy value with ROC evaluation will be displayed with a value of 88% which is very good. Through the ROC curve in Figure 9, it will be possible to show that the model generally has a true positive rate for class 0.0 higher than the target category. However, at low thresholds, the study observed high TPR for target classes with low FPR, meaning that, at low thresholds, the model would be able to differentiate positive classes with greater success. The model with the CNN algorithm with RMSprop in scheduling flights has an accuracy of 0.88.

IV. CONCLUSIONS

Based on the application of the deep learning model using the CNN algorithm and utilizing the Root Mean Square Propagation (RMSprop) technique in optimizing flight scheduling, it can be concluded, among others: Based on the use of a deep learning model with RMSprop which will be used in scheduling optimization, it produces an accuracy value of 88% better than without the use of Root Mean Square Propagation (RMSprop). This research can optimize routes and flight times in scheduling so that this model can be used for scheduling.

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