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IMPLEMENTATION OF HYBRID DEEP LEARNING CNN-LSTM IN COST RECOVERY PREDICTION IN THE CONTEXT OF OPTIMIZING LOW-COST CARRIER STRATEGIC MANAGEMENT AT PT LION MENTARI AIRLINES

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The object of this research is the cost recovery prediction model of low-cost airlines. The challenge faced is the complexity of the airline's financial and operational patterns, which encompass spatial and temporal interactions, making it difficult for a single prediction model to produce accurate and stable estimates. This challenge directly impacts management's ability to develop effective strategies, including fare setting, fuel cost control, and flight route planning. To address this issue, this research implements a hybrid deep learning approach, CNN-LSTM. The CNN is used to extract spatial features from multivariate data, while the LSTM captures long-term temporal dependencies with a complex memory update mechanism. The integration of these two models allows for richer data pattern processing than a single model, resulting in more accurate predictions that align closely with actual conditions. The research interpretation indicates that the hybrid model is able to leverage the strengths of each component: CNN in extracting local features and LSTM in understanding temporal dynamics. This is reflected in the prediction results, which show a smaller deviation from the actual data compared to either CNN or LSTM alone. Based on the test results on cost recovery data for 14 periods, the three models CNN, LSTM, and CNN-LSTM hybrid showed high and stable accuracy in following the actual value pattern. From the first to the fourth period, all models produced results very close to the actual value, with an average difference below 0.02. For example, in the fourth period, the actual value of 0.88 was well predicted by CNN (0.91), LSTM (0.886), and CNN-LSTM (0.876). However, in the sixth to ninth periods, there was a slight decrease in accuracy as the actual value decreased, especially in the ninth period when the value of 0.74 was only predicted by 0.731 by CNN, 0.74 by LSTM, and 0.732 by the hybrid model. The implementation of the CNN-LSTM hybrid not only improves the accuracy and reliability of cost recovery predictions but also provides strategic value for PT Lion Mentari Airlines management, supporting more efficient and optimal decision-making to enhance the low-cost carrier's competitiveness

Keywords: hybrid, CNN-LSTM, recovery prediction, low cost carrier, deep learning, optimization

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1. Introduction

The low-cost carrier (LCC) industry plays a crucial role in the dynamics of global air transportation, particularly in Southeast Asia, one of the fastest-growing markets. Indonesia, as an archipelagic nation with high mobility, is a strategic area for the development of this business model. PT Lion Mentari Airlines (Lion Air), one of the largest LCC airlines, faces challenges in maintaining cost efficiency while maintaining competitiveness [1, 2]. One critical issue is the ability to accurately predict cost recovery, given the fluctuating external variables, such as aviation fuel prices and foreign exchange rates, as well as internal factors such as the difficult-to-predict dynamics of passenger demand [3, 4]. The inability to make accurate predictions can lead to an imbalance between costs and revenue, thus weakening the airline's financial stability. Changes in consumer behavior and seasonal factors can cause instability in passenger numbers. This makes it difficult for management to consistently forecast revenue [5, 6]. The inability to accurately predict revenue and costs leads to a high risk of imbalance between revenue and expenses, which can weaken the airline's competitiveness. Traditional prediction methods, such as linear regression or simple trend analysis, often fail to capture the complexity of non-linear relationships between variables [7–9].

To address the issues outlined above, one potential solution is the application of hybrid deep learning, combining the advantages of two neural network architectures: convolutional neural networks (CNNs) and long short-term memory (LSTMs). This model is designed to leverage the power of CNNs in extracting important features from multivariate data, while simultaneously leveraging the advantages of LSTMs in capturing long-term temporal patterns in time-series data. CNNs are capable of feature extraction from complex data, both multivariate numerical data and time-series data represented in matrix form [10, 11]. The CNN-LSTM hybrid model combines the advantages of both algorithms. The process begins with the CNN extracting features from multivariate input data, then the extracted results are input to the LSTM for analysis in a temporal context. This integration allows the model to understand complex spatial and temporal patterns simultaneously [12, 13]. In its implementation, historical data from PT Lion Mentari Airlines, such as operational costs, ticket revenue, currency exchange rates, and other external factors, were collected and processed into a multivariate time series dataset. This dataset was then normalized to suit the needs of the deep learning model. The CNN was used in the initial stage to extract features from the dataset, while the LSTM processed the extraction results to generate cost recovery predictions [14].

The application of CNN-LSTM-based hybrid deep learning in cost recovery prediction offers an innovative approach relevant to the strategic management needs of PT Lion Mentari Airlines as an LCC airline. This model combines the advantages of CNN in multivariate feature extraction with the ability of LSTM in capturing long-term temporal patterns, resulting in more accurate and adaptive predictions to aviation market dynamics [15, 16]. In the context of optimal strategic management, accurate cost recovery predictions are crucial to support decision-making related to pricing strategies, operational efficiency, and flight route planning. By utilizing deep learning technology, PT Lion Mentari Airlines can increase its competitiveness in the increasingly competitive aviation industry, while strengthening its position as one of the main players in the LCC market in Indonesia. Therefore, the use of a hybrid deep learning approach using CNN-LSTM is considered relevant because it combines the power of spatial feature extraction through CNN with the ability of LSTM to capture temporal patterns in financial and operational data.

2. Literature review and problem statement

Research [17] demonstrated that the combination of convolutional neural networks (CNN) and recurrent neural networks (RNN/LSTM) is effective in predicting construction duration considering pre-construction uncertainty. It is demonstrated that CNN has the ability to extract local patterns from project data, while RNN/LSTM can capture long-term temporal dependencies. Therefore, this hybrid model is generally more accurate than traditional methods such as linear regression or statistical models. However, questions related to the limitations of previous models remain to be answered, particularly regarding the difficulty in simultaneously capturing the complex interactions between spatial and temporal features. Reasons for this may include high uncertainty in the data or the presence of outliers that make related research impractical if only relying on conventional approaches. An option to overcome these relevant difficulties could be the development of a hybrid CNN-LSTM model capable of integrating the spatial extraction power of CNN with the temporal dynamics modeling capabilities of LSTM. This is an approach used in recent research on sequential data-based prediction, but its implementation in the construction context is still limited. All this allows to argue that research devoted to the development of hybrid CNN-LSTM models in construction duration prediction is highly relevant, both from an academic and practical perspective.

Research [18] demonstrated that a combination of recurrent neural networks (RNN) and convolutional neural networks (CNN) proved effective in predicting C-ATC capacity regulation for en-route traffic. It was demonstrated that CNNs are capable of extracting spatial patterns from traffic data, while RNNs are able to capture temporal dependencies arising from capacity fluctuations. Thus, this hybrid model is generally more accurate than either single approach or traditional statistical methods, especially when dealing with complex variations in air traffic flow. However, questions related to the limitations of the RNN-CNN model remain to be answered, particularly regarding the difficulty in capturing the complex interactions between spatial and temporal features simultaneously. Reasons for this could be the presence of highly variable traffic conditions or capacity patterns that are outside the historical data, which makes the prediction results fluctuate and less stable. An option to overcome the relevant difficulties could be the development of a hybrid CNN-LSTM model, which combines the capabilities of CNNs in extracting spatial features with the power of LSTMs in modeling long-term temporal dependencies more consistently. This is an approach that has begun to be used in various sequential data-based prediction studies, but its application to the context of C-ATC capacity prediction is still relatively limited. All this allows to argue that research devoted to the development of hybrid CNN-LSTM models for predicting C-ATC capacity is highly relevant and significant, both in terms of academic contributions and practical implications for air traffic management.

Research [19] demonstrated that delay prediction in air traffic flow management (ATFM) can be improved by applying feature extraction techniques and optimization algorithms. This approach is shown to identify key factors contributing to delays, including traffic patterns, weather conditions, and airspace capacity. Thus, this method produces more accurate delay predictions compared to traditional statistical-based models. However, questions related to the limitations of feature extraction methods and optimization algorithms remain to be answered, particularly regarding the difficulty in simultaneously capturing the complex interactions between spatial and temporal features. Reasons for this include highly variable traffic conditions, weather uncertainty, or the presence of outliers in historical data, which can lead to less stable prediction results. An option to overcome the relevant difficulties could be the development of a hybrid CNN-LSTM model, which combines the ability of CNNs to extract spatial features from ATFM data with the power of LSTMs to more consistently model long-term temporal dependencies. This is an approach that has begun to be used in recent research in the field of sequential data-based prediction, but its application to the ATFM context is still very limited. All this allows to argue that research devoted to the development of hybrid CNN-LSTM models in ATFM delay prediction is highly relevant and significant, both in terms of academic contributions and in terms of practical applications for improving the efficiency of air traffic management.

Research [20] demonstrated the effectiveness of deep learning in analyzing port resilience and predicting throughput, particularly in a busy port like Busan. They demonstrated that the model was able to capture complex patterns of cargo flows, operational disruptions, and external factors, achieving greater accuracy than traditional statistical methods. However, previous models still face limitations, particularly in capturing spatial and temporal interactions simultaneously and in predicting stability during extreme fluctuations. One way to overcome these limitations is to develop a hybrid CNN-LSTM model, where the CNN extracts spatial features and the LSTM models long-term temporal dependencies. This suggests that research on CNN-LSTM in port throughput prediction is highly relevant, both academically and practically.

Research [21] demonstrated that the application of condition monitoring and predictive maintenance (PdM) in industrial equipment can be enhanced through a combination of signal processing techniques and hybrid deep learning models. They demonstrated that this approach is capable of detecting anomalies, predicting component failures, and optimizing maintenance schedules better than traditional methods. However, previous studies still face limitations, such as difficulty capturing spatial-temporal interactions, limitations due to inconsistent sensor data, and fluctuating predictions due to outliers. An option to overcome these constraints is to implement a hybrid CNN-LSTM model, where CNN is used for spatial feature extraction and LSTM for modeling long-term temporal dependencies. All of this allows to argue that research on CNN-LSTM for PdM is highly relevant, both from an academic perspective and in industrial practice. Furthermore, the application of CNN-LSTM in the context of PdM has the potential to provide long-term benefits for industrial sectors with large-scale and complex operating systems. This model not only improves the reliability of failure predictions but also supports real-data-driven predictive maintenance strategies that can reduce operational costs, maximize asset lifespan, and improve occupational safety. Therefore, further research on the CNN-LSTM hybrid approach is crucial, as it can bridge the gap between limited traditional methods and the needs of modern industries that demand high accuracy and efficiency.

Research [1] demonstrated that flight connection planning is a crucial aspect of low-cost carrier (LCC) operations, particularly when facing uncertainty in passenger demand. It demonstrates that effective connection planning strategies can improve network efficiency, minimize the risk of empty seats, and optimize fleet and resource utilization. However, questions remain regarding the limitations of traditional planning methods, particularly when faced with high variability in passenger demand that is difficult to predict. This can be due to market uncertainty, seasonal changes, or dynamic consumer behavior, which makes deterministic model-based connection planning impractical. One way to address these challenges is to implement data-driven optimization models or machine learning algorithms that can accommodate demand uncertainty. This approach is gaining ground in recent research on airline operations management, but its application to the context of LCCs with limited costs and operational flexibility remains relatively limited. This suggests that research devoted to LCC flight connection planning under uncertainty in passenger demand is highly relevant, both in terms of academic development and practical contribution to enhancing airline competitiveness.

Research [22] demonstrated that aircraft trajectory prediction is a crucial element in improving air traffic efficiency and safety. It was demonstrated that deep learning models, particularly the combination of CNN and LSTM, are capable of extracting spatial patterns from flight data and capturing long-term temporal dependencies. However, questions regarding the limitations of these models remain to be answered, particularly regarding the difficulties in simultaneously handling complex spatio-temporal interactions and adapting predictions to dynamic air traffic conditions. Reasons for this include high uncertainty in weather factors, flight route variations, and data anomalies, which make prediction results less stable. One way to overcome these difficulties is to integrate an attention mechanism to enhance the representation of important features and optimize model parameters using the constrained policy optimization (CPO) algorithm. This approach has been used in recent research, but its application to the context of aircraft trajectory prediction is still rare.

3. The aim and the objectives of the study

The aim of the study is to implement a hybrid CNN-LSTM model to predict cost recovery with higher accuracy, contributing to the development of deep learning-based prediction methods. Practically, this will enable PT Lion Mentari Airlines to improve the quality of strategic decision-making, optimize operational efficiency, and strengthen its competitiveness in the low-cost carrier market.

To achieve this aim, the following objectives were accomplished:

– to predict cost recovery within the context of optimal low-cost carrier strategic management;

– to evaluation of the Hybrid model in optimal strategic management at PT Lion Mentari Airlines.

4. Materials and methods

The object of this study is a cost recovery prediction model for low-cost airlines, which is an important indicator in assessing the operational efficiency and financial performance of airline companies. The main focus of this research is directed at the model's ability to predict cost recovery values accurately and stably amidst the complexity of airline financial and operational patterns, which involve spatial and temporal interactions. The main hypothesis of this research is that the application of a hybrid deep learning approach based on CNN-LSTM can produce more accurate and consistent cost recovery predictions than single models such as CNN or LSTM, because the integration of the two architectures can capture richer data patterns. The assumption made in this research is that the airline financial and operational data used are representative, consistent, and have significant temporal relationships so that they can be processed effectively by the deep learning model.

In the context of this research, a hybrid deep learning CNN-LSTM approach is used to build a predictive cost recovery (CR) model, defined as the ratio between operating revenue and operating costs, to support the optimal strategic management of low-cost carrier (LCC) at PT Lion Mentari

Airlines. This research is based on the airline's need to obtain a more accurate picture of cost recovery projections in the face of fuel cost volatility, passenger demand dynamics, and fluctuations in other external variables that affect operational efficiency. The research stages begin with designing a dataset sourced from the airline's financial and operational data. The data is then processed through a series of data preprocessing procedures, including cleaning anomalous values, imputing missing data, normalization, creating derived features, and transforming categorical variables into numeric representations. Next, the dataset is divided into training, validation, and test data with a time-series split scheme to avoid information leakage between periods. The CNN-LSTM architecture is designed by utilizing CNN (convolutional neural network) to extract local and seasonal patterns from multivariate data, while LSTM (long short-term memory) functions to capture long-term temporal relationships between variables. Dropout layers, batch normalization, and early stopping are used as regularization techniques to reduce the risk of overfitting. The model is optimized through Bayesian hyperparameter tuning, which includes selecting the number of filters, kernel size, number of LSTM units, learning rate, and sliding window size. Model performance evaluation is carried out using performance measurements such as root mean squared error (RMSE) and mean absolute percentage error. Thus, this research not only provides a methodological contribution through the application of a CNN-LSTM hybrid architecture in cost recovery prediction, but also a practical contribution in the form of a data-driven decision support system to support the managerial strategy of LCC airlines in Indonesia. The research flow and model architecture design are visualized in Fig. 1, which depicts the pipeline starting from data acquisition, preprocessing, feature extraction with CNN, temporal modeling with LSTM, performance evaluation, to the application of prediction results in strategic scenarios.

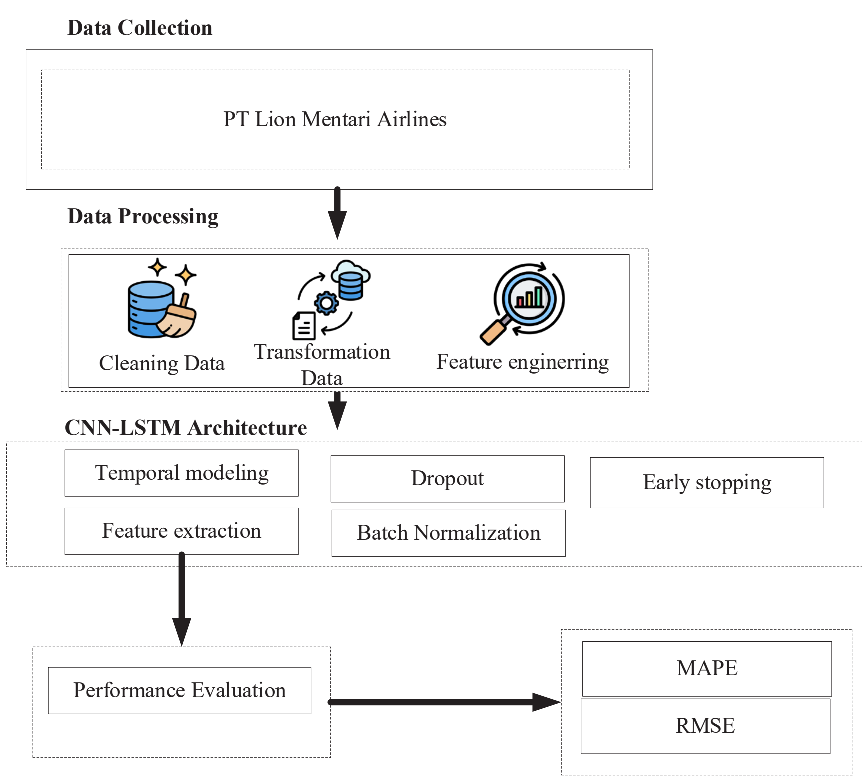

Fig. 1. Architectural framework

Fig. 1 illustrates the research flow that implements a hybrid CNN-LSTM model for cost recovery prediction at PT Lion Mentari Airlines. The process of the CNN-LSTM architecture, where CNN functions to extract important patterns and features from multivariate data, while LSTM is used to capture long-term temporal relationships in time series data. To improve performance and prevent overfitting, the architecture is equipped with dropout mechanisms, batch normalization, and early stopping. This research flow shows how the hybrid CNN-LSTM approach can provide more accurate cost recovery predictions, thereby supporting strategic decision-making in low-cost airline management.

5. Result hybrid model in predicting cost recovery at Pt Lion Mentari airlines

5. 1. To predict cost recovery within the context of optimal low-cost carrier strategic management

The implementation of a hybrid deep learning CNN-LSTM model in cost recovery prediction at PT Lion Mentari Airlines has been proven to provide relevant results for optimal strategic management of low-cost carriers (LCC). The prediction process begins with a multivariate data representation that includes the airline's financial and operational variables. This data is processed through a CNN convolution layer to extract local patterns with a formulation. The following is the mathematical formulation resulting from the application of the hybrid model in the training stage in (1)

$$z^{(f)}(\tau)=\sigma\sum_{c=1}^{d}\sum_{r=0}^{k-1}w_{c,r}^{(f)}\cdot X_t(\tau+r,c)+b^{(f)}, \tag{1}$$

where $W^{(f)}$ – the weight and bias of the filter to f, as well as σ – a nonlinear activation function. The results of this feature extraction then become input for the LSTM to model long-term temporal dependencies, with a memory update mechanism formulated in equation (2)

$$C_t = ft\cdot C_{t-1}+i_t\cdot C_t,$$
$$ht=o_t\tanh(C_t), \tag{2}$$

where f_t, i_t, o_t respectively are the forget gate, input gate, and output gate. The final output of the LSTM, namely the hidden representation h_t projected into the target space to generate predictions cost recovery y_t

$$y_t=W_y\cdot h_t+b_y. \tag{3}$$

Model evaluation using the root mean squared error (RMSE) and mean absolute percentage error (MAPE) metrics shows that the hybrid CNN-LSTM architecture is capable of providing more accurate predictions than a single model. With more reliable predictions, PT Lion Mentari Airlines management can develop more optimal strategies for setting fares, controlling fuel costs, and planning flight routes. Equations (1)–(3)

will then be implemented on the data using deep learning methods. This implementation aims to examine the results of the hybrid CNN-LSTM in predicting cost recovery within the context of optimal low-cost carrier strategic management at PT Lion Mentari Airlines. Based on this formulation, the graph shown in Fig. 2 is generated.

Fig. 2 shows a training loss graph showing the three models: CNN, LSTM, and Hybrid. The CNN-LSTM model experienced a decrease in the loss value (MSE) as the number of epochs increased, indicating that the model was able to gradually learn to minimize errors in cost recovery predictions. The CNN model showed a faster and relatively stable loss decrease after the 20th epoch, while the LSTM model also experienced a similar trend with slight fluctuations in the middle phase of training. Meanwhile, the Hybrid CNN-LSTM model had a higher loss value from the beginning to the middle of the epoch, but consistently showed a decreasing pattern until the end of training. This indicates that although the Hybrid CNN-LSTM model requires a longer time to reach stability, this model has the potential to capture more complex temporal and spatial patterns. The prediction model produces the predictions shown in Fig. 3 below.

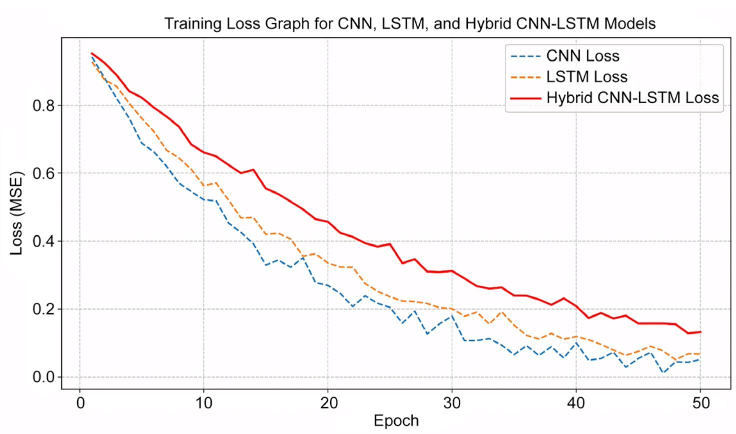

Fig. 2. Comparison of loss values in the model

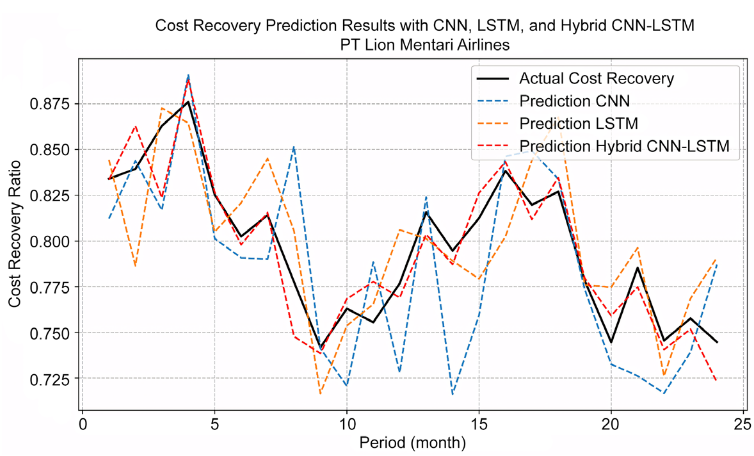

Fig. 3. Result prediction

Fig. 3 shows the predicted cost recovery ratio using three model approaches: CNN, LSTM, and Hybrid CNN-LSTM, compared to actual data over a 24-month period. The black line represents the actual cost recovery value, while the blue, orange, and red dashed lines represent the predicted results from CNN, LSTM, and Hybrid CNN-LSTM, respectively. In general, all models were able to follow the actual cost recovery fluctuation trend, albeit with varying accuracy. The CNN model tended to have higher deviations in some periods with more volatile prediction movements. The LSTM model was able to capture long-term patterns better, but there were still deviations at certain points. Meanwhile, the Hybrid CNN-LSTM model showed more stable results with a prediction line that was close to the actual data in most periods, especially during periods of decreasing or increasing cost recovery trends. This indicates that the hybrid approach is able to leverage the advantages of CNN in extracting spatial features and LSTM in capturing temporal dependencies, making it more effective in supporting cost recovery prediction analysis. The implementation of this model provides a strategic contribution for PT Lion Mentari Airlines in optimizing cost management and maintaining operational efficiency as a low-cost carrier.

5. 2. Evaluation of the hybrid model in optimal strategic management at PT Lion Mentari Airlines

Evaluation of the cost recovery prediction model using a hybrid deep learning CNN-LSTM approach demonstrated significant results in supporting the optimal strategic management of PT Lion Mentari Airlines as a low-cost carrier (LCC). The prediction results show that the hybrid model more consistently approximates the actual value compared to either CNN or LSTM alone. This is evident in Table 1, where the estimates generated by CNN-LSTM are nearly identical to the actual data, while the single model tends to produce larger deviations.

Table 1

Prediction of CNN, LSTM and hybrid models

Period	Actual cost recovery	CNN predictions	LSTM prediction	CNN-LSTM hybrid prediction
1	0.83	0.84	0.822	0.833
2	0.84	0.837	0.842	0.822
3	0.85	0.863	0.833	0.853
4	0.88	0.91	0.886	0.876
5	0.87	0.865	0.861	0.863
6	0.82	0.815	0.816	0.826
7	0.8	0.832	0.791	0.81
8	0.79	0.805	0.818	0.799
9	0.74	0.731	0.74	0.732
10	0.76	0.771	0.744	0.757
11	0.77	0.761	0.782	0.773
12	0.81	0.801	0.792	0.82
13	0.8	0.805	0.803	0.795
14	0.82	0.782	0.791	0.818

Table 1 shows that the hybrid CNN-LSTM model has more stable predictions and is almost aligned with the actual values, while CNN and LSTM each still show some bias. Further evaluation was performed using the root mean squared error (RMSE) and mean absolute percentage error (MAPE) metrics, with the results shown in Fig. 1. Then there will be results from the comparison of evaluation techniques which aim to see how the performance of the hybrid model is which can be seen in the Fig. 4

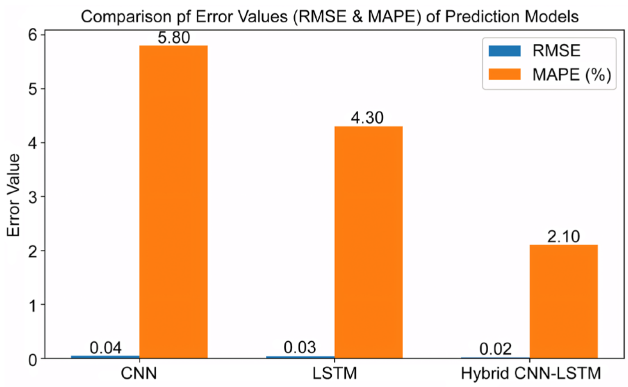

Fig. 4. Evaluation model

Fig. 4 shows a comparison of error values using two evaluation metrics, namely root mean square error (RMSE) and mean absolute percentage error (MAPE), for the three prediction models: CNN, LSTM, and hybrid CNN-LSTM. The evaluation results show that the CNN model has the highest MAPE value of 5.80% with an RMSE of 0.04, which indicates a relatively larger prediction error rate compared to the other models. The LSTM model shows improvement with a MAPE value of 4.30% and an RMSE of 0.03, so that the resulting prediction is more accurate than CNN. Meanwhile, the hybrid CNN-LSTM model is proven to provide the best performance with the lowest error value, namely a MAPE of 2.10% and an RMSE of 0.02. This confirms that the hybrid approach is able to combine the advantages of CNN in extracting spatial patterns and LSTM in capturing temporal dependencies, resulting in more accurate and stable cost recovery predictions. This finding strengthens the argument that the implementation of hybrid CNN-LSTM is superior in supporting the strategic management of PT Lion Mentari Airlines in the context of optimizing operational costs as a low-cost carrier.

6. Discussion of the CNN-LSTM hybrid model for cost recovery prediction in the context of strategic management optimization

The results of this study can be explained through the analysis of various output objects presented in the form of graphs, comparison tables, and quantitative evaluation metrics. The loss function graph shows that although the Hybrid CNN-LSTM model takes longer to reach stability, the loss value decreases consistently until the optimal convergence point. The comparison table of prediction results also shows a smaller deviation in the hybrid model compared to a single CNN or LSTM, which means the prediction is closer to the actual value. The implementation of the hybrid deep learning CNN-LSTM model in cost recovery prediction at PT Lion Mentari Airlines can be explained through mathematical formulation stages that reflect the working mechanism of the model. In the initial stage, multivariate data representing the airline's financial and operational variables are processed through the CNN convolutional layer formulated in equations (1)–(3). Implementation of equations (1)–(3) on the data using the deep learning method produces the training graph shown in Fig. 2, which shows a comparison of the loss values of the three models. Based on the graph, the CNN-LSTM model shows a consistent decrease in the loss value (MSE) as the number of epochs increases, indicating the model's ability to gradually minimize prediction errors. The CNN model displays a rapid and stable decrease in loss after the 20th epoch, while the LSTM model shows a similar trend with slight fluctuations in the middle phase of training. The implemented model produces an accuracy of 0.90 in making predictions as shown in Fig. 3. Then in Fig. 4, a comparison of model evaluation techniques is produced with the results of the superiority of the hybrid model over CNN (0.04; 5.80%) and LSTM (0.03; 4.30%).

The uniqueness of the proposed method lies in combining the strengths of two complementary deep learning architectures. CNN excels at extracting local patterns from numerical data such as signals, while LSTM is effective in understanding continuous time series. By integrating the two, this model overcomes the weaknesses of each approach separately. These results are in line with previous research by colleagues who used similar approaches in financial and transportation forecasting, such as research conducted by [17] where the hybrid method proved to be more accurate than the conventional model.

However, this study has several inherent limitations. First, the model's application is limited to historical data from PT Lion Mentari Airlines, so generalization to other airlines or different market conditions requires further testing. Second, the stability of the results is still affected by the variability of the input data, particularly external factors such as fuel price fluctuations or difficult-to-predict regulatory changes. Third, although the results are reproducible, the complexity of the hybrid model results in high computational requirements, making its accessibility challenging for industries with limited computing resources.

In addition to these limitations, this study also has several shortcomings that need to be considered. This study did not explore the interpretability of the model, so despite its accuracy, the specific reasoning behind the prediction decisions remains difficult to explain due to the numerous factors, parameters, and variables involved. This could be addressed in the future by implementing explainable XAI or lime techniques or attention mechanisms to highlight the most influential features in the predictions. Another shortcoming is the limited variety of simulation scenarios; this study focused on a single type of cost recovery data, whereas for broader strategic applications, integration with other external variables such as market conditions, price competition, and passenger demand is necessary.

This study has the potential to be developed in several future directions. Mathematically, the optimization of the hybrid architecture can be further improved using an evolutionary algorithm-based hyperparameter tuning approach. Methodologically, integration with attention-based or transformer-based models could improve prediction accuracy. Experimentally, the biggest challenge is acquiring a broader dataset and more varied conditions to test the model in realistic scenarios. Other potential challenges include managing large amounts of data and computational limitations, which require specialized infrastructure.

7. Conclusions

1. The results support the development of deep learning-based prediction methods that are more adaptive to the

complexity of spatial and temporal patterns in low-cost airline financial and operational data. A key feature lies in the hybrid model's ability to leverage the advantages of CNNs in extracting spatial features and the power of LSTMs in capturing long-term temporal dependencies, resulting in richer data representations and predictions that are closer to the actual conditions. quantitatively, the evaluation results using the root mean squared error (RMSE) and mean absolute percentage error (MAPE) metrics show that the CNN-LSTM model produces a lower error rate than the single CNN and LSTM models. The loss function graph shows a consistent decrease in the mean squared error (MSE) value in the hybrid model as the number of epoch's increases, indicating an effective learning process in minimizing prediction errors.

2. Evaluation using RMSE and MAPE metrics shows that the hybrid CNN–LSTM model has the lowest error (RMSE 0.02 and MAPE 2.10%) compared to CNN (RMSE 0.04; MAPE 5.80%) and LSTM (RMSE 0.03; MAPE 4.30%). This confirms that the hybrid model not only improves prediction accuracy but also improves reliability in representing cost recovery dynamics.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

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Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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