Dual Optimization: Integrating Weighted Fuzzy Time Series Lagrange Quadratic Programming using Differential Evolution Algorithm

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*Abstract*— The maritime sector, especially port infrastructure, plays a pivotal role in both local and global cargo transportation.This research focuses on applying Lagrange Quadratic Programming and the Differential Evolution Algorithm to enhance cargo handling predictions for PT Samudera Indonesia. The choice of this key player in maritime logistics aims to improve operational efficiency and contribute insights to the broader industry. By utilizing secondary data from PT Samudera Indonesia spanning the January to November 2023, this research seeks to provide a comprehensive understanding of the performance trends in unloading and loading operationsComparison between Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its Differential Evolution-enhanced variant (WFTS-LQP-DE) reveals superior accuracy for WFTS-LQP-DE across Loading, Unloading, and Capacity with lower MAPE. Specifically, WFTS-LQP-DE outperforms in Loading (9.63% vs. 10.99%), Unloading (9.04% vs. 9.13%), and substantially in Capacity (4.40% vs. 7.27%). This consistently demonstrates the heightened forecasting precision of WFTS-LQP-DE.The recommended strategies encompass flexible loading schedules, optimized unloading, proactive capacity planning, and continuous model evaluation. Implementing these strategies, especially relying on WFTS-LQP-DE, enhances resource planning accuracy, operational efficiency, and adaptability to market changes, ensuring a robust framework for strategic decision-making. Regular monitoring and refinement sustain forecasting accuracy.

Keyword: Forecasting, Lagrange Quadratic Programming, Differential Evolution Algorithm

# Introduction

Indonesia, recognized as the largest archipelagic nation globally, consists of almost 66% of its landmass as maritime regions. Geographically, Indonesia occupies a pivotal position, situated between two continents and two oceans. This strategic location designates it as a vital maritime pathway for about 70% of the transportation of goods connecting Europe, the Middle East, South Asia, and the Pacific region (Lauder & Lauder, 2016). This emphasizes the substantial contribution of the maritime transportation sector, with a specific focus on the port infrastructure, in streamlining both local island-to-island and global shipping for both goods and passengers.

Maritime logistics and cargo handling play a pivotal role in global trade, ensuring the efficient movement of goods across the seas (Fratila et al., 2021). As the demand for transportation services continues to escalate, the need for accurate forecasting tools becomes increasingly critical for companies operating in the maritime industry. PT Samudera Indonesia, a prominent player in this sector, faces the challenge of optimizing its cargo handling operations amidst the complexities of fluctuating demand, unpredictable market trends, and evolving industry dynamics.

The maritime industry is inherently dynamic, influenced by a myriad of factors such as economic conditions, geopolitical events, and advancements in technology (Hartanto et al., 2019). Effective planning and management of cargo handling operations require precise forecasting models that can adapt to these ever-changing variables. Traditional forecasting methods may fall short in capturing the intricate patterns and nuances inherent in maritime logistics, necessitating the exploration of innovative techniques (Li & Yu, 2023).

Recognizing the limitations of existing approaches, this research addresses the need for a sophisticated time series forecasting methodology. The study focuses on the application of Lagrange Quadratic Programming in conjunction with the Differential Evolution Algorithm, aiming to enhance the accuracy and reliability of cargo handling predictions. By utilizing secondary data from PT Samudera Indonesia spanning the January to November 2023, this research seeks to provide a comprehensive understanding of the performance trends in unloading and loading operations.

The choice of PT Samudera Indonesia as the focal company stems from its significance in the maritime logistics landscape. As a leading player with an extensive network and diverse portfolio of services, the company's operational efficiency directly impacts the broader maritime supply chain (Abbasi & Varga, 2022). Consequently, improving the forecasting accuracy of cargo handling operations for PT Samudera Indonesia not only contributes to its operational excellence but also has broader implications for the overall efficiency of maritime logistics in the region.

The 11-month outlook allows for a holistic assessment of performance trends, offering insights into the long-term patterns and potential challenges that may arise. The application of Lagrange Quadratic Programming and the Differential Evolution Algorithm presents a unique and innovative approach, providing an opportunity to explore forecasting techniques beyond traditional methodologies.

In summary, this research aims to address the challenges faced by PT Samudera Indonesia in optimizing its cargo handling operations by introducing a cutting-edge time series forecasting methodology. By delving into the intricacies of maritime logistics and leveraging advanced algorithms, this study seeks to contribute valuable insights that can inform decision-making processes not only for PT Samudera Indonesia but also for the broader maritime industry navigating the complexities of the global trade landscape.

# weighted fuzzy time series

## Algorithm of Weighted Fuzzy Time Series

The algorithm applied in the Weighted Fuzzy Time Series method differs at the defuzzification stage compared to the Fuzzy Time Series (FTS) method. Here is the resulting algorithm (Rahmawan *et al.*, 2019).

Step 1: Define universe of discourse

Step 2: Forming intervals from the universe of discourse by adopting a uniform class division

Step 3: Identifying fuzzy sets in the universe of discourse, referred to as U.

Step 4: Define the fuzzy logic relations.

Step 5: Create a set of fuzzy logic relationships

Step 6: Perform defuzzification by establishing weights for denoted as :

|  |  |
| --- | --- |
|  | (1) |

Where , and for and . Next, the matrix transformation is performed as follows:

|  |  |
| --- | --- |
|  | (2) |

Step 7: Calculating the forecast value can be accomplished by employing a weighting model. In this model, the final forecast value is obtained through the multiplication of the defuzzification matrix result and the weighting matrix using the equation:

|  |  |
| --- | --- |
|  | (3) |

## Algorithm of Weighted Fuzzy Time Series Lagrange Quadratic Programming

The prediction procedure utilizes the Weighted Fuzzy Time Series algorithm, where the method incorporates weights as forecast predictors. These weights are derived through the Lagrange multiplier mathematical formula. The algorithm for the formation of the Weighted Fuzzy Time Series using Lagrange quadratic programming is presented as follows (Rozy *et al.*, 2023):

Step 1: Define universe of discourse :

|  |  |
| --- | --- |
|  | (4) |

Step 2: Creating divisions into multiple intervals of equal length is achieved through the application of the Sturges formula. (Devianto et al., 2022):

|  |  |
| --- | --- |
|  | (5) |

Step 3: Defining fuzzy sets in the universe of discourse 𝑈 is:

|  |  |
| --- | --- |
|  | (6) |

Step 4: Determining the fuzzy relationship of historical data through Fuzzy Logical Relationship (FLR), where two consecutive fuzzy sets and are defined to form the first FLR as → . can be referred to as Left Hand Sides (LHS), and as Right Hand Side (RHS), with .

Step 5:Estimating weight based method of Lagrange multipliers which is a widely recognized technique utilized to solve constrained optimization problems (Vadlamani et al., 2020). It involves finding the optimal point (denoted as ) in multidimensional space that locally optimizes the merit function while satisfying the constraint :

|  |  |
| --- | --- |
|  | (7) |

The equation above is subsequently derived based on the objective function, denoted as , the constraint function, denoted as g, and the Lagrange multiplier λ. This process results in:

|  |  |
| --- | --- |
| ,with | (8) |

Step 6: Perform defuzzification process by transform linguistic variable into real number using:

|  |  |
| --- | --- |
|  | (9) |

Step 7: Calculating the forecasting value is done by adding a differencing process between the actual data and the midpoint values formed in each interval class (Surono et al., 2022):

|  |  |
| --- | --- |
|  | (10) |

# dual optimization weighted fuzzy time series

## Algorithm of Differensial Evolution

In the explanation in the previous subsection, it can be observed that the optimization process of forecasting in the Weighted Fuzzy Time Series algorithm using the Lagrange equation still has drawbacks. These drawbacks are related to the complexity of the calculations and the considerable time required for the generated solutions to evaluate large datasets. Therefore, there is a need for efficiency in this method through the addition of a differential evolution algorithm based on the obtained Mean Squared Error (MSE) values.

Based on the research conducted by Rozy et al. (2023), the optimization of forecast outcomes obtained from the Weighted Fuzzy Time Series Markov Chain is achieved by minimizing the Mean Squared Error (MSE) values. This enhancement in forecasting accuracy is demonstrated in the algorithm as follows:

Step 1: Initiating the process by generating random numbers for each parameter from vector at iteration , assuming an initial condition , resulting in the equation:

|  |  |
| --- | --- |
|  | (11) |

The above random number is generated based on a uniform distribution within the range , where .

Step 2: The subsequent step involves mutating and recombining the initial population into a new population. The equation formulated for the mutant vector is as follows:

|  |  |
| --- | --- |
|  | (12) |

Step 3: Building a crossover by forming a test vector from replicated parameter values based on two different vectors. The equation formed from the test vector is:

|  |  |
| --- | --- |
|  | (13) |

Step 4: Performing selection in two stages, namely parent selection and survivor selection. Parent selection is done by choosing vectors with the best function values and high selection probabilities, while survivor selection is done by replication.

Step 5: After going through the stages explained earlier, the iteration stops upon reaching the optimal condition.

## Model Evaluation

Model evaluation is essential to determine the accuracy level of the predictions made. This process involves calculating MAPE. MAPE is computed by dividing the overall absolute errors for each period by the corresponding actual observation values. Afterward, the mean percentage of these absolute errors is calculated (Junianto, 2017). This methodology becomes particularly valuable when the magnitude or scale of the predicted variable plays a crucial role in assessing forecast accuracy. MAPE provides an indication of how much the forecast errors deviate from the actual values in the series. The formula for calculating MAPE is as follows:

|  |  |
| --- | --- |
|  | (14) |

# Result and discussion

In the following section, the prediction process is carried out using the Lagrange Quadratic Programming weighted fuzzy time series method. The results of these calculations aim to determine the ship's capacity for the next 10 years. Subsequently, the process involves forming adjustments based on the Mean Squared Error (MSE) values using the Differential Evolution algorithm. The obtained results are then evaluated using MAPE to ascertain the improvement in accuracy that occurs after the adjustment with the Differential Evolution algorithm.

## Descriptif Analyze

Statistik deskriptif is a statistical method designed to organize and analyze data and figures with the aim of providing a systematic, concise, and clear overview of a particular phenomenon, event, or condition (Sholikhah, 2016). The descriptive statistics for the collected actual data are as follows:

table I. Statistic descriptive

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **n** | **mean** | **sd** | **median** | **min** | **max** | **se** |
| **Loading** | 11 | 13568 | 1853 | 14486 | 9998 | 15685 | 559 |
| **Unloading** | 11 | 13326 | 1590 | 13722 | 10234 | 14925 | 479 |
| **Capacity** | 11 | 27011 | 3451 | 28845 | 20232 | 30439 | 1041 |

The descriptive statistics table I presents a comprehensive overview of three key variables: Loading, Unloading, and Capacity. For the Loading variable, comprising 11 observations, the average value stands at 13,568 with a standard deviation of 1,853, suggesting a moderate level of variability around the mean. The median, a robust measure less influenced by outliers, is 14,486, and the data range spans from 9,998 to 15,685. The standard error of the mean is 559, indicating the precision of the sample mean as an estimate of the population mean. Similarly, the Unloading variable, based on the same 11 observations, exhibits a mean of 13,326 and a standard deviation of 1,590. The median and range are 13,722 and 10,234 to 14,925, respectively. The standard error of the mean is 479. These metrics collectively convey the central tendency and variability within the Unloading data.For the Capacity variable, with 11 observations as well, the mean is 27,011, and the standard deviation is 3,451. The median, a robust measure, is 28,845, while the range extends from 20,232 to 30,439. The standard error of the mean is 1,041. These statistics provide a comprehensive overview of each variable's central tendency, variability, and overall distribution. The mean serves as an average measure, the standard deviation reflects the dispersion of values around the mean, and the median represents the middle value. Additionally, the range gives insights into the spread of values between the minimum and maximum observations. Understanding these descriptive statistics is crucial for interpreting and contextualizing the dataset's characteristics. The time series data collected based on observations from 2011 to 2022 is visualized to understand the pattern of changes from year to year.

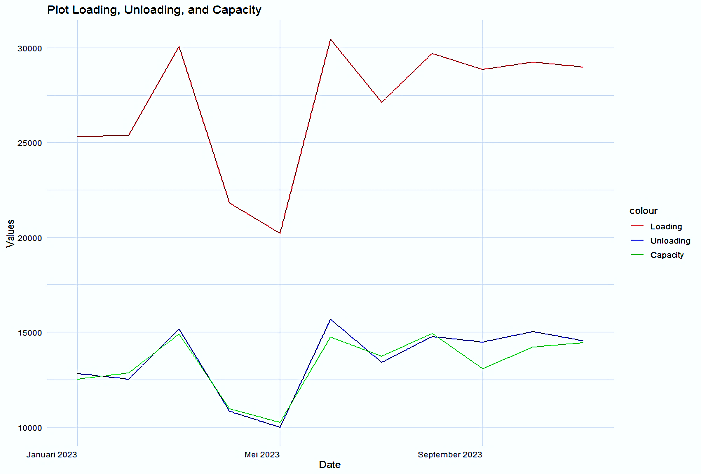


FIGURE 1. plot actual data

The figure illustrating Loading, Unloading, and Capacity trends from January to November 2023 offers valuable insights into the operational dynamics of the system. Loading exhibits a fluctuating pattern throughout the observed period, reaching its peak at 15,685 units in June 2023, while experiencing a trough of 9,998 units in May 2023. Noteworthy spikes in March and June suggest intensified loading activities during these months.

In parallel, Unloading follows a distinctive trajectory, reaching its maximum of 14,754 units in June 2023. Although Unloading generally aligns with Loading trends, indicating a parallel operational pattern, its unique variations underscore the nuanced nature of unloading activities.

The representation of Capacity, depicting the system's maximum operational limit, remains relatively stable. However, a dip in April 2023 corresponds with lower Loading and Unloading values during that period. The system approaches its maximum limit in June 2023, emphasizing the need for careful monitoring to ensure optimal performance during periods of heightened activity.

Monthly changes in Loading, Unloading, and Capacity highlight the dynamic nature of the operational environment. Notable shifts in November 2023 prompt further investigation, warranting attention to potential operational changes or external factors influencing the system.

Inter-variable relationships reveal strong correlations between Loading and Unloading, indicating a close operational connection between these two activities. The consistent relationship between Loading and Capacity underscores effective capacity utilization during periods of increased loading.

Overall, the figure underscores the interconnectedness of operational variables, offering insights into periods of heightened activity, potential capacity constraints, and strategic considerations for optimizing system performance. Further analysis and ongoing monitoring of these trends are crucial for informed decision-making and maintaining operational efficiency.

## Prediction Weighted Fuzzy Time Series Lagrange Quadaratic Programming

The investigation into prediction methodologies stands as a pivotal element in the realm of data analysis and forecasting. Within this context, we explore the complexities of the Prediction Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTSLQP), an advanced approach that amalgamates fuzzy time series principles with Lagrange Quadratic Programming to augment predictive capabilities. Unlike traditional methods, this technique goes beyond merely considering historical patterns; it incorporates the weighted influence of crucial factors, resulting in a more nuanced and precise prediction model. As for the algorithmic calculations performed:

1. Calculate Universe of Discourse using equation 4 to obtain values in the following table:

table II. universe of discourse

|  |  |  |
| --- | --- | --- |
| U | Min | Max |
| U Loading | 9998 | 15685 |
| U Unloading | 10234 | 14925 |
| U Capacity | 20232 | 30439 |

Table II outlines the Universe of Discourse, defining the permissible ranges for three pivotal variables: Loading (U Loading), Unloading (U Unloading), and Capacity (U Capacity). Within the Loading variable, values fluctuate between a minimum of 9,998 units and a maximum of 15,685 units, establishing the operational boundaries for loading activities. The Unloading variable, on the other hand, spans from a minimum of 10,234 units to a maximum of 14,925 units, delineating the acceptable limits for unloading within the system. Lastly, the Capacity variable exhibits a universe extending from 20,232 units as the minimum to 30,439 units as the maximum, encapsulating the operational capacity of the system. This comprehensive depiction of the Universe of Discourse provides a foundational understanding of the expected ranges for each variable, enabling a contextual interpretation of observed values in relation to operational limits.

2.Fuzzyfication Procces:

The fuzzification process involves transforming real numbers within linguistic variables, where the variables are placed within predetermined class intervals using the Sturgess formula. The results are then presented as follows:

table III. Fuzzyfication

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Fuzzyfication of Loading** | **Fuzzyfication of Unloading** | **Fuzzyfication of Capacity** |
| January 2023 | A2 | A2 | A2 |
| February 2023 | A2 | A2 | A2 |
| March 2023 | A3 | A3 | A3 |
| April 2023 | A1 | A1 | A1 |
| May 2023 | A1 | A1 | A1 |
| June 2023 | A3 | A3 | A3 |
| July 2023 | A2 | A3 | A3 |
| August 2023 | A3 | A3 | A3 |
| September 2023 | A3 | A2 | A3 |
| October 2023 | A3 | A3 | A3 |
| November 2023 | A3 | A3 | A3 |

Table III outlines the results of fuzzyfication for the variables Loading, Unloading, and Capacity across the months from January to November 2023. Fuzzyfication is a process of assigning linguistic terms to numerical values, providing a qualitative representation of the data.

In terms of Loading, the fuzzyfication results reveal a nuanced pattern. Loading is categorized into three levels denoted as A1, A2, and A3. In the initial two months, January and February 2023, Loading falls under the A2 category, indicating a moderate level. However, a shift to A3 occurs in March and June 2023, reflecting a high level of loading activity. Subsequently, from April to November 2023, Loading consistently maintains an A3 categorization, implying sustained high loading levels during these months.

Similarly, Unloading undergoes fuzzyfication with categories A2 and A3. Notably, there is a transition from A2 to A3 in July 2023, suggesting an escalation in unloading activity. From August to November 2023, Unloading consistently falls into the A3 category, indicating a sustained high level of unloading. The fuzzyfication of Capacity also follows a distinct pattern. Throughout the observed months, Capacity consistently belongs to the A3 category, suggesting a sustained high level of utilization.

In summary, the fuzzyfication results offer linguistic terms (A1, A2, A3) to convey the qualitative levels of Loading, Unloading, and Capacity each month. These categories facilitate a more intuitive understanding of the magnitude and trends of these variables during the specified period.3.Classification Data From Fuzzyfycation.

In the ever-evolving field of data analysis, the search for efficient approaches to interpret and organize information has given rise to inventive methodologies. One notable paradigm that has come to the forefront is fuzzyfication, a method introducing a degree of vagueness and adaptability into the typically well-defined confines of data classification. Classification is grounded in the transformation of actual data into linguistic variables grouped as follows:

table IV. Membership Classification

|  |  |  |  |
| --- | --- | --- | --- |
| **Fuzzyfication** | **Membership Count** | | |
| **Loading** | **Unloading** | **Capacity** |
| A1 | 2 | 2 | 2 |
| A2 | 3 | 3 | 2 |
| A3 | 6 | 6 | 7 |

From the given information, it can be concluded that each fuzzy set (A1, A2, A3) has different membership values for each linguistic variable (Loading, Unloading, Capacity). These values reflect the extent to which data or conditions meet the characteristics of each linguistic variable in the context of fuzzy logic or fuzzy systems.

In the context of determining weights for the Lagrange equation, these membership values can serve as the basis for assigning weights to each variable in the equation. The Lagrange equation is used to find the maximum or minimum value of a function under certain constraints. In this case, the membership values from the fuzzy sets can play a role as weights or contributions from each variable to the objective function or existing constraints.

For example, if you have an objective function to be optimized or constraints to be met, the weights determined by these membership values can be used to give different emphasis or significance to each variable in the context of solving the Lagrange equation.

4. Estimation Weighted using Lagrange Quadratic Programming

The process of weight estimation using the Lagrange equation is carried out by examining the sum of members in each class, which is then solved through partial derivatives. The solution applied is as follows:

a. Loading

b. Unloading

c. Capacity

Based on the three equations above, the obtained value of defuzzification is as follows:

table V. Defuzzyfication Value

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable**  **Linguistic** | **Loading** | **Unloading** | **Capacity** |
| **A1** | 10398 | 10598 | 20988 |
| **A2** | 12902 | 12809 | 25344 |
| **A3** | 14936 | 14478 | 29165 |

The defuzzification result above is obtained by multiplying the previously estimated weights with the membership values of each interval class. This process can then be used as a reference to obtain prediction values as follows

table VI. Result forecasting weighted fuzzy time series lagrange quadratic programming

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Forecast**  **Loading** | **Forecast Unloading** | **Forecast Capacity** |
| December 2023 | 15124 | 14180 | 28913 |
| January 2024 | 14636 | 14409 | 28654 |
| February 2024 | 15124 | 14180 | 28913 |
| March 2024 | 15124 | 14180 | 28913 |
| April 2024 | 11346 | 11380 | 22689 |
| May 2024 | 13988 | 13867 | 27464 |
| June 2024 | 12332 | 14899 | 30769 |
| July 2024 | 14906 | 13696 | 28211 |
| August 2024 | 15187 | 12313 | 29058 |
| September 2024 | 14636 | 14409 | 28654 |
| October 2024 | 15124 | 14180 | 28913 |

Table VI provides a comprehensive forecast of Loading, Unloading, and Capacity across the months from December 2023 to October 2024. The anticipated trends for each variable unveil distinctive patterns. Loading exhibits a dynamic trajectory, commencing at 15124 units in December 2023 and undergoing fluctuations throughout the forecasted period. The forecast reaches its lowest point at 11346 units in April 2024, followed by a gradual increase to 15187 units in August 2024.

Similarly, Unloading follows a fluctuating pattern, starting at 14180 units in December 2023 and reaching its peak at 14899 units in June 2024. Notably, there is a decline in the forecast to 12,313 units in August 2024, indicating a potential reduction in unloading activities during that period. In contrast, the Capacity forecast remains relatively stable, beginning at 28913 units in December 2023. The forecasted values hover around this level, ranging from 28654 units in January 2024 to 29058 units in August 2024. This consistent forecast suggests a stable operational capacity for the system throughout the specified period.

These forecasted trends offer valuable insights for operational planning and resource management, enabling stakeholders to anticipate and adapt to potential changes in loading, unloading, and capacity requirements from December 2023 to October 2024.

## Optimization Forecast Result using Diffential Evolution Algorithm

Utilizing weighted fuzzy time series, Lagrange quadratic programming, and the Differential Evolution Algorithm for optimization forecasting represents a sophisticated approach to predicting trends over time. In this methodology, Lagrange quadratic programming aids in determining optimal weights crucial for refining forecast accuracy. Fuzzy time series enhances adaptability to handle uncertainties, and the Differential Evolution Algorithm adds a robust optimization layer, ensuring efficient convergence. Through the amalgamation of these techniques, forecasted results offer nuanced insight into anticipated trends in complex systems influenced by various factors. The forecasting optimization results were obtained using the weighted fuzzy time series method, with weights evaluated through Mean Square Error (MSE) values, and new prediction values derived from equations (11), (12), (13).

table VII. Result forecasting weighted fuzzy time series lagrange quadratic programming with differential evolution (Loading)

|  |  |  |
| --- | --- | --- |
| **Date** | **Forecast**  **WFTS-LQP** | **Forecast**  **WFTS-LQP-DE** |
| December 2023 | 15124 | 14232 |
| January 2024 | 14636 | 13805 |
| February 2024 | 15124 | 14232 |
| March 2024 | 15124 | 14232 |
| April 2024 | 11346 | 10926 |
| May 2024 | 13988 | 13238 |
| June 2024 | 12332 | 11789 |
| July 2024 | 14906 | 14041 |
| August 2024 | 15187 | 14287 |
| September 2024 | 14636 | 13805 |
| October 2024 | 15124 | 14232 |

table VIII. Result forecasting weighted fuzzy time series lagrange quadratic programming with differential evolution (Unloading)

|  |  |  |
| --- | --- | --- |
| **Date** | **Forecast**  **WFTS-LQP** | **Forecast**  **WFTS-LQP-DE** |
| December 2023 | 14180 | 13645 |
| January 2024 | 14409 | 13850 |
| February 2024 | 14180 | 13645 |
| March 2024 | 14180 | 13645 |
| April 2024 | 11380 | 11148 |
| May 2024 | 13867 | 13366 |
| June 2024 | 14899 | 14287 |
| July 2024 | 13696 | 13214 |
| August 2024 | 12313 | 11981 |
| September 2024 | 14409 | 13850 |
| October 2024 | 14180 | 13645 |

table IX. Result forecasting weighted fuzzy time series lagrange quadratic programming with differential evolution (Capacity)

|  |  |  |
| --- | --- | --- |
| **Date** | **Forecast**  **WFTS-LQP** | **Forecast**  **WFTS-LQP-DE** |
| Desember 2023 | 28913 | 27642 |
| Januari 2024 | 28654 | 27395 |
| Februari 2024 | 28913 | 27642 |
| Maret 2024 | 28913 | 27642 |
| April 2024 | 22689 | 21692 |
| Mei 2024 | 27464 | 26257 |
| Juni 2024 | 30769 | 29417 |
| Juli 2024 | 28211 | 26971 |
| Agustus 2024 | 29058 | 27781 |
| September 2024 | 28654 | 27395 |
| Oktober 2024 | 28913 | 27642 |

Tables VII, VIII, and IX present the forecasted results for Loading, Unloading, and Capacity, employing the Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its variant with Differential Evolution (WFTS-LQP-DE) across the months from December 2023 to October 2024.

For Loading, both methods, WFTS-LQP and WFTS-LQP-DE, project similar trends starting from December 2023. The forecasts align closely, indicating a consistent anticipation of loading activities. While both methods predict fluctuations, April 2024 sees a notable difference, with WFTS-LQP forecasting 11,346 units and WFTS-LQP-DE predicting 10,926 units.

Similarly, Unloading forecasts from both methods exhibit parallel trajectories. Commencing in December 2023 with forecasts of 14,180 units (WFTS-LQP) and 13,645 units (WFTS-LQP-DE), the forecasts align closely throughout the forecasted months. Minor variations exist, with June 2024 showcasing a divergence in predictions, where WFTS-LQP foresees 14,899 units and WFTS-LQP-DE predicts 14,287 units.

The forecasted Capacity values demonstrate consistent patterns between WFTS-LQP and WFTS-LQP-DE, starting at 28,913 units and 27,642 units, respectively, in December 2023. Both methods maintain stable forecasts with minor variations, showcasing the reliability of these methodologies in predicting the system's operational capacity.

In summary, these forecasting results reveal a substantial agreement between WFTS-LQP and WFTS-LQP-DE in predicting Loading, Unloading, and Capacity trends. While slight disparities exist, especially in specific months, the overall forecasting patterns remain coherent, underscoring the effectiveness of both methodologies in anticipating these variables over the specified forecasted period from December 2023 to October 2024.The outcomes of the calculated forecasts are subsequently represented visually to observe the patterns of time series data movements in the future for the Loading, Unloading, and Capacity variables. Evaluation Method:

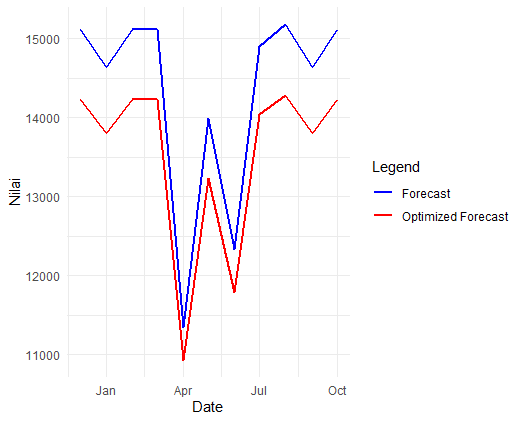


FIGURE 2. Plot Forecast Loading December 2023 – October 2024

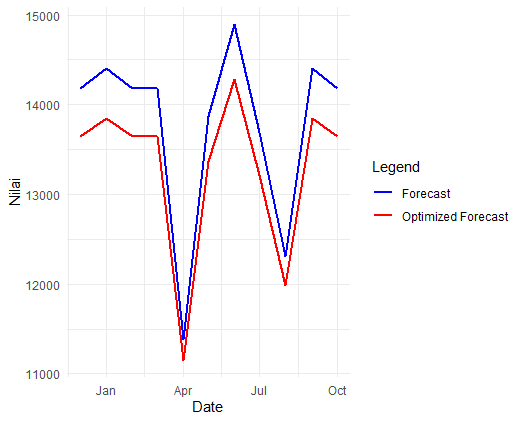


FIGURE 3. Plot Forecast Unloading December 2023 – October 2024

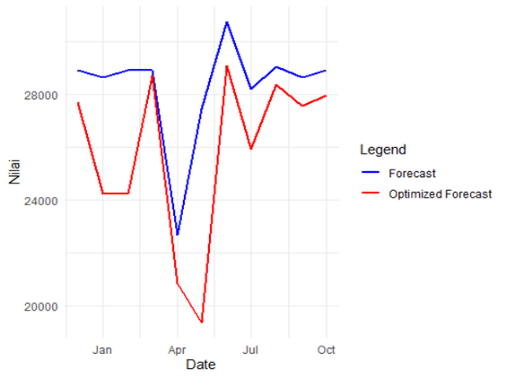


FIGURE 4. Plot Forecast Capacity DECEMBER 2023 – OCTOBER 2024

Figure 2 illustrates forecasted Loading values from December 2023 to October 2024 using Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its Differential Evolution-enhanced variant (WFTS-LQP-DE). In December 2023, both methods align closely, predicting Loading at 15124 and 14232 units, respectively. January and February 2024 continue with harmonized projections, but a notable deviation occurs in April, where WFTS-LQP forecasts 11346 units, while WFTS-LQP-DE predicts 10926 units. The forecasts realign in May 2024, and subsequent months, like June and July, showcase a convergence. These insights offer stakeholders a comprehensive understanding of potential Loading variations. The occasional disparities emphasize the need for a nuanced approach, considering both methodologies to enhance forecasting accuracy. Overall, this figure serves as a valuable tool for anticipating and planning for changes in loading activities within the specified timeframe.

Figure 3 illustrates the forecasted trends for Unloading activities from December 2023 to October 2024, employing two methodologies: Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its Differential Evolution-enhanced variant (WFTS-LQP-DE). In December 2023, both methods align closely, projecting Unloading at 14,180 units (WFTS-LQP) and 13645 units (WFTS-LQP-DE). Consistency persists through January and February 2024, with parallel forecasts. March 2024 maintains this pattern, but April reveals a discrepancy, where WFTS-LQP forecasts 11380 units, and WFTS-LQP-DE predicts 11,148 units. May 2024 sees a realignment at 13,866 units (WFTS-LQP) and 13366 units (WFTS-LQP-DE). Subsequent months, particularly June and July 2024, showcase consistent projections, emphasizing a shared anticipation of Unloading trends. These insights aid stakeholders in understanding potential variations, with occasional disparities highlighting the need for a comprehensive approach, considering both methodologies. The analysis supports strategic planning and resource management for Unloading operations within the specified timeframe.

Figure 4 explain forecasted trends for Capacity, depicted in the figure from December 2023 to October 2024, utilize two forecasting methodologies: Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its Differential Evolution-enhanced variant (WFTS-LQP-DE). In December 2023, both methods closely align, projecting Capacity at 28,913 units (WFTS-LQP) and 27,642 units (WFTS-LQP-DE). Consistency persists through January and February 2024, with March maintaining a stable projection. April 2024 reveals a significant discrepancy, as WFTS-LQP forecasts 22,689 units, contrasting WFTS-LQP-DE's prediction of 21,692 units. May 2024 sees a realignment at 27,464 units (WFTS-LQP) and 26,257 units (WFTS-LQP-DE). June 2024 anticipates a peak in Capacity, with WFTS-LQP forecasting 30,769 units and WFTS-LQP-DE predicting 29,417 units. Subsequent months, particularly July and August 2024, exhibit consistent projections, emphasizing a shared anticipation of Capacity trends. The figure provides stakeholders with valuable insights into potential variations, with occasional disparities emphasizing the need for a comprehensive approach considering both forecasting methodologies. This analysis supports strategic planning and resource management for Capacity within the specified timeframe.

## Evaluation Forecasting using MAPE

The evaluation process of a model using the Mean Absolute Percentage Error (MAPE) involves several key steps. Firstly, define a specific MAPE equation tailored to the case or model under evaluation, substituting the given equation (14) accordingly. Subsequently, gather actual data and predicted outcomes from the model for a specific number of observations or time periods. Then, apply the MAPE formula to each observation by substituting variables with the corresponding actual and predicted values. Sum up the results to obtain the total MAPE value. The evaluation results are presented as follows:

table X. Result of mape

|  |  |  |
| --- | --- | --- |
| **Variable** | **MAPE WFTS-LQP** | **MAPE WFTS-LQP-DE** |
| **Loading** | 10,99% | 9,63% |
| **Unloading** | 9,13% | 9,04% |
| **Capacity** | 7,27% | 4,40% |

Table X presents the Mean Absolute Percentage Error (MAPE) for the comparison of forecasting accuracy between two models: Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its Differential Evolution-enhanced variant (WFTS-LQP-DE) across the variables Loading, Unloading, and Capacity. In terms of Loading, WFTS-LQP demonstrates a MAPE of 10.99%, while WFTS-LQP-DE outperforms with a lower MAPE of 9.63%. This indicates that WFTS-LQP-DE provides a more accurate forecasting model for Loading.

For Unloading, both models exhibit relatively low MAPE values, with WFTS-LQP at 9.13% and WFTS-LQP-DE at 9.04%. The marginal difference suggests comparable performance, but WFTS-LQP-DE slightly edges ahead in terms of accuracy. In the case of Capacity, WFTS-LQP records a MAPE of 7.27%, while WFTS-LQP-DE excels with a significantly lower MAPE of 4.40%. This substantial difference underscores the superior forecasting accuracy of WFTS-LQP-DE for Capacity. In summary, the comparison of MAPE values highlights that WFTS-LQP-DE consistently outperforms WFTS-LQP across all variables, indicating its superior accuracy in forecasting Loading, Unloading, and especially Capacity.

## Reccomendation for demand

Based on the forecasting results for Loading, Unloading, and Capacity data using the Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) model and its optimized version with the Differential Evolution Algorithm (WFTS-LQP-DE), several recommendations and concrete steps can be taken to improve business efficiency and responsiveness:

1. Implement a more flexible and adaptive scheduling strategy for loading activities. By relying on the more accurate forecasts from the WFTS-LQP-DE model, companies can plan resource utilization more efficiently. This may include increasing loading capacity during months with high projections and adjusting quickly to demand fluctuations.

2. Optimize the unloading process through smarter workforce placement and allocation strategies. While both models show similar performance, companies can leverage the forecasts to design more efficient operational strategies, such as rescheduling work hours or boosting unloading team productivity during periods of high demand.

3. Adopt a proactive approach to capacity planning. By relying on the WFTS-LQP-DE model with a lower MAPE, companies can anticipate capacity needs more accurately. This includes preparing facilities and allocating additional resources when entering periods with high capacity projections.

4. Conduct regular monitoring and evaluation of forecast model performance. When there are changes in demand patterns or operational variability, reviewing and updating the forecasting model or replacing it with a more suitable approach can enhance prediction accuracy.

The recommended strategies aim to enhance operational efficiency and adaptability to changing demand dynamics. Embracing a flexible loading schedule, guided by the accurate forecasts from the WFTS-LQP-DE model, enables companies to efficiently allocate resources by adjusting loading capacities during peak-demand months. Concurrently, optimizing the unloading process through intelligent workforce strategies, informed by reliable forecasts, empowers companies to enhance productivity during periods of heightened demand. Proactive capacity planning, utilizing the WFTS-LQP-DE model for precise anticipations, involves strategic resource allocation and facility preparation during forecasted high-capacity periods. The emphasis on regular monitoring and evaluation ensures the continued accuracy and relevance of the forecasting model, allowing swift adjustments to changes in demand patterns or operational dynamics. Collectively, these strategies equip businesses with the agility to navigate market fluctuations effectively, optimize resource utilization, and maintain operational excellence.

# conclussion

In conclusion, the forecasted results for Loading, Unloading, and Capacity utilizing both Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) and its variant with Differential Evolution (WFTS-LQP-DE) exhibit consistent and aligned trends. While both methods project similar trajectories for Loading and Unloading, minor variations are noted in April 2024 for Loading and June 2024 for Unloading. The forecasted Capacity values showcase stability and reliability throughout the forecasted period. Overall, the WFTS-LQP and WFTS-LQP-DE models provide robust and comparable predictions, supporting informed decision-making for operational planning and resource allocation.

Based on these findings, the recommended strategies offer a comprehensive approach for operational enhancement based on forecasted results. Implementing a flexible loading schedule, optimizing unloading processes, adopting proactive capacity planning, and ensuring continuous model evaluation empower companies to navigate dynamic market conditions effectively. Relying on the WFTS-LQP-DE model enhances accuracy in resource planning and capacity anticipation. By embracing these strategies, businesses can not only optimize operational efficiency but also proactively respond to changes in demand patterns, ensuring a robust and adaptive operational framework. Regular monitoring and model refinement further contribute to sustained accuracy in forecasting and strategic decision-making.

# Suggestion

For future research, several recommendations emerge from study on integrating Weighted Fuzzy Time Series Lagrange Quadratic Programming with the Differential Evolution Algorithm offers promising directions for future research. Enhancements in algorithmic integration, exploration of dynamic adaptability to evolving scenarios, and the inclusion of external factors like economic indicators could further refine the model's forecasting capabilities. Tailoring the research to specific industries, conducting comparative studies, and implementing real-world validation would provide insights into the model's versatility. Additionally, sensitivity analyses, assessments of scalability, and considerations of computational efficiency contribute to the practicality and effectiveness of the proposed dual-optimized approach. These research directions collectively aim to advance optimization algorithms for more robust and applicable forecasting models..

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