Real-time Scheduling Optimization with Deep Learning-powered Demand Forecasting in Water Transportation

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***Abstract*— The notable demand volatility in water transportation often lead to capacity shortages or deficits for roll-on/roll-off ship. Thus, how to enhance the quality of port operations using artificial intelligence (AI) technology? We proposed a two-stage real-time scheduling optimization approach, which comprises a prediction model based on deep learning and a scheduling decision module grounded in expert rules. Two key innovations are involved (1): Thoroughly leveraging relevant data concerning transportation demand by utilizing a Temporal Fusion Transformer (TFT) for demand prediction. (2): Establishing a scheduling optimizer based on long-term expert rules to match the flight schedules with future 2-3 hours of demand. Case study validate that the application of AI in port scheduling significantly elevates the quality of transportation services and economic efficiency.**

Keywords—water transportation, scheduling optimization, demand prediction, deep learning, temporal fusion transformer

I. Introduction

Water transportation exhibits notable demand uncertainty and volatility, leading to challenges such as port congestion and underutilized ships. Real-time scheduling optimization, facilitated by smart technology, are crucial for efficient ship allocation and improved transport quality.

The operational model for roll-on/roll-off transportation involves advanced ferry information disclosure to the public, real-time demand forecasting, and subsequent ferry schedule adjustments, with the core challenge being accurate demand forecasting. Industry practices typically rely on the expertise of port personnel, lacking efficiency and precision. In academia, various Machine Learning (ML) models have been explored, including Long Short-Term Memory (LSTM)[1] and Artificial Neural Network (ANN)[2]. However, these, struggle with intricate factors, especially static elements like seasonality and holidays[3]. Transformer-based Deep Learning (DL) models like the Temporal Fusion Transformer (TFT)[4] are designed for time series forecasting, incorporating static data and accommodating demand fluctuations. Consequently, we proposed a TFT-based demand prediction model for real-time scheduling optimization. To our knowledge, this is the first application of TFT for real-time scheduling optimization, making it a rare practical use of deep learning forecasting models within the realm of port operations.

II. Methodology

A. Overview

In this study, we employed two-stage method based on demand prediction-driven scheduling optimization, as depicted in Fig. 1. This two-stage approach consists of a prediction model relying on deep learning and a scheduling decision module grounded in expert rules.

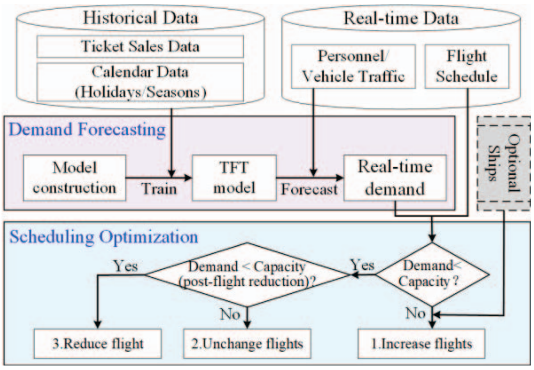

Fig. 1. An overview of the scheduling optimization method. Sensor data (ticket sales data and calendar data) are provided to the TFT model. The scheduling optimization module makes diverse optimization suggestions using real-time flight schedules, predicted demand, and rules.

B. Demand Forecasting based on TFT model

For superior forecasting performance, we employed various types of data as inputs to the predictive model, including static, known, and observed inputs. An attention-based TFT model was developed, featuring innovative components such as a gating module, variable screening network, static information encoders, multi-head attention module, and temporal fusion decoder, as depicted in Fig. 2.

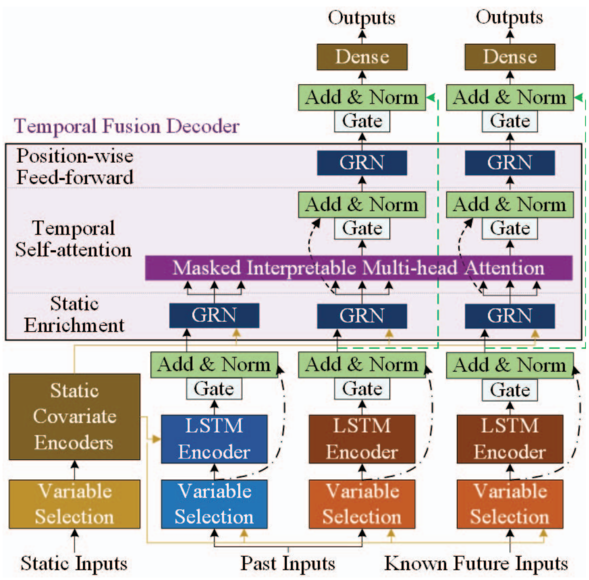

Fig. 2. The structure of Temporal Fusion Transformer.

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In contrast to previous time series forecasting models, TFT utilizes static input data to generate three context vectors, one of which defines the static enrichment layer function as Eq. (1). Further information can be found in reference[4]。

$$\theta(t,n) = GRN_{\theta}\left(\tilde{\phi}(t,n), c_e\right) \tag{1}$$

C. Real-time Scheduling Optimization

Utilizing the demand forecasts, scheduling optimization module was conducted based on the expert rules to generate scheduling advices for the next 2-3 hours. Concisely, the predicted demand, quantified as the number of vehicles, is multiplied by their respective lengths. This prediction is then compared with the capacity allocated before optimization to determine whether to increase, decrease, or maintain the number of flights. The specific algorithm is as follows:

Algorithm: Real-time Scheduling Optimization.

Input: predicted demand $\mathcal{D}_t$, flight $\mathcal{F}_t$, optional ships $\mathcal{S}_o$
Output: optimization advices Θ_t, potential flight $\acute{\mathcal{F}}_t$ and ship $\mathcal{S}_t$

calculate *capacity* $\mathcal{C}_t(\mathcal{F}_t)$ for the next 2-3 hours by flight schedul and rated capacity
if *predicted demand* $\mathcal{D}_t > \mathcal{C}_t(\mathcal{F}_t)$ **then**
  calculate *capacity* $\mathcal{C}_t(\acute{\mathcal{F}}_t)$ when reduce *ship* $\mathcal{S}_t$ from $\mathcal{F}_t$
  if $\mathcal{D}_t \geq \mathcal{C}_t(\acute{\mathcal{F}}_t)$ **then**
    generate $\Theta_t = \{reduce\ flight\}$, $\acute{\mathcal{F}}_t = \mathcal{F}_t \not\subset \mathcal{S}_t$
  else
    generate $\Theta_t = \{unchange\ flight\}$, $\acute{\mathcal{F}}_t = \mathcal{F}_t$, $\mathcal{S}_t = \emptyset$
else
  adding *ship* $\mathcal{S}_t$ from $\mathcal{S}_o$ to $\mathcal{F}_t$ yield $\acute{\mathcal{F}}_t$ such that *capacity* $\mathcal{C}_t(\acute{\mathcal{F}}_t) \geq \mathcal{D}_t$; $\Theta_t = \{increase\ flight\}$
return $\Theta_t, \acute{\mathcal{F}}_t, \mathcal{S}_t$

III. CASE STUDY

A. Data Description

We evaluated the model performance on a real-world dataset. Historical data utilized to train the predictive model includes transportation demand from vehicle ticketing data for the period of 2022.11.01-2023.10.31, calendar data. The real-time data contains demand data for 2023.11.01 and schedules that dispatch at 1-hour intervals. Scheduling optimization was executed at 15:30 for the next 2-3 hours being 17:30 and 18:30.

B. Results

We plotted the values for real demand, forecasted demand, original capacity, and optimized capacity at the time points of 17:30 and 18:30 in Fig. 3. It is evident that the original capacity configuration fails to meet transportation demands, while the forecasted demand closely approximates the actual values. Furthermore, we recommend increasing flights, resulting in optimized capacity meeting the real demand. Fig.3 (b) apparently showcases that the optimized capacity meets demand adequately with minimal deviation.

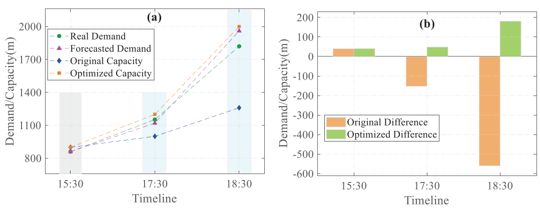

Fig. 3. The results of forecasted and optimized demand and capacity. The right showcases the discrepancies between the real demand and capacity.

Table 1 illustrates the discrepancies between forecasted demand, original capacity, and optimized capacity in comparison to real demand. Positive values indicate that the capacity exceeds the real demand. Notably, at both time points, the forecasted demand aligns closely with the actual values, with errors not exceeding 10%. Furthermore, the optimized capacity consistently meets the real demand.

TABLE I. DISCREPANCIES BETWEEN CAPACITY AND REAL DEMAND

Flight Time	**Real Demand /m**	**Discrepancies with Real Demands /m**		
		Forested Demand	***Original Capacity***	***Optimized Capacity***
17:30	1152	-32	-152	48
18:30	1820	140	-560	180

C. Effects of Scheduling Optimization

It is crucial to underscore that for port and shipping enterprises, the punitive costs associated with failing to meet transportation demands during ferry operations exceed those of underutilization. As depicted in Fig. 4, an extra flight is assigned to transportation duties at both 17:40 and 18:40, with ship selection predicated on factors such as availability and capacity. In practical scenarios, the outcomes of scheduling optimization predominantly remain constant, with a subset involving reducing voyages.

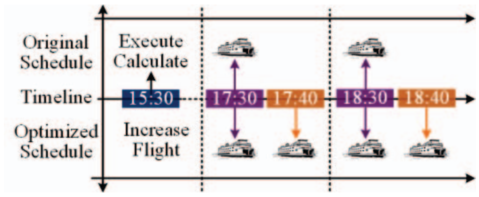

Fig. 4. The comparison of scheduling between the original and optimized.

IV. CONCLUSION

To enhance the service quality and economic benefits of water transportation, we proposed an AI-driven real-time scheduling optimization method. Owing to the comprehensive extraction of dynamic and static information, The Temporal Fusion Transformer (TFT) is employed to perform demand forecasting tasks. The performance of demand forecasting has achieved high precision, thereby improving the accuracy of scheduling optimization. We observe that the application of AI holds substantial economic value and societal significance. Consequently, further research is warranted, involving the incorporation of more data, diverse models, and the embedding of more expert knowledge.

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