Inland Waterway Freight Demand Forecasting with Spatio-temporal Dynamic Graph Attention-based Multi Attention Model

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1 INTRODUCTION

As a sustainable transportation mode, inland waterway transport (IWT) has gained more and more attention in recent years. In alignment with the European Union's sustainable and smart mobility strategy, transport via inland waterways and short sea shipping is expected to increase by about 25% by 2030 and 50% by 2050, relative to the 2015 levels. However, the volume of cargo transported through Germany's inland waterways has declined. Due to significant investments in port facilities and their developmental delays, accurate and reliable demand information is essential for politicians to adjust policies and port manager to plan and manage vacant resources.

Compared to other transportation modes, IWT is easier to be influenced by external factors due to the unique geographical situation. For example, IWT is vulnerable to water levels and extreme weather events Christodoulou *et al.* (2020). Hence, it will be not enough to do the forecasting solely based on historical demand, which make it even more changeling to get the accurate demand forecasting due to the complicated spatial and temporal relationships.

Recent advancements in machine learning technologies present opportunities to surpass the traditional assumptions inherent in ARIMA models and incorporate covariate data into predictive analyses. In response, our project has leveraged state-of-the-art machine learning models to address existing forecasting challenges. Consequently, port managers can obtain more precise demand forecasts, allowing for timely strategic adjustments. Furthermore, policymakers can employ these methods to evaluate the impact of their initiatives, such as subsidy policies, and ascertain their efficacy in shifting cargo transport to IWT.

2 Methodology

2.1 Data Description

Our dataset contains monthly records of IWT cargo demand from January 2000 to November 2022 in Germany. It includes different types of cargos, like general and container cargos, and gives detailed information about the origin and destination of freight, as well as the freight type.

2.2 Model details

In contrast to traditional static graph representations, our research applies dynamic graph analysis to capture the changing conditions of various ports over time. This approach allows for the integration of temporal changes and inter-port dynamics, which are crucial for a comprehensive understanding of the inland waterway transport system. In detail, our model considers various inter-port relationships, including geographical distance and previously established trade connections. Moreover, our model integrates node features at each port into the volume flow analysis, accounting for variables such as water levels and conditions that can significantly impede transport, including floods, weed infestations, and ice formation. These features are meticulously aggregated from a network of water measurement stations, allowing us to compile comprehensive feature matrices for each port at each temporal snapshot.

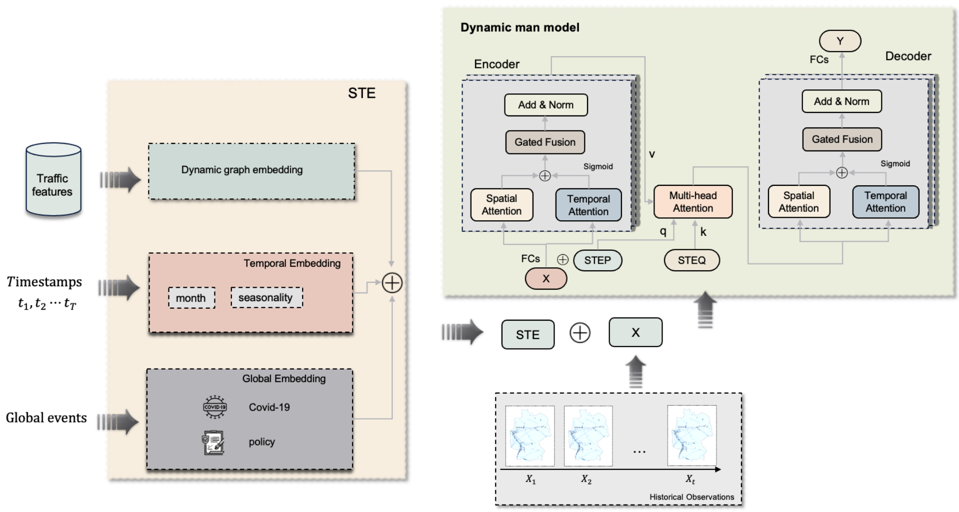

Figure 1 – *GAT-DAMN model*

In addition to these node features, we identify hinterland connections—particularly those stemming from rail terminals—as pivotal in influencing demand dynamics within the inland waterway network. The type of cargo also plays a decisive role in shaping flow patterns; thus, it is included as a critical component of the node feature matrices. By incorporating these diverse yet interconnected factors, our approach provides a multidimensional perspective on the demand fluctuations in inland waterway transport. After gathering both dynamic and static adjacency matrices along with node features, we applied GAT model Veličković *et al.* (2018) to generate new feature matrices. These matrices serve as the aggregated spatial features for subsequent analysis. In our model's treatment of temporal features, we consider not only the typical annual trends and seasonality but also the impacts of significant external events that have the potential to disrupt established patterns. This includes the global disruption caused by the COVID-19 pandemic as well as the effects of changes in subsidy policy that directly influence transport logistics. The generated spatial and temporal features are then fused to be the inputs of the encoder-decoder framework. Inspired by the work by Zheng *et al.* (2020), we have adapted to enhance the model's focus on these two critical factors, spatial and temporal factors, distinguishing our approach from traditional transformer models. This allows our approach to accommodate the fluctuating conditions that are characteristic of this mode of transport, enhancing the accuracy and relevance of our forecasting.

3 Results

3.1 Result comparison

To assess the necessity of advanced modeling techniques, this research employs multiple forecasting methods for IWT demand. These methods range from statistical techniques such as Historical Averages (HA) and Autoregressive Integrated Moving Average (ARIMA), to shallow machine learning models like Random Forest (RF) and Multilayer Perceptrons (MLP), and include deep learning strategies such as Long Short-Term Memory (LSTM) networks and Transformers. We forecast demand for 1, 3, 6, 12, and 24 periods ahead, using MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) as metrics for our study. The comparative performance results are detailed in Table 1. The results indicate that our model outperforms the comparative forecasting models in terms of accuracy.

Table 1 – *Model Performances Comparison*

Model	Month	General Cargo		Container Cargo	
		RMSE	MAE	RMSE	MAE
HA		66.48	29.30	30.16	17.14
ARIMA	1	64.43	35.32	53.36	29.94
	3	62.79	34.45	53.20	29.90
	6	62.36	34.16	53.40	30.20
	12	62.63	34.03	53.61	30.41
	24	66.63	34.64	53.63	30.54
MLP	1	52.73	25.86	23.99	16.01
	3	62.83	27.04	24.53	16.55
	6	55.17	25.71	26.67	18.13
	12	55.59	25.66	25.55	16.63
	24	57.03	25.85	28.70	18.26
RF	1	63.03	27.56	28.52	17.32
	3	67.35	28.49	28.52	17.11
	6	61.15	27.71	29.15	17.02
	12	65.73	28.06	29.34	17.15
	24	63.19	27.71	30.35	17.26
LSTM	1	59.65	26.61	24.72	15.54
	3	58.28	26.57	24.75	15.76
	6	58.83	26.78	24.39	15.41
	12	60.99	28.97	24.79	15.61
	24	57.63	26.50	25.71	15.87
Transformer	1	58.61	28.24	22.38	14.55
	3	57.83	28.49	23.06	14.67
	6	57.24	28.46	23.16	14.67
	12	59.60	28.36	24.32	15.11
	24	59.81	28.05	25.11	15.24
GAT-DMAN	1	41.06	17.82	19.74	11.35
	3	41.19	18.38	16.68	10.62
	6	43.53	18.47	20.35	12.24
	12	44.12	19.91	21.35	13.24
	24	44.40	21.04	21.49	12.94

3.2 Model Performance

To demonstrate the efficacy of our model across ports of varying sizes, we present Figure 2, which illustrates the comparative performance

To demonstrate the efficacy of our model across ports of varying sizes, we refer to Figure 2 which illustrates the varying performance across small, medium, and large ports. This figure reveals that our model excels in predicting for medium and large ports, while small ports pose measurement challenges common to all models.

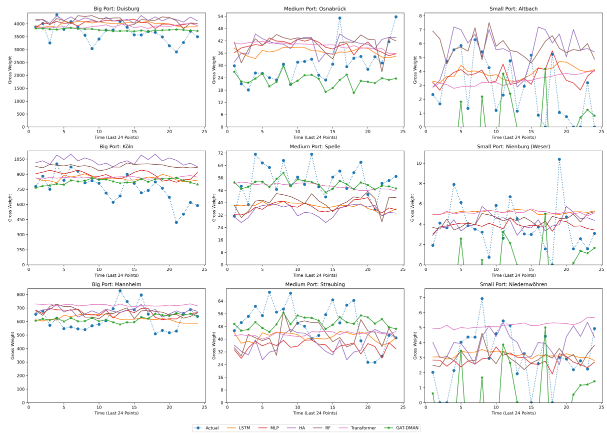

Figure 2 – *IWT transport quantities change*

4 Discussion

In conclusion, our findings provide practical insights for inland waterway port managers to address resource management challenges precipitated by volatile demand flows. Our approach offers a data-driven foundation for enhancing predictive accuracy, thereby enabling more informed and timely investment decisions. Furthermore, the increased precision of our forecasting models offers policymakers a reliable metric by which they can evaluate and adjust their strategies, such as revising subsidy policies, to better promote the adoption of greener transportation mode.

Due to data limitations, this work does not cover all possible factors, including various policies related to inland shipping and infrastructure information. Future research aims to include more variables to enhance the model's accuracy once the data become available. Additionally, the applicability of this model could be tested in other research fields.

5 AKNOWLEDGEMENTS

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