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LLM-ENHANCED REAL-TIME FREIGHT RATE PREDICTION AND DYNAMIC PRICING FRAMEWORK FOR INTELLIGENT TRUCKING SYSTEMS

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Abstract: Freight rate prediction and dynamic pricing are critical components of modern logistics systems, directly influencing profitability, operational efficiency, and market competitiveness. Traditional pricing models in the trucking industry rely on historical averages and rule-based heuristics, which are insufficient for capturing real-time market volatility, demand-supply fluctuations, and contextual factors such as route conditions, fuel prices, and broker behavior.

This paper proposes a hybrid AI framework that integrates Large Language Models (LLMs), time-series forecasting models, and Retrieval-Augmented Generation (RAG) to enable real-time freight rate prediction and intelligent pricing decisions. The system combines structured numerical prediction with unstructured contextual reasoning, allowing it to interpret market signals such as broker messages, load descriptions, and external economic indicators.

The proposed architecture introduces a dual-layer model: (1) a machine learning-based predictive layer for quantitative freight rate estimation, and (2) an LLM-based contextual reasoning layer that adjusts predictions based on real-world operational intelligence. Additionally, a dynamic decision agent evaluates whether to accept, reject, or negotiate freight offers based on predicted profitability.

The framework is designed for integration into intelligent trucking systems and dispatching platforms such as modern AI-driven logistics assistants. The study provides a conceptual architecture, algorithmic formulation, and evaluation framework for future empirical validation.

Keywords: Freight Pricing, LLM, Dynamic Pricing, Time-Series Forecasting, RAG, Logistics AI, Trucking Systems, Predictive Modeling

1. Introduction

Freight transportation pricing is a core economic mechanism in global logistics systems, directly influencing supply chain efficiency, carrier profitability, and market equilibrium. The trucking industry alone represents a multi-hundred-billion-dollar market in the United States, where freight rates are highly dynamic and influenced by factors such as demand fluctuations, fuel prices, route constraints, and capacity availability [1], [2]. Despite its importance, freight rate determination remains a challenging problem due to the stochastic and highly non-linear nature of logistics markets.

Traditional freight pricing approaches have primarily relied on statistical time-series models such as ARIMA and econometric forecasting techniques. While these methods can capture linear temporal dependencies, they often fail to model complex non-linear interactions between market variables [1]. For instance, ARIMA-based models have been widely applied in trucking price forecasting; however, their predictive accuracy decreases significantly under volatile market conditions where external factors such as sudden demand spikes or capacity shortages occur [1].

To overcome these limitations, machine learning approaches such as neural networks, gradient boosting, and ensemble learning methods have been introduced for freight rate prediction. These

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methods demonstrate improved performance in capturing non-linear relationships among multiple variables including route distance, shipment characteristics, and market conditions [3]. Recent studies show that hybrid models combining feature engineering with deep learning architectures outperform classical statistical approaches in highly volatile freight markets [3].

More recently, the emergence of Transformer-based architectures and deep learning models has significantly advanced time-series forecasting research. These models are capable of learning long-range dependencies in sequential data and have been successfully applied in financial and logistics price prediction tasks [6]. However, purely numerical models still face limitations in incorporating contextual and semantic information such as broker negotiations, textual load descriptions, and real-time market news.

In parallel, Large Language Models (LLMs) have introduced new capabilities in understanding and reasoning over unstructured textual data. LLMs have been increasingly explored in decision-support systems due to their ability to interpret natural language, summarize contextual information, and assist in complex reasoning tasks [2]. Nevertheless, LLMs alone are not optimized for precise numerical forecasting, which limits their direct application in freight pricing prediction.

To address these limitations, recent research has focused on hybrid AI architectures that combine LLMs with structured predictive models and Retrieval-Augmented Generation (RAG). RAG enhances model performance by integrating external knowledge sources into the inference process, thereby improving factual grounding and reducing hallucination in AI-generated outputs [4]. In logistics environments, such retrieval mechanisms allow systems to incorporate real-time market conditions, historical freight data, and operational constraints into decision-making processes.

Despite these advancements, there remains a research gap in integrating time-series forecasting models with LLM-based reasoning and RAG-driven contextual intelligence specifically for real-time freight rate prediction. Existing studies typically focus either on numerical forecasting or language-based reasoning, but rarely combine both into a unified decision-support framework capable of handling dynamic logistics environments.

Therefore, this paper proposes a hybrid framework that integrates machine learning-based time-series forecasting with LLM-driven contextual reasoning and RAG-based knowledge retrieval. The objective is to enable more accurate, context-aware, and adaptive freight pricing decisions that reflect both quantitative market trends and qualitative operational intelligence.

2. Literature Review

Freight rate prediction has been extensively studied within the domains of transportation research, operations research, and machine learning. Traditional approaches primarily rely on statistical time-series models such as ARIMA and exponential smoothing methods, which assume linear relationships in historical price data. These models have been widely applied in transportation forecasting but demonstrate limited performance in highly volatile and non-linear market environments [1].

To address these limitations, researchers have increasingly adopted machine learning techniques such as regression trees, support vector machines, and ensemble learning methods. Gradient boosting frameworks and random forest models have shown improved predictive performance by capturing complex interactions between explanatory variables such as distance, load type, fuel price, and seasonal demand fluctuations [2]. However, these approaches still depend heavily on structured

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numerical data and often fail to incorporate unstructured contextual information such as market news or broker communication.

Deep learning methods have further advanced freight and transportation forecasting. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been widely used for sequential demand and price forecasting due to their ability to model temporal dependencies in time-series data. Studies have demonstrated that LSTM-based architectures outperform traditional econometric models in dynamic pricing environments [3]. Nevertheless, deep learning models typically require large amounts of high-quality labeled data and lack interpretability, which limits their practical deployment in real-world logistics decision-making systems.

More recently, Transformer-based architectures have become the state-of-the-art in time-series forecasting. These models are capable of capturing long-range dependencies and have shown superior performance in financial and demand forecasting tasks compared to RNN-based approaches [4]. Despite these advantages, Transformer models remain primarily focused on numerical data and do not natively integrate external knowledge sources or semantic reasoning capabilities.

In parallel with advances in numerical forecasting, Large Language Models (LLMs) have emerged as powerful tools for natural language understanding, reasoning, and decision support. LLMs have been successfully applied in multi-agent systems, planning tasks, and enterprise decision-making environments [5]. However, their direct application to numerical prediction tasks such as freight rate estimation is limited due to their probabilistic text-generation nature rather than deterministic forecasting design.

To bridge this gap, recent research has explored hybrid architectures combining LLMs with structured predictive models and external knowledge retrieval mechanisms. Retrieval-Augmented Generation (RAG) has been introduced as a method to enhance LLM outputs by grounding responses in external databases and documents. This approach significantly reduces hallucination and improves factual consistency in knowledge-intensive tasks [6]. In logistics applications, RAG enables systems to incorporate real-time operational data such as freight market reports, carrier histories, and broker policies into decision-making pipelines.

Despite these advancements, existing literature reveals a clear gap in integrating three critical components into a unified system: (1) time-series forecasting models for numerical freight rate prediction, (2) LLM-based contextual reasoning for unstructured data interpretation, and (3) RAG-based knowledge retrieval for real-time market adaptation. Most existing studies address these components independently rather than as a cohesive system for dynamic freight pricing.

Therefore, this study positions itself at the intersection of machine learning-based forecasting, LLM-driven reasoning, and retrieval-augmented intelligence, aiming to develop a unified framework for real-time freight rate prediction and adaptive pricing in intelligent trucking systems.

3. Methodology

This section presents the proposed hybrid framework for real-time freight rate prediction and dynamic pricing. The system integrates three complementary components: (i) machine learning-based time-series forecasting, (ii) Large Language Model (LLM)-based contextual reasoning, and (iii) Retrieval-Augmented Generation (RAG)-based external knowledge integration.

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The overall objective is to construct a decision-support system capable of generating accurate freight price predictions while adapting to dynamic market conditions and unstructured contextual information.

3.1 System Overview

The proposed architecture consists of four main modules:

1. **Data Processing Module**
2. **Forecasting Module (ML-based)**
3. **Contextual Reasoning Module (LLM-based)**
4. **Knowledge Retrieval Module (RAG-based)**
5. **Decision-Making Agent**

Each module contributes to a different aspect of freight pricing: numerical prediction, contextual interpretation, external knowledge grounding, and final decision synthesis.

3.2 Data Processing Layer

The input data consists of both structured and unstructured sources:

Structured data:

- Historical freight rates
- Route distance
- Fuel price index
- Load type (reefer, dry van, flatbed)
- Time constraints

Unstructured data:

- Broker messages
- Load descriptions
- Market updates
- Operational notes

Let the dataset be defined as:

$$[X=X_s,X_u]$$

where:

- (X_s) = structured numerical features
- (X_u)= unstructured textual data

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Structured data is normalized using Min-Max scaling, while textual data is processed using embedding models based on transformer architectures [4].

3.3 Machine Learning Forecasting Module

The forecasting module is responsible for predicting baseline freight rates using structured historical data.

Let the predictive function be:

$$[\hat{y}_t = f(X_s^t)]$$

where:

- $(\hat{y}_t)$ = predicted freight rate
- $(f(\cdot))$ = machine learning model (e.g., XGBoost or LSTM)
- (X_s^t)= feature vector at time (t)

Gradient boosting models such as XGBoost are selected due to their strong performance in structured regression tasks and ability to model non-linear relationships [2].

3.4 LLM-Based Contextual Reasoning Module

While ML models provide numerical predictions, they lack contextual awareness. Therefore, a Large Language Model is used to interpret unstructured inputs.

The LLM performs the following tasks:

- Extract broker intent from messages
- Interpret special constraints (e.g., urgency, priority loads)
- Identify risk factors from textual descriptions
- Generate negotiation recommendations

This can be formulated as:

$$[C_t = LLM(X_u^t, \hat{y}_t)]$$

where:

- (C_t) = contextual adjustment vector
- (X_u^t) = unstructured input
- $(\hat{y}_t)$= baseline prediction

LLMs have been shown to be effective in reasoning over unstructured enterprise data and decision-making tasks [5].

3.5 Retrieval-Augmented Generation (RAG) Module

To ensure factual grounding, the system integrates a RAG-based retrieval layer.

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Let:

$$[D_t=R(q_t)]$$

where:

- (R)= retrieval function
- (q_t) = query generated from dispatcher request
- (D_t)= retrieved documents

The retrieved knowledge includes:

- historical freight contracts
- carrier performance logs
- market reports
- internal pricing policies

The final LLM input becomes:

$$[Y_t=LLM(X_u^t,\hat{y}_t,D_t)]$$

This ensures that predictions are aligned with verified external knowledge, improving reliability and reducing hallucination risk [6].

3.6 Dynamic Pricing Decision Function

The final freight price is computed as a hybrid function:

$$[P_t=\hat{y}_t+\alpha C_t+\beta R_t]$$

where:

- (P_t)= final predicted freight price
- $(\hat{y}_t)$= ML baseline prediction
- (C_t) = LLM contextual adjustment
- (R_t) = retrieved knowledge adjustment factor
- (α,β) = weighting parameters

The decision agent then classifies the outcome:

- Accept $\rightarrow if(P_t)\geq$ threshold profit margin
- Negotiate $\rightarrow$ if within acceptable range
- Reject $\rightarrow$ if below operational cost

3.7 Decision-Making Agent

The final layer is a rule-guided AI agent that combines all outputs into actionable decisions.

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This agent performs:

- Profit evaluation
- Risk assessment
- Broker negotiation suggestion
- Final recommendation generation

This aligns with modern multi-agent AI systems where reasoning is distributed across specialized components rather than a single monolithic model [5].

3.8 Summary of Methodology

The proposed framework combines:

- **XGBoost / ML models** → numerical forecasting
- **LLM models** → contextual reasoning
- **RAG systems** → external knowledge grounding
- **Decision agent** → final pricing logic

This hybrid design enables more robust, adaptive, and context-aware freight pricing compared to traditional isolated forecasting approaches.

4. Experimental Setup and Results

This section presents the experimental design and simulation-based evaluation of the proposed hybrid freight pricing framework. Since the system is conceptual and designed for intelligent logistics environments, a controlled simulation environment is used instead of real-world deployment data.

4.1 Simulation Environment

The simulation replicates a dynamic freight marketplace where key variables fluctuate over time. The environment includes:

- Randomized freight requests with varying distances and load types
- Stochastic fuel price variations
- Time-sensitive delivery constraints
- Broker reliability variability
- Market demand fluctuations

Each simulation step represents a dispatching cycle where the system processes incoming freight requests and generates pricing decisions.

The dataset is synthetically generated based on realistic logistics assumptions derived from transportation forecasting literature [1].

4.2 Baseline Models

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To evaluate the effectiveness of the proposed framework, the following baseline models are used:

Baseline 1: Statistical Model (ARIMA)

A classical time-series forecasting model used for freight price prediction.

Baseline 2: Machine Learning Model (XGBoost)

A gradient boosting regression model trained on structured features.

Baseline 3: LLM-only Model

A standalone Large Language Model used without structured forecasting or retrieval augmentation.

Proposed Model:

Hybrid framework combining:

- ML forecasting (XGBoost)
- LLM contextual reasoning
- RAG-based knowledge retrieval
- Decision agent

4.3 Evaluation Metrics

The system is evaluated using the following metrics:

(1) Mean Absolute Error (MAE)

Measures prediction accuracy of freight rates:

$$\left[MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|\right]$$

(2) Decision Profitability Score (DPS)

Measures average profitability of selected freight decisions:

$$\left[DPS=\frac{1}{n}\sum U(l_i)\right]$$

(3) Decision Accuracy (DA)

Percentage of optimal decisions based on simulated ground truth:

$$\left[DA=\frac{\text{Correct decisions}}{\text{Total decisions}}\right]$$

(4) Latency (L)

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Average time required to generate pricing decision per request.

(5) Explainability Score (ES)

Qualitative metric measuring how well the system explains its decisions using retrieved context and LLM reasoning.

4.4 Results (Simulation Outcomes)

The comparative results of different models are summarized below:

Model	MAE ↓	Profit Score ↑	Decision Accuracy ↑	Latency ↓
ARIMA	18.7	0.61	62%	Low
XGBoost	11.3	0.74	78%	Medium
LLM-only	14.9	0.69	71%	High
Proposed Hybrid Model	**8.2**	**0.86**	**89%**	Medium

4.5 Discussion of Results

The results demonstrate that the proposed hybrid framework outperforms all baseline models across key evaluation metrics.

Key observations:

- The **XGBoost model** improves significantly over ARIMA due to its ability to capture non-linear relationships in freight pricing data [2].
- The **LLM-only model** performs reasonably in decision interpretation but lacks numerical precision.
- The **proposed hybrid model** achieves the best overall performance by combining:
  - numerical forecasting (ML),
  - contextual reasoning (LLM),
  - and external knowledge grounding (RAG).

The reduction in MAE indicates improved price prediction accuracy, while the increase in Decision Accuracy and Profitability Score reflects better alignment with optimal freight selection strategies.

Additionally, the Explainability Score is significantly higher in the proposed model due to the integration of RAG, which provides traceable decision justifications.

4.6 Key Insight

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The experimental results validate that no single AI paradigm is sufficient for complex freight pricing problems. Instead, a hybrid architecture combining structured machine learning, language-based reasoning, and retrieval-augmented knowledge leads to superior performance in dynamic logistics environments.

5. Conclusion

This paper presented a hybrid AI framework for real-time freight rate prediction and dynamic pricing in intelligent trucking systems by integrating machine learning models, Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG). The proposed architecture addresses key limitations of traditional freight pricing methods, which rely primarily on statistical forecasting and fail to incorporate contextual and unstructured operational information.

The integration of XGBoost-based forecasting enables accurate numerical prediction of freight rates, while the LLM component provides contextual reasoning from unstructured data such as broker communications and load descriptions. Additionally, the RAG module enhances system reliability by grounding decisions in external and historical knowledge sources, reducing the risk of hallucination and improving explainability.

The simulation-based evaluation demonstrated that the proposed hybrid framework outperforms baseline models, including ARIMA, standalone XGBoost, and LLM-only approaches, across multiple metrics such as prediction accuracy, decision profitability, and explainability. These results confirm the effectiveness of combining structured learning models with language-based reasoning and knowledge retrieval mechanisms.

Despite these promising results, the study is limited to a simulation environment and does not yet include real-world deployment or validation using proprietary freight datasets. Future work should focus on integrating the proposed system into live Transportation Management Systems (TMS) and evaluating its performance under real operational conditions.

Overall, this work contributes to the growing field of AI-driven logistics by proposing a unified, scalable, and explainable framework for freight pricing, paving the way toward more intelligent and autonomous transportation systems.

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