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INTELLIGENT TRAFFIC FLOW PREDICTION USING TIME-SERIES MODELS

A.O. Belous[1], K.V. Belous[2], PhD (Econ.)
[1]Odesa Polytechnic National University (Odesa)
[2]Odesa National Maritime University (Odesa)

Traffic congestion leads to wasted time, increased fuel consumption, and environmental damage. To mitigate these effects, predicting traffic flow with high accuracy is crucial. Traditional statistical models offer limited capabilities in handling nonlinear and complex patterns in traffic data. In contrast, intelligent methods based on time-series analysis and machine learning provide better flexibility and adaptability [1].

In this study, we investigate the application of three time-series models for predicting urban traffic flow, namely ARIMA (AutoRegressive Integrated Moving Average), LSTM (Long Short-Term Memory), and Facebook Prophet. Each of these models offers a unique approach to forecasting and is suitable for different characteristics of traffic data. ARIMA is a traditional statistical model that excels in capturing autocorrelations within stationary time-series data. It uses a combination of autoregressive terms, differencing, and moving averages to model historical patterns and is often effective for simple, linear trends.

In contrast, LSTM is a deep learning architecture capable of learning long-term dependencies in sequential data, making it ideal for complex traffic systems with non-linear and dynamic behavior. Its ability to remember previous states and adapt to fluctuating input makes it powerful in real-time traffic prediction [2]. Meanwhile, Facebook Prophet is designed to handle time-series data with multiple seasonality components, such as hourly, daily, or weekly cycles, which are commonly observed in traffic patterns. Prophet also accommodates missing data and is relatively robust to outliers, providing reliable predictions with minimal tuning.

The traffic datasets used in our project include hourly vehicle count data collected from road sensors across major urban intersections. The data were cleaned, normalized, and enriched with contextual information like time of day, weekdays versus weekends, and holidays to better capture traffic behavior. Models were trained and tested using a chronological split, and their performance was evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which measure prediction accuracy and sensitivity to large errors, respectively. Preliminary results show that while ARIMA performs well for short-term, consistent data, LSTM and Prophet outperform it in longer-term and more variable scenarios [3].

The experimental evaluation revealed notable differences in the performance of the time-series models. Among them, the Long Short-Term Memory (LSTM) model consistently delivered the highest prediction accuracy across all tested scenarios. Its ability to capture complex temporal dependencies proved particularly valuable during peak traffic hours and in datasets with high variability. The ARIMA model demonstrated reliable performance in more stable and stationary traffic environments, especially for short-term forecasting, but struggled with non-linear trends and irregularities. On the other hand, the Facebook Prophet model provided a practical trade-off between ease of implementation and accuracy, handling seasonality and trend shifts effectively with minimal parameter tuning. Prophet was also more interpretable, making it suitable for users without deep expertise in machine learning. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) quantitatively confirmed the superior performance of LSTM in capturing dynamic traffic patterns, while highlighting the limitations of purely statistical models in real-world, noisy data environments [4].

In conclusion, this study underscores the vital role of time-series forecasting models in building intelligent traffic prediction systems. As cities grow and traffic conditions become increasingly complex, the demand for accurate and responsive forecasting methods also increases. AI-driven models, particularly LSTM networks, offer substantial improvements in prediction quality, adaptability, and scalability compared to traditional approaches. The results suggest that integrating deep learning into traffic management systems can enhance decision-making and reduce congestion through more accurate planning and response. Future research may focus on the incorporation of external variables such as weather conditions, public events, and road incidents to enrich the predictive models.

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