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Modelling and Forecasting Traffic Crashes and Fatalities in Greece

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Abstract

Traffic crashes remain a major public health and socioeconomic challenge in Greece and worldwide, underscoring the need for data-driven methodologies to support effective prevention strategies and policy design. Despite recent improvements in infrastructure and law enforcement, the frequency of traffic crashes continues to impose a significant societal burden and needs further research. The present study aims to add to current knowledge and thus carries out a comprehensive analysis and forecasting of crashes and fatalities in Greece, by utilizing an extensive time series dataset spanning 1996–2022, examined at both weekly and monthly resolutions. The utilized dataset was enriched with socioeconomic indicators, seasonal patterns as well as policy-related variables to capture temporal fluctuations and structural changes in crash dynamics. Prior to modelling, the data underwent preprocessing and feature engineering to create lag variables, cumulative indicators and binary policy flags, thereby enhancing and better representing temporal dependencies.

The proposed methodological framework combines traditional statistical models, such as the Auto Regressive Integrated Moving Average (ARIMA) and its seasonal extension (SARIMA) with advanced Deep Learning architecture based on Long Short-Term Memory (LSTM) neural networks. The main objective was to assess and compare the predictive performance of traditional linear approaches with nonlinear recurrent models capable of learning long term dependencies. Each time-series model was tuned via grid-based parameter search and afterwards its performance was reported on a fixed out-of-sample holdout period. Evaluation was conducted using quantitative performance metrics, including the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), so as to allow for comparative analysis. The results demonstrate that the LSTM model performs slightly better than the ARIMA and SARIMA models across all configurations, particularly in short-term forecasts of traffic crashes and fatalities. The reason behind these findings, is that the neural network effectively captured nonlinear relationships, seasonal patterns and exogenous influences, such as economic and legislative changes which conventional statistical models were not capable of adequately representing. The present analysis also revealed that crash occurrence exhibits strong seasonal trends, characterized by pronounced peaks during summer and holiday periods, as well as moderate correlations with selected socioeconomic variables.

Overall, the study highlights the capabilities of deep learning methods when modelling complex and non-stationary crash data and demonstrates the potential of machine learning for advancing predictive analytics in transport safety

research in Greece, where related studies are relatively limited. Lastly, the findings of our study provide a solid foundation for proactive decision-making and the development of targeted, evidence-based road safety strategies in Greece and beyond.

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1. Introduction

Road safety has long been a critical issue in political, social and scientific domains, particularly since the mid-20th century. The rapid growth in vehicle ownership, combined with urbanization and the expansion of road networks has led to a significant increase in traffic crashes, resulting in severe consequences, including loss of life, serious injuries, and substantial economic costs (Dalal et al., 2013). Over time, efforts to understand crash causes have led to the development of structured data collection systems and prevention policies at an international level (Peden & World Health Organization, 2004). In Greece, the sharp rise in vehicle usage since the 1980s was not matched by equivalent improvements in infrastructure, traffic regulation, or driver education. As a result, traffic crashes occurred more frequently and were more severe, particularly affecting younger groups and vulnerable road users. Although recent years have seen improvements through infrastructure upgrades, stricter legislation, and the adoption of monitoring technologies, road crashes remain a major challenge.

Despite the progress, traffic crashes continue to be a leading cause of premature death and serious injury worldwide. The problem is dynamic, influenced by temporal and social factors, and therefore requires continuous reassessment. Reducing crash numbers and fatalities is not only a matter of prevention policies but also of properly understanding their crash mechanism. In this context, accurate forecasting crash trends is essential for supporting data-driven decision-making and enabling more effective road safety strategies. Therefore, the purpose of this paper is to develop, implement, and evaluate time series models for forecasting road crashes and fatalities in Greece as relevant studies for Greece are relatively limited. The study also aims to add to current knowledge and capture the temporal dynamics of crashes, identify seasonal patterns, and estimate future trends using both traditional statistical methods and modern machine learning approaches. For this reason, a comprehensive analysis and forecasting of crashes and fatalities in Greece was conducted, by utilizing an extensive time series dataset spanning 1996–2022, examined at both weekly and monthly resolutions. It is noted that our analysis focuses exclusively on the frequency of crashes and fatalities, without focusing on crash injury severity. While fatalities are considered, they are treated as a separate time series rather than as part of a severity modelling framework. Hence, as frequency and severity are typically influenced by different risk factors, they should ideally be analyzed jointly or within an integrated framework as a few recent studies indicate (Bonera et al., 2024; Barabino et al., 2024), however, this approach is out of the scope of the present paper.

2. Literature Review

According to the World Health Organization, approximately 1.19 million deaths were recorded in 2021, corresponding to 15 deaths per 100,000 population, while traffic crashes remain the leading cause of death for individuals aged 5–29 (WHO, 2023). Beyond human losses, traffic crash occurrence imposes substantial economic burdens, accounting for 1% to 3% of GDP in many countries and disproportionately affecting the most productive age groups. In Greece, although notable progress has been achieved since 2014, recent data indicate setbacks, with a 2.9% increase in road fatalities in 2024 and a low performance in terms of road safety among EU countries. These trends highlight the need for continuous and systematic interventions. Traffic crashes are the result of complex interactions

among human, vehicle, environmental as well as socioeconomic factors, with human behavior remaining the dominant contributor. Key risk factors include speeding, alcohol consumption, lack of protective equipment, and driver distraction while socioeconomic factors significantly influence crash patterns, with disadvantaged populations being more exposed to higher risks (WHO, 2023). In Greece, the economic crisis after 2009 led to reduced mobility and a substantial decline in fatalities, although improvements were uneven across regions and user groups (Mpogas et al., 2017). More broadly, economic activity is closely linked to traffic volume and crash occurrence, with periods of growth typically increasing mobility and risk, while recessions tend to reduce them. In response, Greece has adopted a National Road Safety Strategy aligned with the Vision Zero framework, aiming to reduce fatalities by 50% by 2030 and ultimately achieve zero deaths by 2050 through infrastructure improvements, stricter enforcement, and enhanced public awareness (WHO, 2023).

In terms of crash numbers forecasting, time series models have been widely applied in literature. For instance, SARIMA models showed high accuracy in forecasting traffic fatalities in China, while ARIMA and SARIMA variants have also been successfully applied in Iran and Malaysia (Azhari et al., 2022; Qian et al., 2020). Moreover, Long Short-Term Memory (LSTM)-based models have been successfully applied in traffic crash forecasting across multiple contexts. Previous studies have shown that LSTM outperformed alternative deep learning models in monthly crash prediction tasks, achieving lower forecasting errors and better identification of high-risk periods (Angadi & Halyal, 2024). Hybrid approaches have also proven effective, as for example, LSTM and Gradient Boosted Regression Trees (GBRT) models achieved very high predictive accuracy to support road safety monitoring and intervention planning (Zhang et al., 2020).

3. Theoretical Background

3.1. ARIMA / SARIMA

Among the various approaches available, traditional time series models such as Auto Regressive Integrated Moving Average (ARIMA) and Seasonal Auto Regressive Integrated Moving Average (SARIMA) have been widely used due to their strong theoretical foundation and interpretability. These models are particularly effective in capturing temporal dependencies. In most real-world applications though, time series data exhibit strong seasonal patterns, such as increased crash frequency during summer periods or weekends, making simple ARIMA models insufficient. To address this limitation, the SARIMA model extends ARIMA by incorporating seasonal components, allowing it to capture both short-term dependencies and recurring temporal structures (Deretić et al., 2022).

The application of ARIMA and SARIMA models relies on key assumptions, including stationarity of the time series (or its differenced form), white-noise residuals, and adequate model fit without overfitting. Stationarity is typically assessed using statistical tests such as the Augmented Dickey–Fuller (ADF) test, while residual autocorrelation is evaluated using the Ljung–Box and Box–Pierce tests. Model performance is commonly measured using error metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and MAPE (Mean Absolute Percentage Error). The mathematical formulations of the ARIMA model are presented below.

$$\Phi(B) (1 - B)^d y_t = \Theta(B) \varepsilon_t \quad (1)$$

Where:

$$B \text{ is the back } \Theta(B^s) \text{ shift (lag) operator defined as } B y_t = y_{t-1}. \quad (2)$$

y_t is the observed value of the time series at time t .

ε_t is the white-noise error term at time t , assumed to have zero mean and constant variance.

$\Phi(B)$ is the non-seasonal autoregressive (AR) polynomial operator.

$\Theta(B)$ is the non-seasonal moving-average (MA) polynomial operator.

d is the order of non-seasonal differencing required to achieve stationarity.

The AR and MA polynomial operators are defined as:

$$\Phi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p \quad (3)$$

and

$$\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q \quad (4)$$

The mathematical formulation of the SARIMA model is presented below.

$$\Phi_p(B^s) \Phi(B) (1-B)^d (1-B^s)^D y_t = \Theta_Q(B^s) \Theta(B) \varepsilon_t \quad (5)$$

Where additional definitions exist:

$\Phi_p(B^s)$ is the seasonal autoregressive (SAR) polynomial operator.

$\Theta_Q(B^s)$ is the seasonal moving-average (SMA) polynomial operator.

D is the order of seasonal differencing.

The seasonal polynomial operators are defined as:

$$\Phi_p(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_p B^{Ps} \quad (6)$$

and

$$\Theta_Q(B^s) = 1 + \Theta_1 B^s + \Theta_2 B^{2s} + \dots + \Theta_Q B^{Qs} \quad (7)$$

3.2. LSTM Neural Networks

Machine learning approaches to time series forecasting have also gained increasing importance in road safety research because they can model nonlinear relationships, incorporate heterogeneous variables and adapt to complex temporal patterns more effectively than traditional statistical methods. Among these, Recurrent Neural Networks (RNNs) were designed for sequential data, but their ability to capture long-term dependencies is often limited by vanishing-gradient problems during training. To overcome this limitation, Long Short-Term Memory (LSTM) neural networks introduce a memory cell and gating mechanisms that regulate which information is retained, updated, or discarded over time, making them particularly suitable for crash forecasting where temporal dependencies may span long periods. This capability is especially relevant in road safety applications, where crash occurrence is influenced by recurring seasonal effects, mobility patterns, weather conditions, and broader socioeconomic changes.

4. Methodology

4.1. Data Collection, Preprocessing and Feature Engineering

The required crash data were collected from the Greek crash database SANTRA, which is provided by the Department of Transportation Planning and Engineering of the National Technical University of Athens. The SANTRA database consists of all crash data in Greece, which are filled in high detail by the Police immediately after the occurrence of a crash. The present dataset for this analysis included all recorded crashes and fatalities in Greece from year 1996 to 2022, aggregated at both monthly and weekly levels.

Prior to model development, the dataset underwent preprocessing to improve temporal consistency and predictive usefulness. The main preprocessing steps included variable type conversion, date harmonization, and the construction of explicit time indices for weekly and monthly analysis. Feature engineering then introduced seasonal descriptors such as season, quarter, and binary summer/winter indicators, together with holiday and special-event markers, in order to encode recurring temporal patterns that are not fully captured by the raw series alone. In addition, lag-based variables, rolling averages and cumulative indicators were created to better represent persistence effects and the potential influence of institutional interventions on crash dynamics. For the LSTM framework in particular, the modelling process also incorporated additional exogenous variables which were collected from the Hellenic Statistical Authority (EL.STAT.) and intended to enrich the sequence representation beyond the historical crash counts alone. These included exogenous variables such as fuel prices, GDP-related indicators and policy-related features (e.g., legislative interventions and traffic regulations), allowing the neural network to learn crash dynamics not only from past observations but also from external temporal drivers.

4.2. ARIMA / SARIMA Modeling Methodology

The statistical modelling procedure was designed as a sequential workflow in which each time series was first converted into an appropriate weekly or monthly time-series object and then examined through diagnostic plots and statistical tests to identify its internal structure. The implementation of the statistical models was carried out using the R programming language, primarily leveraging the forecast package (Hyndman et al., 2026), which provides functions for automated and manual model selection, diagnostic checking and residual analysis.

The initial stage focused on assessing stationarity and seasonality, since these properties determine the suitability of ARIMA and SARIMA specifications. Where needed, normal and seasonal differencing were applied to stabilize the mean structure before model estimation. Candidate models were then identified through a combination of Autocorrelation and Partial Autocorrelation Function (ACF/PACF) inspection, manual specification, and automated selection, allowing both theory-guided and data-driven parameterization. This was followed by comparisons across alternative specifications for crashes and fatalities separately, as well as across weekly and monthly resolutions, so that the modelling process could account for different temporal granularities.

Model estimation and evaluation were conducted using a chronological 80/20 train-test split, where earlier observations were used for training and the most recent period was reserved for out-of-sample validation. To improve adequacy beyond the initial candidates, residual diagnostics were used as a core filtering stage rather than a secondary check, since acceptable forecasting error alone was not considered sufficient if the residual structure still contained systematic autocorrelation. In parallel, log transformations were examined to reduce variance instability and improve fit in cases where the raw series exhibited stronger heterogeneity.

4.3. LSTM Modelling Methodology

The LSTM methodology followed a structured deep-learning pipeline consisting of sequence preparation, hyperparameter selection, model training, and forecast generation. The implementation was carried out in Python, utilizing deep learning libraries such as TensorFlow and Keras (Chollet et al., 2015; Martín Abadi et al., 2015), which provide flexible tools for constructing and training recurrent neural network architectures, including LSTM layers. To accelerate the training process and handle the computational demands of the models, GPU acceleration was employed through NVIDIA CUDA, enabling parallel processing and significantly reducing training time (Vingelmann and Fitzek, 2020). The first step involved transforming the time series into supervised learning sequences while preserving temporal order, so that the neural network could learn dependencies across past observations without violating the chronological structure of the data. Separate models were developed for crashes and fatalities and for weekly and monthly datasets, allowing the neural architecture to adapt to different temporal resolutions. Hyperparameter tuning was treated as an essential part of the methodology, with grid-search procedures used to identify appropriate settings for the architecture and training process before final model estimation. In particular, the grid search explored combinations of key hyperparameters such as the number of LSTM layers and units, time steps (input window size), learning rate, and dropout rate, with model selection based on performance on a validation set. The dataset was split into training and testing subsets using a chronological split (e.g., 80% training and 20% testing) to preserve temporal ordering and avoid information leakage.

4.4. Model Evaluation

Model performance was assessed using a set of complementary statistical and forecasting metrics to compare the predictive capability of the ARIMA, SARIMA, and LSTM approaches in a consistent manner. Forecast accuracy was primarily quantified through Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Additional percentage-based and scale-independent measures, such as Symmetric Mean Absolute Percentage Error (SMAPE) were considered to enable more robust comparisons across datasets with different magnitudes and seasonal characteristics. In regard with the LSTM models, the coefficient of determination R^2 was further used to assess the proportion of variance explained by the neural network predictions. As mentioned before, in the case of ARIMA and SARIMA, evaluation did not rely solely on forecasting accuracy but also incorporated diagnostic checks of model adequacy through residual analysis, including tests for remaining autocorrelation and the verification of white-noise behaviour.

5. Results

Among the statistical time series approaches examined, the best-performing models that simultaneously satisfied both forecasting accuracy and residual diagnostic criteria were exclusively SARIMA-based specifications, highlighting the importance of modelling seasonality in crash data. The strongest overall performance was achieved by the monthly crashes model SARIMA(1,0,2)(1,0,3)[12], which recorded a MAPE of 12.33% a RMSE of 121.38 and a MAE of 86.62. For the weekly crash times series, although certain SARIMA specifications achieved relatively low forecasting errors, such as Log SARIMA(2,1,1)(0,1,1)[48] with a MAPE of 18.72%, none of the examined models passed the residual adequacy checks. This indicates that, despite acceptable predictive accuracy, the models failed to fully capture the underlying temporal structure of the data, leaving significant autocorrelation in the residuals.

For the monthly fatalities time series, the most suitable model was identified as SARIMA(1,0,2)(1,1,1)[12], achieving a MAPE of 17.14%, a RMSE of 10.65 and a MAE of 8.71, with alternative seasonal specifications producing similar but slightly inferior results. In the case of weekly fatalities, the best-performing model that satisfied the residual diagnostics was Log SARIMA(3,0,3)(0,1,3)[48], with a MAPE of 29.92%, reflecting the increased difficulty of modelling higher-frequency data.

Overall, the monthly series consistently yielded better forecasting performance for the statistical models compared to the weekly data. This can be attributed to the smoother behaviour and reduced noise in aggregated monthly observations, which enhances the ability of ARIMA/SARIMA models to capture underlying trends and seasonal patterns. Figure 5-1 illustrates the comparison between the actual and predicted values generated by the best-performing SARIMA models. The observed time series is depicted by the red solid line, whereas the blue dashed line represents the predicted values.

In contrast to the traditional statistical approaches, the LSTM-based models demonstrated a higher predictive performance across all examined datasets, particularly in short-term forecasting. The best-performing configuration was observed in the monthly crash dataset, where the LSTM model achieved a MAPE of 6.43%, RMSE of 66.57, and MAE of 44.32 for a one-step ahead prediction, significantly outperforming the corresponding SARIMA models. Similarly strong performance was observed in the weekly crash dataset, where the LSTM model achieved a MAPE of 10.44%, RMSE of 20.10, and MAE of 15.54 for a one-step ahead prediction, demonstrating its ability to effectively model higher-frequency data despite increased variability and noise. For the weekly fatalities forecasting, the model achieved even higher predictive accuracy for a one-step ahead prediction, with a MAPE of 8.56%, RMSE of 1.14, and MAE of 0.99, along with a high explanatory power ($R^2 = 0.95$), indicating excellent fit and generalization capability. In the case of monthly fatalities, the LSTM model also performed consistently well, achieving a MAPE of 10.30%, RMSE of 6.18, and MAE of 4.33 for a one-step ahead prediction. The best-performing LSTM models for both monthly crashes and monthly fatalities were trained using a single time step and 256 LSTM units. For the monthly crashes model, the architecture included 64 dense units, a dropout rate of 0.2, the Mean Squared Error (MSE) loss function, a learning rate of 0.001, a batch size of 64, and 200 training epochs. The monthly fatalities model employed the same configuration, except that it utilized 256 dense units and the Huber loss function.

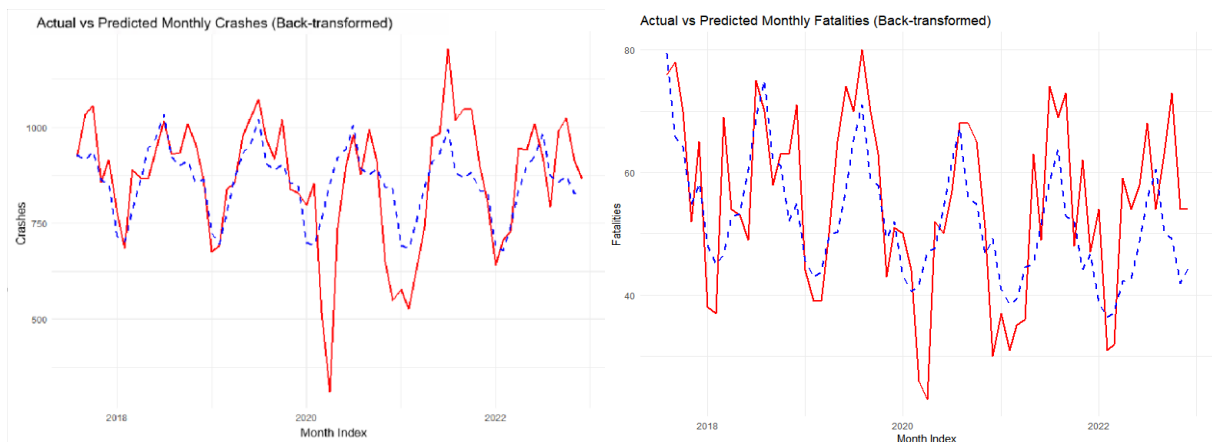


Figure 5-1: Actual vs Predicted values of the Best SARIMA Models for Monthly Traffic crashes and Fatalities

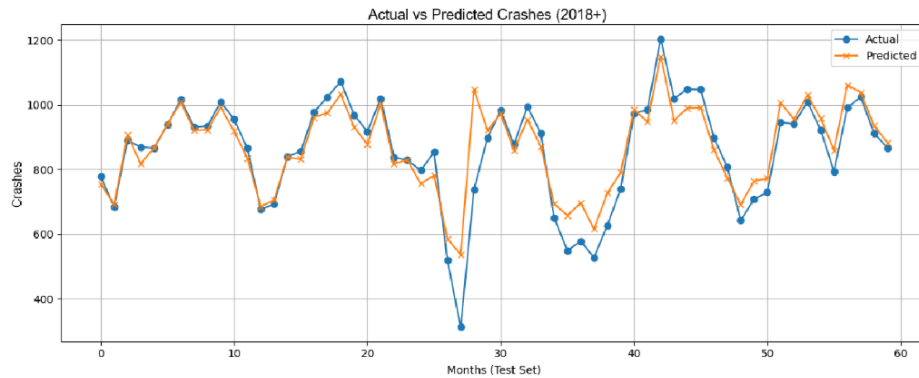


Figure 5-2: Actual vs Predicted Monthly Crashes with the LSTM NN Model

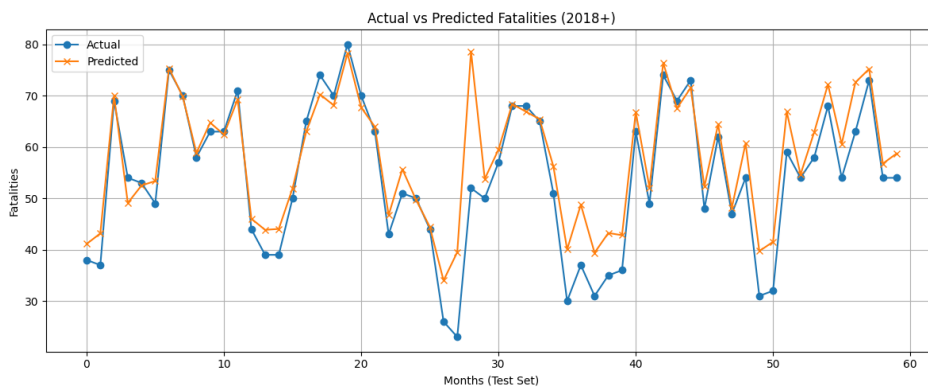


Figure 5-3: Actual vs Predicted Monthly Fatalities with the LSTM NN Model

6. Conclusions

The present study contributes to the understanding of road safety trends in Greece through a comprehensive analysis and forecasting of crashes and fatalities using an extensive time series dataset spanning 1996–2022 and examined at both weekly and monthly resolutions, as relevant studies for Greece are relatively limited. The dataset was also enriched with socioeconomic indicators, seasonal patterns and policy-related variables to better capture temporal fluctuations and structural changes in crash dynamics. The results indicate that the LSTM models evaluated in this study achieved higher forecasting accuracy than the ARIMA and SARIMA models under the examined experimental settings, suggesting that nonlinear approaches may be better suited for capturing complex temporal dependencies, seasonal effects, and exogenous influences. These findings highlight the potential of machine learning methods for advancing predictive analytics in road safety research and supporting evidence-based decision-making.

However, a number of limitations should be acknowledged. The analysis was conducted using a single chronological train-test split and aggregated national-level data, limiting the assessment of model robustness and the ability to capture spatial heterogeneity and localized risk patterns. Future research could address these limitations through rolling validation approaches and sensitivity analyses, using spatially disaggregated and crash-level datasets, by addressing both crash frequency and injury severity and considering attention-based and transformer-based architectures.

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