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RESEARCH

A New Approach to Interoperability within the Smart City Based on Time Series-Embedded Adaptive Traffic Prediction Modelling

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Abstract
The rapid urbanization observed over recent decades has led to important challenges in urban mobility, notably traffic congestion, pollution, and inefficient energy consumption. Concurrently, the rise in electric vehicles (EVs) offers a promising shift towards sustainable urban transport yet introduces complexities such as the need for extensive charging infrastructure and effective energy demand management. This study addresses these challenges by proposing a predictive model for real-time and future traffic volume estimation, leveraging historical data, real-time information, scheduled city events, and the availability of EV charging infrastructure. The methodology proposed employs actuarial techniques to create a comprehensive framework that predicts traffic patterns and optimizes energy resources within smart cities. By integrating variables such as historical traffic patterns and real-time data, our model provides accurate traffic forecasts essential for urban planning and energy distribution. We utilize a time-series based algorithm to predict traffic, validated through real data from pilot projects in Ljubljana, Slovenia. The study's findings underscore the model's potential to enhance urban mobility and energy efficiency, providing a robust tool for city planners and policymakers.

Keywords Urban mobility · Electric vehicles · Traffic prediction · Smart cities · Energy management · Predictive modelling

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1 Introduction

Over the past few decades, the increasing global urbanization has led to an unprecedented rise in urban mobility (Miskolczi et al. 2021). This phenomenon has exacerbated traffic problems in cities around the world, resulting in congestion, increased pollution, and inefficient energy consumption (Lu et al. 2021). Concurrently, the surge in electric vehicles (EVs) represents a substantial transformation in urban transport, promoting more sustainable mobility (Dlugosch et al. 2022), though it introduces new and significant challenges, such as the need for adequate charging infrastructure (Aduama et al. 2023; Gauglitz et al. 2020) and efficient energy demand management (Bibri and Krogstie 2020).

The urbanization phenomenon is closely linked to population growth in major urban centres. Every year, millions of people worldwide relocate to cities, seeking better job opportunities, education, and essential services (Hamnett 2024; Salov and Semerikova 2023). This has led to a substantial increase in population density in urban areas, further intensifying the challenges related to mobility and traffic management (Zhang et al. 2023). Demographic projections indicate that this trend toward concentration in major urban centres will continue to grow (Wang and Long 2023), necessitating innovative and effective solutions to accommodate an ever-increasing number of residents and vehicles in the same urban space.

In this context, access to and analysis of large volumes of mobility data become essential tools to address these challenges. The ability to predict traffic volume in different areas and at different times can facilitate not only urban planning and traffic management but also the optimization of the electrical supply network and the distribution of the energy resources needed to support the growth of the electric vehicle fleet.

This paper proposes an innovative method that uses advanced data analysis techniques and predictive modelling to estimate traffic volume in real-time and with future projections. This method integrates variables such as historical traffic patterns, real-time information, scheduled city events, and the availability of EV charging infrastructure, among others. With our proposal, we aim to offer a tool that not only improves traffic management and urban mobility but also optimizes the allocation of energy resources in an increasingly electrified urban environment.

Our methodology leverages applied quantitative techniques and actuarial analysis to construct a thorough framework aimed at solving mobility-related issues, with a specific focus on traffic management within the Smart City context. By identifying patterns and formulating informed predictions about future occurrences, we address a longstanding and common social challenge, especially in relation to various interoperability strategies within a smart city.

We propose an adaptive algorithm embedded in time series to predict traffic and explore whether accuracy can be improved by addressing the problem in a continuous self-improvement manner. We assess the accuracy of the proposed error estimations using real data to improve interoperability in the city. This approach not only aims to enhance the responsiveness and efficiency of urban infrastructures but also to foster sustainable and adaptive development in the face of the growing challenges of modern urbanization.

The structure of this paper is outlined as follows: Sect. 2 provides a review of related work. In Sect. 3, we analyze the issues that need addressing and introduce our proposed model. Sections 4 and 5 delve into the validation and design of a time-series system for traffic prediction, which is to be integrated into the mobility model for Smart Cities. Section 6 is dedicated to the development of model validation, while Sect. 7 discusses a practical case study to estimate the prediction error. Finally, Sect. 8 offers some conclusions and outlines potential future lines of research.

2 Background

Smart cities are redefining urban management by leveraging advanced technologies to address challenges related to mobility, energy, and environmental sustainability (Wu et al. 2021). As cities face increasing urbanization and energy demands, smart mobility and efficient traffic management become essential components for enhancing the quality of urban life (Zhao et al. 2017). Smart mobility systems, supported by large volumes of data and wireless connectivity, enable more effective traffic management, and optimize transport flows to reduce congestion. Cassandras (2017) demonstrates how Connected Automated Vehicles (CAVs) can increase efficiency at traffic-light-free intersections, optimizing traffic coordination and minimizing usual delays and congestion in large cities. Chatfield and Reddick (2016) examine how smart cities, using information infrastructures and distributed renewable energies such as smart microgrids, significantly contribute to the reduction of carbon emissions in urban environments, promoting more sustainable and efficient development.

In addition to improving mobility, efficient energy management in smart cities is crucial for the sustainability and efficiency of urban mobility systems. Ejaz et al. (2017) discuss the importance of efficient energy management in the context of the Internet of Things (IoT) in smart cities, providing a framework for energy optimization and harvesting, which is essential for extending the lifespan of low-power devices used in urban infrastructure.

The need to reduce energy consumption and CO2 emissions becomes even more critical in the context of smart cities. Mekhum (2020) highlights cities, which contribute to 70% of global CO2 emissions, must adopt the concept of Smart Energy City (SEC) to radically address energy demand through renewable sources. Abdallah and El-Shennawy (2013) also emphasize the relevance of smart grids for improving energy efficiency and facilitating the integration of renewable energies. On the other hand, Badai (2021) proposes innovative solutions such as the use of autonomous electric vehicles and the management of residual energies to optimize energy consumption and reduce CO2 emissions.

Various methods/technologies have been proposed/used recently with the same goal: to try to reduce the energy needs derived from mobility in cities. Chen et al. (2022) propose an efficient and smart street lighting system based on IoT architecture, which uses smart electric poles with sensors to adjust LED lamps through a controller that optimizes energy use based on traffic flow and the presence of occupants. In Pieroni et al. (2018), there is a discussion on how to improve the Quality of Life (QoL) and the Quality of Services (QoS) in cities through the use of Information and Communication Technologies (ICT) to collect and analyze large amounts of data, with a particular focus on the implementation of a Smart Energy Grid that uses

Blockchain technology to facilitate the exchange of information and the buying/selling of energy among involved nodes.

Together, these technologies and strategies not only aim to solve the immediate problems of congestion and energy management but also seek to ensure the long-term sustainability of urban environments. By integrating smart mobility systems with advanced energy management, smart cities can transform into models of efficiency, sustainability, and high quality of life for their citizens. Nevertheless, efficient energy management in large cities is a very complex problem (Guo et al. 2022), and it is necessary to propose new methods that can improve interoperability between different technologies and platforms used. These methods should focus on optimizing energy consumption, integrating renewable sources, and adapting systems to changing demand patterns. For this, it is crucial to develop algorithms that not only manage energy resources efficiently in real-time but also anticipate future needs based on predictive analysis and historical data.

The mobility model presented in this document, based on a traffic prediction algorithm, addresses an issue that has not yet been deeply treated in the literature: the impact of electric vehicles concerning the energy needs in the city. This model is necessary to complete our initial algorithms that attempted to predict energy demand in the city and estimate the availability of energy supply in the network of charging stations.

The preliminary results of this research were presented in Fernandez et al. (2018), where we began to design different parts of the algorithms to manage the energy supply in the network of charging stations in the city. However, many points needed to be improved in these algorithms to make electric vehicles interoperate with the city not only to control and manage the energy supply from a control center but also to design and integrate a required traffic forecast system, which had not been considered at that time due to its mathematical complexity.

3 Prediction Problem to be Addressed and Proposed Model

As mentioned, it is of paramount importance to describe traffic management in the Smart City. This will allow us to reach conclusions on how to develop a new interoperability model that lets us predict behavior and that self-learns from itself to optimize all available resources. This problem posed an innovative challenge to the entire European society.

The formulation of the problem requires, on one hand, a mathematical description of the traffic movements in the city at each time t, and, on the other hand, proceedings to obtain the real recurrences in the traffic. This leads to the definition of patterns whose similarities are analyzed with actuarial tools and allow us to find predictions based on the traffic measured at the current time and before.

Let F_t be the random variable representing the units of vehicle volume per unit of time, such as 'vehicles per hour' or 'vehicles per day', at time t. In other words, the traffic prediction at time t. So, these units allow traffic flow to be analyzed at specific time intervals and help evaluate density and usage patterns on a given transportation network. It can be built then a family of continuous random variables depending on time. To avoid working with continuous variables like time, we decide to discretize this family of continuous variables. To do this, we sample at certain times of the day, represented by slots. Let $J = \{k \in \mathbb{Z}\}_{k \leq t}$ be the set of indexes associated to these slots. We have therefore got a series of random variables $\{F_t\}_{t \in J}$ dependent on each other and temporarily ordered.

As F_t depends on the traffic measurement at time $t - i$, $i > 0$, we can say that $F_t = \phi\left(\{F_{t-n}\}_{n \geq 1}\right)$, being ϕ the function of recurrence representing that dependence. So, without loss of generality, we can approximate ϕ by a linear combination of $\{F_{t-n}\}_{n \geq 1}$, becoming necessary to ensure that this linear dependence is valid for a forecast of traffic as close as possible to reality. Using the so called simple and partial autocorrelation functions, we do it in the next section.

When approximating $\boldsymbol{\phi}\left(\{F_{t-n}\}_{1 \leq n \leq p}\right)$ for the commented linear combination of $\{F_{t-n}\}_{n \geq 1}$ we can write the error made as follows:

$$\boldsymbol{\phi}\left(\{F_{t-n}\}_{1 \leq n \leq p}\right) \cong \boldsymbol{approx}\left(\{F_{t-n}\}_{1 \leq n \leq p}\right) = a_0 + \sum\nolimits_{k=1}^{p} a_k F_{t-k} \tag{1}$$

where $\{a_i\}_{1 \leq i \leq p}$ are the dependency coefficients between the current traffic forecast and the previous one.

$$\epsilon_t = F_t - \boldsymbol{approx}\left(\{F_{t-n}\}_{1 \leq n \leq p}\right) = F_t - \left(a_0 + \sum\nolimits_{k=1}^{p} a_k F_{t-k}\right) \tag{2}$$

Therefore F_t can be written as the time series:

$$F_t = a_0 + \sum\nolimits_{k=1}^{p} a_k F_{t-k} + \epsilon_t \tag{3}$$

Hence the estimation model of traffic forecast at time *t* is defined by this formulation, autoregressive of order *p*, as it can be seen in Frees et al. (2014) and author (year).

The $p+1$ parameters $\{a_j\}_{j=0}^{p}$ define the lineal regression function $f\left(\{F_{t-k}\}_{k=1}^{p}, \{a_j\}_{j=0}^{p}\right) = approx\left(\{F_{t-k}\}_{k=1}^{p}, \{a_j\}_{j=0}^{p}\right)$ which best approximates F_t from $\{F_{t-k}\}_{k=1}^{p}$. To find the value of these parameters we will require that the mean square error when approximating F_t for $f\left(\{F_{t-k}\}_{1 \leq k \leq p}\right)$ is minimum.

Let M be the number of data obtained from the traffic measurements in previous slots. The function to minimize is then the following one:

$$MSE(f) = \sqrt{\frac{1}{M}\sum\nolimits_{t=1}^{M}\left(f\left(F_{t-k}, 1 \leq k \leq p\right) - F_t\right)^2} = \sqrt{\frac{1}{M}\sum\nolimits_{t=1}^{M}\left(a_0 + \sum\nolimits_{k=1}^{p} a_k F_{t-k} - F_t\right)^2} \tag{4}$$

Without loss of generalization, it is the same to minimize $MSE(f)$ as to minimise its square. Therefore, this will lead us to minimize its square to simplify the associated calculations:

$$\begin{aligned} E &= (MSE\,(f))^2 \\ &= \frac{1}{M}\sum\nolimits_{t=1}^{M}\left(f\,(F_{t-k}, 1\leq\ k\leq\ p) - F_t\right)^2 \\ &= \frac{1}{M}\sum\nolimits_{t=1}^{M}\left(\ a_0 + \sum\nolimits_{k=1}^{p} a_k\,F_{t-k} - F_t\right)^2 = E\,(a_0, a_1, \ldots\ , a_p) \end{aligned} \tag{5}$$

To minimize this non-linear expression, the critical points of this new error function E must be obtained. To achieve our results and according to Frees et al. (2014), we will match the gradient of E to zero. This implies calculating the roots of each one of the partial derivatives of the error function.

$$\frac{\partial\,E}{\partial\,a_0} = 0 \rightarrow\ \sum\nolimits_{t=1}^{M} 2\left(a_0 + \sum\nolimits_{k=1}^{p} a_k\,F_{t-k} - F_t\right) = 0 \tag{6}$$

$$\frac{\partial\,E}{\partial\,a_i} = 0 \rightarrow\ \sum\nolimits_{t=1}^{M} 2\left(a_0 + \sum\nolimits_{k=1}^{p} a_k\,F_{t-k} - F_t\right) F_{t-i} = 0\ ,\quad 1\leq\ i\leq\ p \tag{7}$$

Developing these $p+1$ equations, the coefficients $\{a_i\}_{i=0}^{p}$ will be found by solving the next system.

$$\left\{ \begin{array}{r} M\,a_0 + \sum\nolimits_{k=1}^{p} a_k\,\left(\sum\nolimits_{t=1}^{M} F_{t-k}\right) = \sum\nolimits_{t=1}^{M} F_t \\ a_0\sum\nolimits_{t=1}^{M} F_{t-i} + \sum\nolimits_{k=1}^{p} a_k\,\left(\sum\nolimits_{t=1}^{M} F_{t-k} F_{t-i}\right) = \sum\nolimits_{t=1}^{M} F_t F_{t-i}\ ,\ 1\leq\ i\leq\ p \end{array} \right\} \tag{8}$$

In this way, by using algorithms to solve systems of linear equations, we obtain the coefficients for the traffic prediction approximation in each time slot. This allows us, in the next step, to estimate the potential error by validating the proposed model.

4 Methodology to Validate the Proposed Model

In the same way as the traffic measurement at time t depends on predicted traffic in previous slots, it is important to note that the error in predicting traffic at t also naturally depends on the prediction error from previous slots. To examine the relationship between the traffic prediction at a given slot i and the prediction i slots earlier, we calculate the simple autocorrelation coefficient of order i, as expressed below:

$$SAC_i\,[(\,F_t - \mu\ )(\,F_{t-i} - \mu\ )] = r_i = \frac{\sum\nolimits_{t=1}^{M}(F_t - \mu\,)(F_{t-i} - \mu\,)}{(p-i)\sum\nolimits_{t=1}^{M}(F_t - \mu\,)^2/p}, \tag{9}$$

where μ represents the mean of the random variable F_t. This mean is easily obtained from the historical traffic data provided by the prediction algorithm, which is designed and described in the following section.

This set of coefficients r_n come from the simple autocorrelation function (SAF) for our purpose in the urban model. The SAF will be a sequence where $SAF\,(n) = r_n$, $1\leq\ n\leq\ p$, being $SAF\,(0) = r_0 = 1$.

However, the SAF is not enough to validate the prediction of traffic at slot n . It is also necessary to remove the possible effect of intermediate results between two given predictions. To achieve our goal, it is vital to follow the proceeding it is designed.

Once obtained the simple autocorrelation coefficients r_n, the Yule-Walker (Kallas et al. 2013) equations let us state that these r_n are a linear combination of $\{r_j\}_{j<n}$, the smallest order autocorrelation coefficients:

$$r_n = \sum_{i=1}^{p} \alpha_i r_{n-i} \ , \quad 1 \leq n \leq p \tag{10}$$

The partial autocorrelation coefficients s_n, and so the proportionality constants α_i, can be calculated as follows:

$$s_1 = r_1 \begin{bmatrix} r_0 & r_0 \\ r_1 & r_1 \end{bmatrix}^{-1} \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \begin{bmatrix} * \\ \alpha_2 \end{bmatrix}, \qquad s_2 = \alpha_2 \begin{bmatrix} r_0 & r_1 & r_2 \\ r_1 & r_0 & r_1 \\ r_2 & r_1 & r_0 \end{bmatrix}^{-1} \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} = \begin{bmatrix} * \\ * \\ \alpha_3 \end{bmatrix}, \qquad s_3 = \alpha_3 \tag{11}$$

The partial autocorrelation function (PAF) for our problem is therefore defined with the coefficients s_n, being obtained recurrently. These coefficients of order n, s_n, show the correlation between two samples separated in *n* slots when the linear dependence between the two samples is suppressed due to intermediate values.

Both functions, SAF and PAF, validate the autoregressive model of order p because the SAF coefficients do not cancel out quickly while the first PAF coefficients define a rapidly convergent recurrence to zero. This implies that the behavior of the considered time series follows a linear autoregressive model of at least order 2 (according to the consequences of Yule-Walker equations), that is, $p \geq 2$.

5 Traffic Forecasting Time-Series Based Algorithm

To design the time-series based algorithm to predict the traffic, the boundary conditions to determine the prediction tasks are required. These initial conditions are defined by different factors influencing the traffic behavior like tourist movements, school holidays, destination, temperature during the day, among others. Through direct observation, the traffic movements in the city present a repetitive daily pattern:

- A stationary behavior is ensured from a statistical point of view.
- The same pattern can be observed in traffic during working days, for instance. This leads us to guarantee that traffic behavior is similar in the week.

Once obtained the time series $F_t = a_0 + \sum_{k=1}^{p} a_k F_{t-k} + \epsilon_t$ and developed the procedure to validate its dependence by analyzing the SAF and PAF related functions, the next step is to discriminate F_t into two components, one related to stochastic information and the other one with stationary information, being the first one not feasible to calculate precisely. This last part of F_t is the one characterizing the behavior and traffic variations between apparently similar days. The methodology we have developed to forecast the traffic, the final data series, at any moment t, is composed by the next processed (shown in Fig. 1) we have defined to design the associated algorithm:

i. Once collected the data associated to the traffic in previous moments (historic data) it is of paramount importance to calculate the mean values at each moment t defined. This series composed by the mean values will be called stationary or deterministic part of the process.
ii. Next step will consist of subtracting these mean values from the (real) data that we have at t. So we can get the traffic variations at each time t of the day. This second series will be called stochastic traffic data in our process.

   These two first steps build our model we will apply recurrently to proceed with an ecological inference, as we can see in the next steps:

   a. Firstly, the mean square error between the traffic variations at time t and those obtained in the stochastic data series will be minimized. So the traffic variations in the next slots will be able to be approximated. The more relevant step in this calculation is the previous step where the stochastic part is obtained.
   b. The model will be modified with the new coefficients calculated, leading then to a new model. Therefore, a new series is generated to compare with the previous ones.
   c. These comparisons lead to a continuous modification of the stochastic time series, which give us the ones related to the different slots of the day.

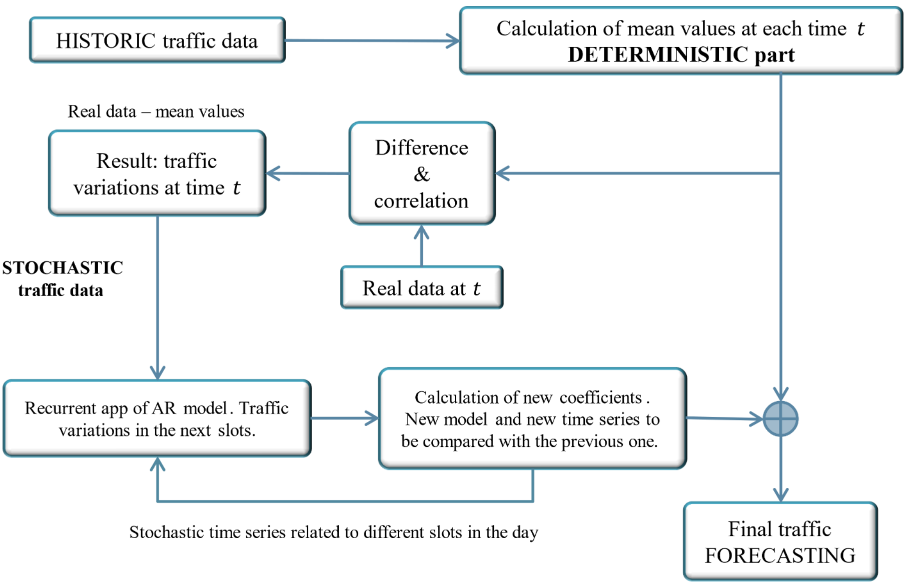

Fig. 1 Traffic prediction algorithm

iii. Finally, the addition of this calculated stochastic parts and the deterministic part obtained in the first step will let us get the prediction of traffic at the moment t, given as a time series.

To see convergence, the procedure will need a few hundred iterations for our traffic prediction model. To get a more accurate estimate, we can:

- Experiment with different hyperparameters and model architectures to find the optimal configuration for the specific dataset and problem.
- Monitor the training process and adjust hyperparameters as needed to improve convergence.
- Use early stopping to prevent overfitting and reduce training time.

By carefully considering these factors, our traffic prediction algorithm will be optimized for efficient convergence.

6 Model Validation

The initial data we used to obtain the final data and validate our model come from the interoperability information system between full electric vehicles and the smart grid, implemented and tested in Ljubljana (Slovenia) as part of the final pilot results of the European MOBINCITY project (Mobincity 2015). The MOBINCITY project ("Smart Mobility in Smart City"), funded by the European Union under Grant Agreement Number 314,328, aimed to develop solutions for integrating electric vehicles into the smart city environment, optimizing both energy management and user experience. The platform developed enabled electric vehicles to dynamically connect to the grid and coordinate energy consumption based on resource availability and grid requirements.

The tests fields for the pilot were divided into two main categories. The first group was called partial validation, and it included the software validation and testing some functionalities such as recovering and updating the route or the reservation module that had to be tested as a first step to the second group of tests. The second group (system integration) of field tests was focused on testing long-chain functionalities involving almost all the components and actors available for the pilot. The main functionalities of the system were tested, including the trip planning and the re-routing process considering several constraints, like the traffic status, the user behavior, or the batteries status.

Figure 2 shows the geographic area selected for the field tests, which includes all the energy and transport infrastructure information required to make the system work and validate all its functionalities. The simulation scenario considers various environmental and operational parameters:

- Weather: clear skies with dry road conditions, according to the day we have taken as reference, April 2, 2023, as explained above.
- Traffic data: real-time traffic data collected from sensors, cameras, and GPS devices is incorporated to accurately monitor flow within different areas, especially the pilot area highlighted in the figure. These data were provided for us by the city

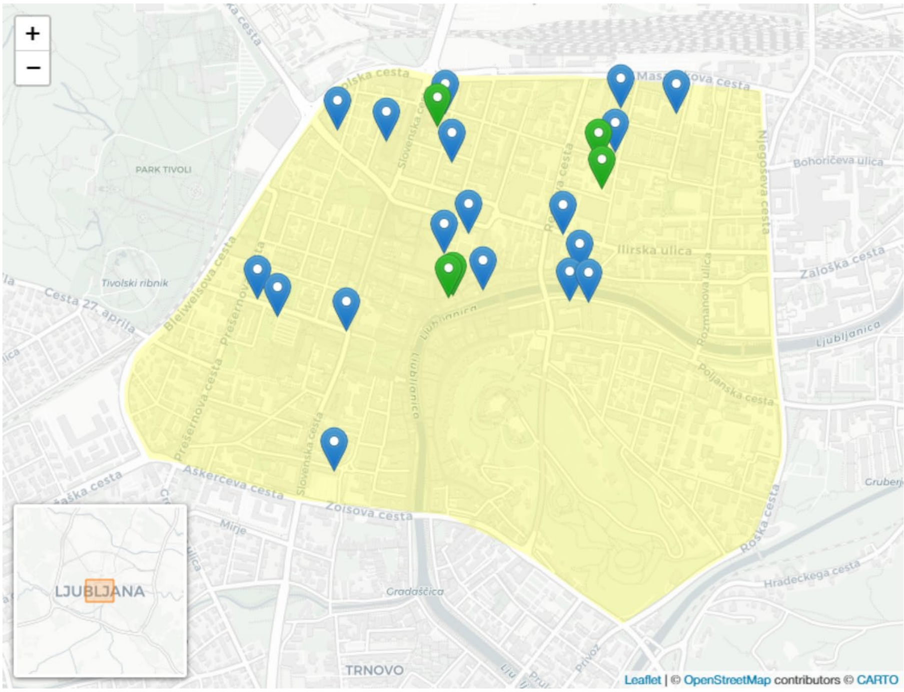

Fig. 2 Selected geographic area for field tests in Ljubljana, Slovenia. The yellow shaded region marks the pilot study zone, while blue points indicate parking facilities and green points denote charging stations

hall of Ljubljana, as explained.

- Infrastructure: charging stations marked in green, providing critical points for energy demand analysis, while parking facilities are indicated in blue. The parking facilities are particularly important for the study as they account for periods when EVs are stationary. Moreover, the positions of the CS (charging stations) will be constraints to consider not only in this study but also to implement our results in the cities in Europe, where our research is focused.
- Historical traffic data: historical traffic information for similar conditions is also used to enhance model accuracy and support more robust predictions. As explained before, this will be used to apply our study to other cases, maybe more complex, being our research important reference to proceed.

This setup enables a realistic and comprehensive assessment of the system's performance under actual urban conditions.

7 Continuous Self-improvement of the Model Based on Error Estimation

Based on the data discussed in the previous section, we analyzed the time series for a full day (April 2, 2023), including the original data, the stationary data, and the resulting stochastic data. For this day, we first calculated the SAF of our series F_t , finding that the SAF values should not be considered significant according to the Yule-Walker equations. This SAF shows slow convergence and includes too many significant terms, with the coefficients not converging rapidly to zero. As previously noted, this indicates that the dependency model should be linear autoregressive. To determine the exact order of dependency or autoregression, it is essential to conduct an additional analysis using the PAF, generally aiming for a model order below 5. To demonstrate how to estimate prediction error, we present a practical case using a second-order autoregressive model $(p = 2)$, defined as follows:

$$F_t = 0.7F_{t-1} - 0.3F_{t-2} \tag{12}$$

Starting with this initial time series, we determine the coefficients for a new time series using the designed algorithm. This involves using the initial model and minimizing the mean square error, as previously described. The updated coefficients then create a refined model, which is used to generate a new series for comparison with the previous one. The resulting model is:

$$F_t = 0.651F_{t-1} - 0.2985F_{t-2} \tag{13}$$

This model allows for the generation of new data series iteratively. The output of Eq. (13) serves to create a stochastic time series for different times of the day, as shown in Fig. 1. The final traffic prediction series at time t is obtained by adding this stochastic component to the deterministic part calculated in the initial step, where we derived average values for each time of day.

For this study, we use traffic data from a specific simulation day, April 2, 2023, provided by the city hall of Ljubljana (Slovenia). In this context, traffic intensity is measured in terms of vehicular flow (vehicles per hour or per unit of time) or vehicular density (number of vehicles per kilometer). In our model, we express intensity as a percentage, using the average value as a reference point.

In the following figures, we illustrate both the stationary data series (after calculating average values for each time of day from historical data) and the final data series, representing the traffic prediction at three different times of day.

Figure 3 corresponds to traffic data from April 2, 2023, recorded at 2:15 AM (sample 27) and the traffic prediction derived from the previous sample's data.

Similarly, Fig. 4 displays traffic data from the same day (April 2, 2023) at 11:35 AM (sample 139) along with the traffic prediction based on prior sample data.

Finally, Fig. 5 shows traffic data from April 2, 2023, at 11:15 PM (sample 279) and the corresponding prediction derived from the preceding sample.

From this analysis, we observe that the prediction error remains within an acceptable range, demonstrating the practical calculation of prediction error, though further

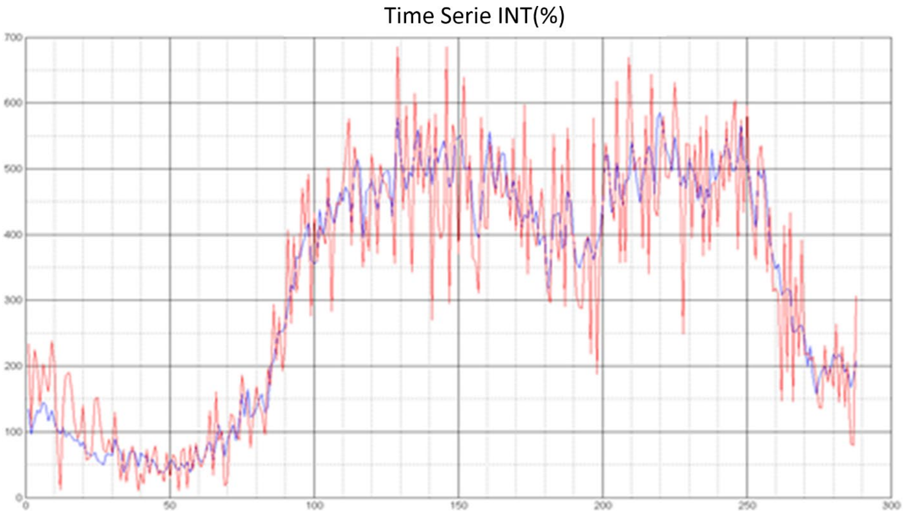

Fig. 3 The predicted series (shown in red) is compared against the observed traffic sample (in blue). Sample number 27, April 2, 2023, 02:15 AM

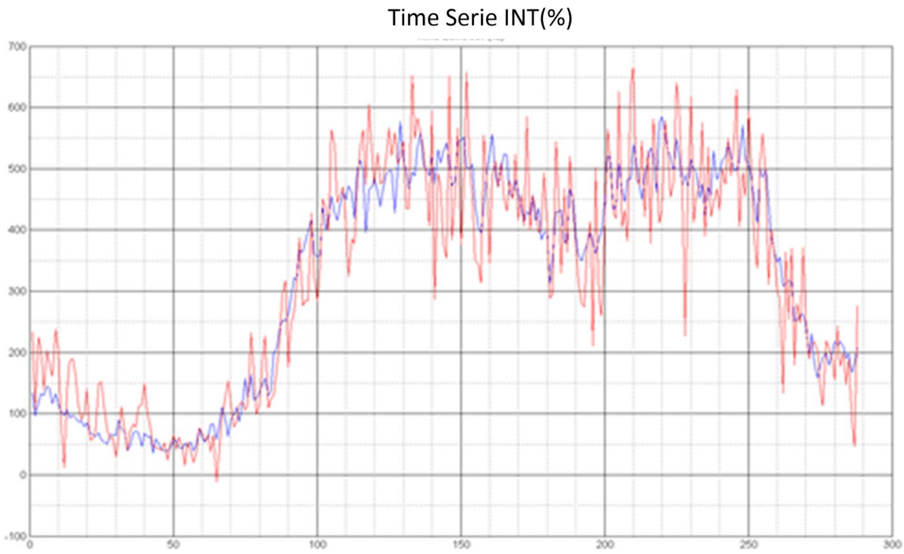

Fig. 4 The predicted series (shown in red) is compared against the observed traffic sample (in blue). Sample number 139, April 2, 2023, 11:35 AM

improvement is possible. To further reduce the error, the order of dependency p would need to be higher than 2. As we incorporate more historical data, our prediction accuracy will continue to improve, enabling us to refine traffic forecasts continuously.

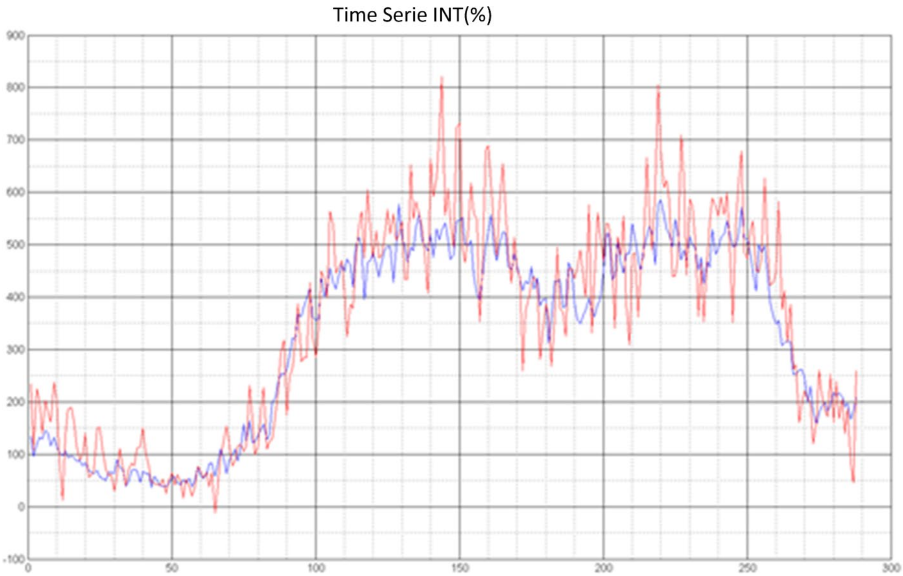

Fig. 5 The predicted series (shown in red) is compared against the observed traffic sample (in blue). Sample number 279, April 2, 2023, 11:15 PM

8 Conclusions and Future Work

This study presents a robust framework for urban traffic management and energy resource allocation within the context of Smart Cities, leveraging advanced data analysis techniques and predictive modeling. The developed methodology enables accurate real-time and future traffic pattern predictions, providing an essential tool for urban planning. This approach also contributes to optimizing energy distribution within the EV charging network, maximizing efficient use of energy resources in urban environments.

Our model also introduces a continuous self-improvement capability based on error estimation, allowing real-time adjustments as new data is collected. This flexibility is crucial for managing variability and fluctuating traffic demands in densely populated urban areas. Additionally, it complements our previous work (Fernandez and Pérez 2024), which addresses EV charging control in the context of demand-side energy management through a predictive control approach. Together, these studies offer a broader framework that considers both traffic flow optimization and energy distribution for EVs, aligning charging operations with periods of lower traffic and demand.

From a practical perspective, implementing this model provides significant benefits for urban mobility planning and management by offering real-time traffic data and predictive analysis, key elements for decision-making in growing cities. The simultaneous optimization of the EV charging network ensures efficient energy supply, reduces peak demand, promotes sustainable mobility, and enhances overall energy efficiency across the city.

As future work, we will consider incorporating covariates as blocking factors for different prediction models, which will expand the model's scope and improve its accuracy by capturing additional elements that influence traffic. Examples of such covariates include weather conditions, school schedules, or major city events, which can significantly impact daily and hourly traffic patterns. For instance, incorporating weather as a covariate could improve predictions by accounting for variations in traffic flow due to rain or extreme temperatures, while school schedules and major events could explain and adjust for localized surges in traffic. This extension will further position our contributions within the state of the art in traffic prediction, in line with the existing literature.

Additionally, our research will focus on expanding the model's scope to include high-power vehicles, such as buses, vans, and electric trucks, which constitute a significant component of urban transport systems. We also envision integrating the charging system with smart home technologies, improving energy efficiency in residential areas. Another promising direction is applying our model to other sectors, such as agriculture, facilitating optimal energy distribution and usage across a broader range of activities within Smart Cities. Through these future developments, we anticipate that our model will advance traffic and energy management systems and contribute to the sustainable development of urban environments globally.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

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