Traffic Flow Prediction at Intersections: Enhancing with a Hybrid LSTM-PSO Approach

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***Abstract*—The growing challenge of increasing traffic volumes presents a real challenge for road safety, emergency response and overall transport efficiency. Intelligent transportation systems play a fundamental role in solving these challenges, through accurate traffic prediction. In this study, we propose a hybrid model that combines the Long-Term Memory Algorithm (LSTM) and Particle Swarm Optimization (PSO) to predict traffic flow more accurately at intersections. Our approach takes advantage of the strength of PSO, a robust optimization technique inspired by swarm intelligence, to optimize the hyperparameters of the LSTM algorithm. Through in-depth benchmarking, we evaluate the performance of our hybrid LSTM-PSO model against other existing models. By evaluating measures such as root meansquare error and mean absolute error, we demonstrate the superior efficiency of the proposed hybrid model. Our results highlight the effectiveness of our approach in outperforming alternative models, offering a promising solution for intelligent transportation systems to accurately predict traffic flow at intersections and improve overall traffic management efficiency.**

***Keywords*—Deep learning; intersection congestion; intelligent transport systems; traffic flow prediction**

I. Introduction

Transportation networks play an essential role in reinforcing economic and societal activities by facilitating the mobility of people, goods, and services. The reliability and efficiency of these transport systems are of great importance in fostering economic growth, as they establish the necessary links between producers, suppliers, and consumers, ensuring the continuous flow of goods and services. Furthermore, these transportation systems act as catalysts for access to employment, education, and healthcare facilities, meeting the indispensable needs of communities [1].

The integration of Intelligent Transport Systems (ITS) with Artificial Intelligence (AI) presents an opportunity to anticipate the movement of vehicles, enabling the implementation of efficient traffic management strategies that aid authorities in optimizing resource allocation and mitigating congestion at intersections. Through the utilization of machine learning algorithms trained on historical traffic data, ITS can accurately forecast forthcoming traffic flow patterns. This precise traffic flow prediction empowers ITS to dynamically adjust crucial factors such as traffic light timings, lane assignments, and speed limits, among others, with the aim of optimizing traffic flowand averting congestion at intersections. Consequently, the fusionof ITS and AI holds the potential to alleviate congestion, enhance travel durations, and augment overall traffic management [2].

The field of traffic prediction has experienced significant advancements in recent years, thanks to the emergence of AI techniques [3]. Machine learning, deep learning, and probabilistic reasoning stand out as three prominent techniques employed in traffic prediction. ML algorithms leverage historical traffic data to analyze patterns and make precise predictions regarding future traffic conditions [4]. DL models, on the other hand, utilize multi-layered neural networks to extract intricate features from raw traffic data, leading to improved prediction accuracy [5]. Additionally, probabilistic reasoning techniques rely on statistical models and probability theory to estimate traffic patterns by combining historical data with current contextual information [6]. Congestion estimation involves the process of predicting traffic flow parameters to assess the level of congestion on road networks. This estimation is accomplished by considering several parameters, including traffic speed [7], density, speed [8], and congestion index [9]. These parameters provide invaluable insights into the flow and congestion levels within road networks, thereby enabling effective prediction and proactive management of traffic conditions.

The principal aim of this contribution is to develop a prognostic system by integrating the Long Short-Term Memory (LSTM) algorithm with particle swarm optimization (PSO) to achieve precise predictions of traffic flow at intersections and alleviate traffic congestion. This work builds upon our previous research [10]. The PSO optimization technique is employed to refine the hyperparameters associated with training the LSTM model. This hybrid model leverages the memory capabilities of LSTM to capture temporal dependencies in traffic data while optimizing its performance with PSO. To assess the efficacy of our hybrid model, we utilized a publicly available dataset [11] containing data gathered from four distinct intersections collected over a time frame spanning from November 2015 to June 2017. Following data transformation and pre-processing, we conducted a comparative analysis between our hybrid model and existing models, selecting the most superior performing model based on RMSE and MAE metrics.

The structure of the paper is organized as follows: SectionII provides a brief review of the relevant literature. In Section III, we describe our data and methods. Section IV is dedicated to presenting the proposed solution, followed by a performance evaluation in Section V. Section VI covers the experimental and benchmarking results. Finally, Section VII concludes the paper and discusses future perspectives.

II. Related Work

Traffic flow prediction is essential for effective traffic management. Techniques range from traditional statistical methods to advanced DL and optimization algorithms, which have been successfully applied for accurate predictions, aiding in better traffic management and decision-making.

Navarro-Espinoza et al. [12] conducted a study addressing urban traffic congestion, where ML and DL techniques were employed to predict traffic flow at intersections. The proposed models aimed to facilitate adaptive traffic control systems by remotely adjusting traffic lights or timing based on predicted flow patterns. Evaluation of various ML and DL algorithms revealed that the Multilayer Perceptron Neural Network (MLP-NN) emerged as the top performer, achieving an R-Squared and EV score of 0.93. This indicated its suitability for implementation in smart traffic light controllers. Despite achieving impressive results with Multilayer Perceptron Neural Network (MLP-NN), it's important to note that MLP-NN may encounter limitations in handling high-dimensional and noisy traffic data, potentially leading to overfitting.

Boukerche et al. [13] proposed a study focusing on ITS, which garnered attention in recent years due to promising applications like Vehicular Cloud and intelligent traffic controls. Achieving these goals relied on accurate traffic flow prediction systems, with ML. The study provided a comprehensive review of ML models, categorizing them based on theory and analyzing their suitability for different prediction tasks. Additionally, challenges and auxiliary techniques in traffic prediction were discussed. While ML emerged as a prominent method, it's crucial to acknowledge the limitations of ML models, including their sensitivity to data distributions and potential challenges in adapting to dynamic traffic conditions.

N. Katambire et al. [14] investigated the impact of rising travel demand and vehicle ownership on traffic efficiency, particularly at intersections. They explored time series forecasting methods like LSTM and ARIMA models to predict future traffic rates, favoring LSTM for monthly traffic flow prediction. Additionally, the study proposed an adaptive traffic flow prediction system using vehicle-to-infrastructure communication and IoT technologies to enhance junction control and service quality in real-time. Despite LSTM's effectiveness in capturing temporal dependencies, it may encounter challenges in adapting to abrupt changes in traffic patterns, particularly at intersections.

Jang et al. [15] explored solutions for traffic congestion in smart cities by investigating traffic flow prediction methods such as LSTM and GRU models. The study utilized various data sources including regular traffic data, predictable event data, and meteorological data to enhance prediction accuracy and effectively forecast traffic congestion levels. In this study, three simulation architectures were tested for traffic flow prediction. Simulation 1 with basic architectures (Vanilla) showed limitations in accuracy. Simulation 2 introduced stacked architectures, improving predictions but with longer training times. Simulation 3 used encoder-decoder architectures, showing comparable results to stacked models but with shorter training times. Despite LSTM generally outperforming GRU, neither achieved exceptional performance due to potential data inadequacies. It's essential to recognize that both models may face limitations in handling potential data inadequacies, which could impact prediction accuracy, especially in dynamic urban environments.

Giraka et al. conducted [16] research on predicting turning volumes at urban intersections using Seasonal Autoregressive Integrated Moving Average (SARIMA) models. this study specifically addresses unsignalized three-leg intersections. By using data from the preceding three days, the SARIMA model effectively forecasts the next day's turning volumes, achieving a Mean Absolute Percentage Error (MAPE) of less than 10%. While SARIMA effectively forecasts turning volumes, it may encounter challenges in adapting to unexpected traffic events or anomalies, potentially affecting prediction accuracy in real-world scenarios.

In their study [17], the authors proposed a novel approach that combined Support Vector Regression (SVR) with PSO to enhance the accuracy of vehicle traffic prediction. The proposed method was compared with other techniques like multiple linear regressions and neural networks. PSO was employed to optimize the input parameters of SVR, including penalty C, radius, and kernel function. The evaluation metric used was RMSE, which served as the fitness function for PSO. While this approach demonstrates improvements over other models, it's important to acknowledge the computational complexity associated with SVR and potential challenges in scalability when applied to large-scale traffic datasets.

Moumen et al. presented their study [18] based on a DL approach that treats traffic flow from four intersections as a distributed system using Gated Recurrent Units (GRUs) in the same dataset that we used for our study. The performance of their model was evaluated using RMSE metrics, achieving RMSE values of 0.245881 at intersection 1, 0.558597 at intersection 2, 0.606137 at intersection 3, and 1.024198 at intersection 4. Despite achieving competitive results, it's crucial to recognize GRU's limitations in handling irregular traffic events and variations, which could impact prediction accuracy in dynamic urban environments.

Deekshethaet al. [19] conducted a comprehensive study on traffic prediction employing advanced ML techniques using the same dataset that we employed in for study. Leveraging the capabilities of Sklearn, Keras, and TensorFlow libraries, they constructed a sophisticated regression model to forecast traffic flow, underscoring the importance of considering the limitations of individual algorithms in adapting to diverse traffic conditions and data distributions.

Yin et al. [2] used the same dataset that we employed for our study but focused specifically on the traffic data collected from the first three intersections between November 2015 and January 2016. By utilizing a stacking ensemble learning model, they predicted traffic flow for multiple phases. The resulting MAE values for phases 1, 2, and 3 were 2.730, 3.708, and 4.347, respectively. However, it's essential to acknowledge the potential complexity and computational overhead associated with ensemble methods, particularly in real-time prediction scenarios.

According to our knowledge, we find that despite competitive results, the majority of ML and DL techniques mentioned in this section do not address all challenges related to traffic and intersection congestion. Their limitations concern the management of irregular traffic events and variations, the sensitivity to data distributions which could impact the accuracy of forecasts in dynamic urban environments, the management of large and noisy traffic data, potentially leading to overfitting. Additionally, we note that it is essential to recognize the potential complexity and computational burden associated with ensemble methods, particularly in real-time forecasting scenarios. In general, computational complexity negatively impacts AI models to be applied to large-scale traffic datasets. Additionally, and despite the effectiveness of AI models in capturing temporal dependencies, they may have difficulty adapting to abrupt changes in traffic patterns, particularly at intersections. This motivates us to propose our approach having the advantage of meeting these challenges such as the management of irregular traffic events and variations, sensitivity to data distributions, real-time forecasting scenarios, reduced computational complexity, management of large-scale traffic datasets. Our approach is based on a hybrid LSTM-PSO model which is validated using empirical traffic data.

Building on the strengths of LSTM which has demonstrated its effectiveness in modeling temporal dependencies in traffic data, we further optimize the model hyperparameters using PSO to improve its adaptability to dynamic traffic conditions and address the limitations identified in previous approaches. PSO plays a crucial role in guiding the LSTM model to avoid local optima during the parameter optimization process, ensuring that the model converges to more globally optimal solutions. By leveraging LSTM with PSO optimization, our model offers a robust solution for accurate and reliable traffic flow prediction, capable of overcoming challenges such as data inadequacies and fluctuations in traffic patterns. Through empirical evaluation and comparative analysis, we demonstrate the efficacy of our approach in improving prediction accuracy and facilitating informed decision-making in traffic management scenarios. respectively. Sections III and IV highlight our methodology used in more details.

III. Data and Methods

A. Data Description

In this research, we used a precious dataset, which serves as a valuable resource for researchers and practitioners alike [2].

The dataset used in our work comprises a comprehensive collection of 48120 vehicle records, meticulously collected from four intersections. This rich dataset includes four key attributes date and time, intersection, vehicles, and identifier, enabling comprehensive analysis and exploration. Covering a significant period, the dataset includes one-hour intervals starting on November 1, 2015, and ending on June 30, 2017, as visually shown in Fig. 1. The extensive temporal coverage of the dataset facilitates a comprehensive understanding of traffic patterns and trends over a substantial duration, enabling valuable insights and robust analysis for our research.

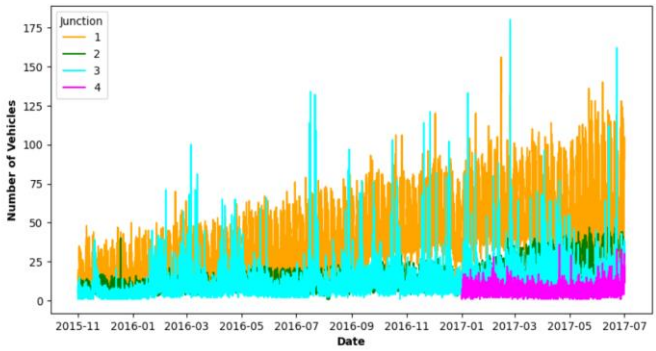

Fig. 1. Traffic prediction dataset.

B. Data Processing

The dataset that was collected contains limited and sparse traffic records that span across different time periods. Through our analysis, we explored the data by considering different time-related characteristics. This investigation revealed notable variations among the four intersections. While all intersections experienced an annual increase in the number of vehicles, it is worth noting that data availability for the fourth intersection was relatively restricted, as depicted in Fig. 2.

Furthermore, we observed that the number of vehicles tends to rise in June, which can be attributed to the summer season and school breaks, representing a period of heightened activity as shown in Fig. 3. Analyzing the data over the course of a day, we identified a consistent pattern of increased vehicle numbers during peak hours and a subsequent decrease during nighttime, as demonstrated in Fig. 4. Additionally, we found that traffic appears to be more stable on weekdays, with fewer vehicles on the road, while it becomes more fluid and less congested on Saturdays and Sundays, as illustrated in Fig. 5.

By examining these temporal patterns and variations in the data, we gained valuable insights into the dynamics of traffic behavior across different time periods and days of the week. These observations provide a comprehensive understanding of the factors influencing vehicle volumes and traffic flow, allowing us to better comprehend and model the patterns exhibited by the collected dataset.

Upon careful examination and analysis, we have observed that the datasets corresponding to the four intersections possess distinctive scopes and characteristics. Recognizing the significance of accurately capturing and representing the unique attributes of each intersection, it becomes imperative to partition the dataset accordingly. By dividing the dataset into separate segments corresponding to each intersection, we ensure that our analysis and modeling efforts are adapted to the specific characteristics and patterns exhibited by each intersection. This mechanism allows us to focus on intersections individually to obtain their specific traffic patterns in a more granular manner. By isolating the data for each intersection, we can apply specific modeling techniques and algorithms that are best suited to capture the intricacies and variations unique to that particular intersection. This approach enables us to achieve more accurate and insightful results, as we can account for the specific factors that influence traffic behavior at each intersection.

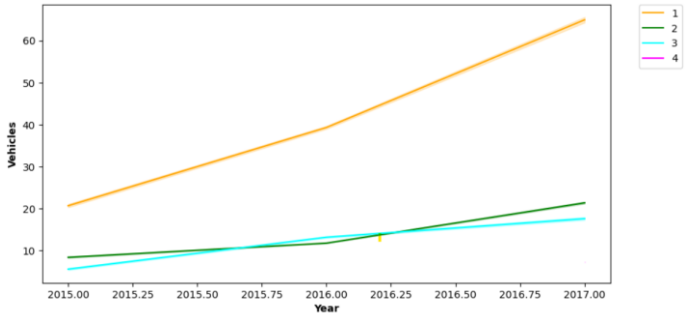

Fig. 2. The number of vehicles during years.

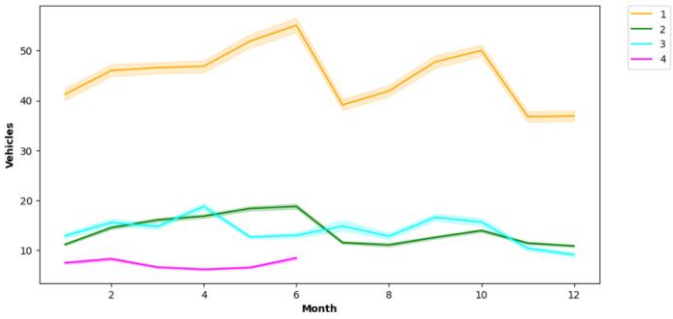

Fig. 3. The number of vehicles during months.

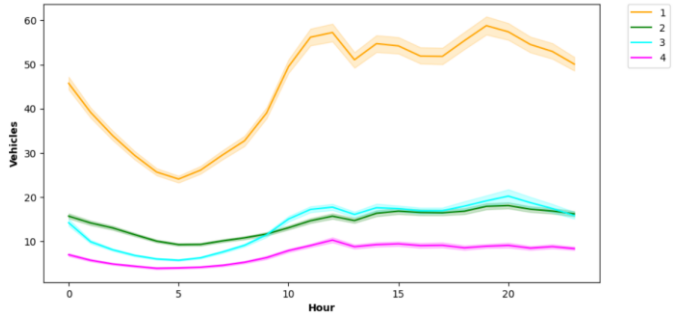

Fig. 4. The number of vehicles during hours.

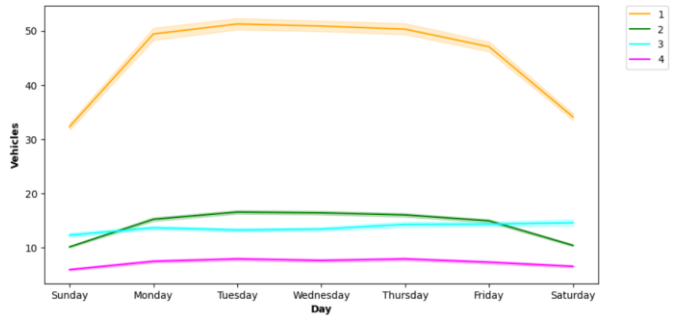

Fig. 5. The number of vehicles during days.

Through the careful partitioning of the dataset, we can better understand the nuances of traffic flow at each intersection and develop more targeted models and predictions. This segregation not only facilitates a more comprehensive analysis of each intersection but also ensures that the models derived from the data accurately reflect the characteristics and dynamics of each specific location.

C. Data Standardization

We implemented data standardization by applying function 1. This preprocessing step eliminates the potential biases caused by variables with differing ranges and variances, allowing the models to effectively capture and learn from the data patterns without being influenced by the scale of the features. The function applied for data standardization aids in normalizing the data and enhancing the performance and interpretability of our models.

$$X_{new} = (X_i - \bar{X}) / s \quad (1)$$

where:

X_i: data point values

$\bar{X}$: the mean value

S: The standard deviation

D. Data Differencing

A stationary time series is characterized by unchanging properties that remain consistent over time. This means that the values of the time series at different time points are not affected by trends or seasonality. In contrast, non-stationary time series exhibit patterns like seasonality that impact the values and characteristics of the series as time progresses.

A commonly used method to convert a non-stationary time series into a stationary one is to calculate the distance between the actual observation and the next one, known as differencing. The process of differencing is employed to enhance the stability of the average value of a time series by eliminating fluctuations in its overall level, thereby reducing patterns of trends and seasonality.

The graphical representations provided in Fig. 2, 3, 4, and 5 clearly demonstrate the existence of seasonality and a noticeable upward trend in the time series data. To enhance the effectiveness of our models, it is crucial to transform the time series data into a stationary form. To achieve this, we employed differencing techniques that aim to eliminate the seasonality patterns. However, it is important to note that the specific differencing technique utilized will vary for each intersection, as theses intersections exhibit distinct periodic seasonality characteristics. By tailoring the differencing approach to each intersection's unique seasonal patterns, we can effectively mitigate the influence of seasonality and improve the performance of our models.

The differencing technique employed for each intersection can be summarized as follows:

- Intersection 1: The computation involves taking the difference between weekly values.
- Intersection 2: The calculation entails determining the difference between consecutive days.
- Intersections 3 and 4: The approach involves utilizing the difference between hourly values.

IV. Proposed Solution

The proposed approach merges the capabilities of LSTM and PSO to create a resilient model. LSTM excels in modeling

sequences with its powerful capabilities, while PSO steps in to meticulously refine the hyperparameters and increase the efficiency of the LSTM model. This combined approach strives to capitalize on the respective strengths of both methodologies, ultimately improving predictive performance. The following paragraphs describe the subtleties of integrating LSTM and PSO within this hybrid approach.

A. LSTM

The LSTM Model is a leading research paradigm in the field of DL, which has attracted particular attention for its application to traffic prediction in ITS. Hochreiter [20] presented the LSTM model as an advance on the conventional framework of recurrent neural networks (RNN). This innovative architecture deals with the limitations of traditional RNNs, presenting improved capabilities for capturing and retaining long-term dependencies, which proves particularly advantageous for modeling complex temporal patterns, such as those encountered in traffic prediction scenarios [21].

LSTM has the capacity to model the stochastic nature inherent in traffic data, enabling spatio-temporal characteristics to be identified. In the context of traffic networks, those based on LSTM retain both short- and long-term data in their memory, relying on this accumulated information to make predictive decisions in the present moment. This marks a departure from conventional DL methods, where output decisions are generally made without the intervention of memory [22]. The use of memory in LSTM-based traffic models contributes to a more nuanced and context-sensitive decision-making process, improving the network's ability to capture and adapt to the dynamic patterns inherent in traffic data, Fig. 6 illustrates the fundamental structure of the LSTM model.

The LSTM architecture is characterized by the incorporation of three fundamental gates: the forget gate, the input gate and the output gate. These gates collectively govern the flow of information within the network [23]. In addition, the LSTM stores the current and previous states of cells, constituting long-term memory, as well as the hidden states representing short-term memory. The complex interaction of these elements contributes to the model's ability to effectively capture and handle temporal dependencies. In the following sections, we explain the individual roles and functionalities of the forget, input, and output gates in the LSTM architecture.

1) The forget gate: At time step t, the LSTM's forget gate processes x_t and h_{t-1} through σ. yielding f_t values between 0 and 1. These values, when multiplied with c_{t-1}, decide whether to retain r forgot previous states: 0 means forgetting, introducing new critical information, while 1 means preservation *[24]*. The function performed by the forget gate is represented as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (2)$$

Here, W_f and b_f denote the respective weighting and bias matrices associated with the forget gate.

2) The input gate: The Input Gate in an LSTM model combines $\tan h$ and sigmoid functions to update the cell state. Tanh generates a vector $\tilde{C}_t$ from input data and previous memory, while sigmoid's output i_t represents the importance of current input. Multiplying i_t with $\tilde{C}_t$ and adding it to the previous cell state updates the current state, determining the significance of input for information retention [25].

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tan h\,(W_c[h_{t-1}, x_t] + b_c) \quad (4)$$

Here, W_i and W_c represent the weighting matrices for the input gate of the sigmoid and hyperbolic tangent ($\tan h$) functions, respectively. Additionally, b_i and b_c denote the corresponding bias terms for W_i and W_c.

3) The output gate: The Output Gate in LSTM model incorporates three vectors: C_t, x_t and h_{t-1}, producing the current hidden state h_t through the following mathematical relationships:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \tan h\,(C_t) \quad (6)$$

Here, o_t represents the output of the sigmoid function, obtained by applying the weighting matrix W_o to $[h_{t-1}, x_t]$ and adding the biasing factor b_o. The multiplication process involves multiplying the corresponding elements of the matrices [26].

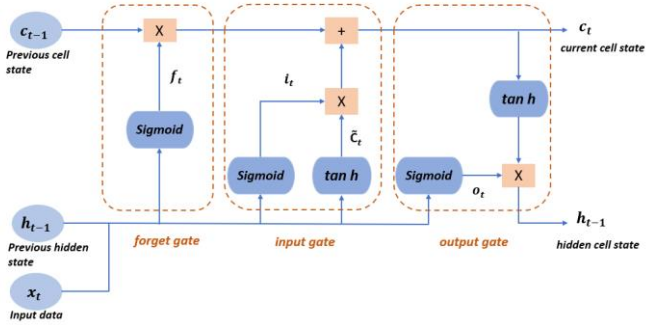

Fig. 6. The foundational architecture of LSTM model.

B. PSO

Particle Swarm Optimization is a nature-inspired meta-heuristic optimization technique that emulates the collective behavior of birds in flight and fish in schools. The fundamental objective of PSO is to iteratively enhance a solution based on a given quality measure, commonly referred to as the fitness function [27].

The PSO algorithm initiates by generating a set of particles (solutions) randomly. These particles represent potential solutions, and their relative positions are adjusted iteratively to search for the optimal solution. In each iteration, every particle undergoes an update process by comparing two critical values: the particle's personal best solution (pBest) achieved thus far, and the global optimal solution (gBest) obtained by the entire swarm of particles. Therefore, each particle maintains a memory of both its best individual solution and the best global solution, empowering it to make informed adjustments to its position during the optimization process [28].

By continuously updating their positions based on the comparison between personal and global best solutions, the particles in PSO strive to collectively navigate the solution space. This behavior enables them to exploit promising regions and explore new areas, ultimately converging toward the optimal solution. The iterative nature of PSO, along with its ability to leverage global and personal knowledge, makes it a powerful optimization technique for addressing complex problems [29].

The following relations are used to update all weights:

$$v_i^{t+1} = \omega\, v_i^t + c_1 r_1 \left(p_{best_i}^t - x_i^t\right) - c_2 r_2 \left(g_{best}^t - x_i^t\right) \quad (7)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

where, the variable v denotes the velocity vector, and the parameters c_1 and c_2 act as cognitive and social coefficients, respectively, to govern the swarm's behavior. The inertia weight ω, along with the two random real numbers r_1 and r_2, both between 0 and 1, and the current generation t, also play a crucial role in the formulation.

C. LSTM-PSO

The synergy between LSTM and PSO exploits the strengths of each: LSTM excels at capturing temporal dependencies, while PSO efficiently navigates the complex landscape of hyperparameters [30]. This combined approach not only accelerates the optimization process, but also increases the possibility of discovering hyperparameter configurations that improve the performance of the LSTM model for tasks such as traffic flow prediction. The scientific rationale resides in PSO's ability to address the challenges associated with the complex and highly dimensional search space inherent in LSTM hyperparameter tuning, thus contributing to the effectiveness and efficiency of the modeling process [31].

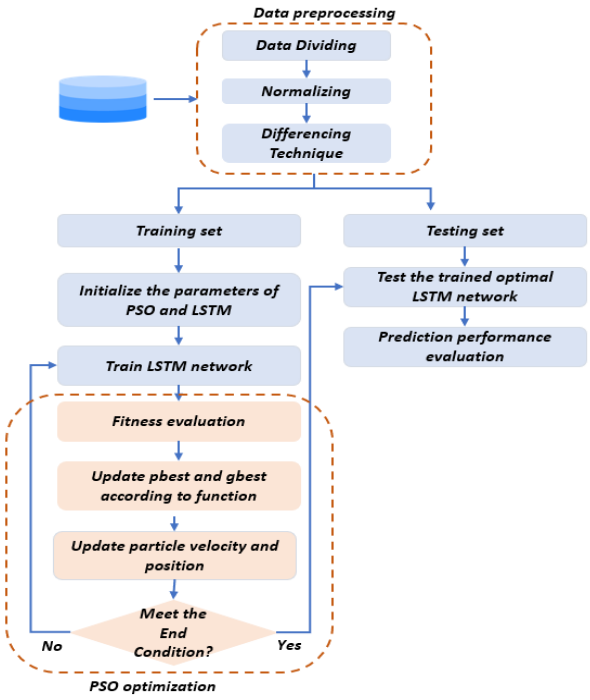

Fig. 7. The proposed approach.

The LSTM-PSO computation process involves begins with data processing, followed by the division of the dataset into training and testing sets. The PSO algorithm is initialized with specified parameters, and a population of particles, representing potential hyperparameters for the LSTM. The fitness of each particle is evaluated by training the LSTM with the corresponding hyperparameters. PSO dynamically updates particle positions based on personal and global best-known positions. The process continues by continuously updating the velocity and position of each particle until termination conditions are met. The hyperparameters from the particle with the best fitness are then used to train the final LSTM model. The resulting model is evaluated on a testing dataset, and the optimized hyperparameters are saved for future use, presenting a comprehensive approach to enhance the LSTM's performance in the regression task, as visually shown in Fig. 7.

V. Performance Evaluation

When evaluating the performance of our model for traffic flow prediction, we employed commonly used evaluation metrics, including MAE and RMSE [28, 29].

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \quad (9)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - x_i)^2} \quad (10)$$

Where:

n: The simple size in the testing set.

x_i: observed values.

y_i: predicted values.

VI. Experiment and Results

1) Parameter setting Of LSTM-PSO: The efficiency of model learning depends on the selection of appropriate model parameters. Table I illustrates the precise initialization parameters used in the LSTM-PSO model following experimental calibration. The values of these parameters were identified in iterative testing and refinement.

TABLE I. Parameter Setting LSTM-PSO

Parameter	Value
Population size	20
Self-learning factor	1.5
Group learning factor	2
neurons	150
Number of hidden layers	5
Epoch	100
Batch Size	150

2) Computational results: This research aims to develop a traffic flow prediction system using a hybrid LSTM-PSO model. The work follows a systematic approach, starting with a pre-processing phase where the dataset is divided into four parts based on the intersections. This division allows for independent

analysis of each intersection, considering their unique characteristics and traffic patterns. The datasets are then normalized to ensure consistent scaling and improved model performance. Additionally, the differentiation technique is applied to enhance data quality by highlighting traffic flow changes.

During the second phase, our hybrid LSTM-PSO model, integrating neural networks with optimization techniques, is trained alongside four additional models for each segment of the dataset. Evaluation of these models is conducted using MAE and RMSE metrics, standard for regression tasks, to gauge their effectiveness. These metrics provide insights into the models' average error magnitudes. The best-performing model is selected based on the evaluations, characterized by the lowest MAE and RMSE values.

To evaluate the short-term traffic flow prediction performance, each neural network model under consideration was trained on 80% of the dataset time intervals and cross-validated, with testing conducted on the remaining 20% of the same datasets. Subsequently, we developed an LSTM neural network. Following this, the PSO technique was employed to fine-tune the LSTM hyperparameters, resulting in the prediction of the target hyperparameters.

The experimental results comparing conventional LSTM-PSO, LSTM, Random Forest Regressor, K Neighbors Regressor, and Decision Tree Regressor algorithms are presented in Table II, Fig. 8 and Fig. 9. For the first intersection, our hybrid model LSTM-PSO obtained an RMSE of 0.15258 and an MAE of 0.0898. Meanwhile, at the second intersection, it recorded an RMSE of 0.3574 and an MAE of 0.2441. Moving on to the third intersection, the model achieved an RMSE of 0.4227 and an MAE of 0.1672. Finally, at the fourth intersection, it attained an RMSE of 0.6857 and an MAE of 0.4751.

The empirical evidence in the table confirms that our hybrid model, LSTM-PSO, consistently surpasses other models like LSTM, RFR, KNR, and DTR in minimizing both MAE and RMSE values across all intersections in our dataset. This demonstrates LSTM-PSO's adeptness in capturing the underlying patterns and dynamics of traffic flow data, resulting in more precise predictions. Its superior performance stems from leveraging LSTM networks for sequence modeling and PSO for fine-tuning model hyperparameters. Consequently, LSTM-PSO emerges as a robust and effective solution for short-term traffic flow prediction tasks, benefiting from PSO's effectiveness in exploring the search space and LSTM's ability to quickly adapt to local optima. This synergy enables exploration of diverse parameter regions, potentially yielding superior global solutions while the stochastic behavior of PSO aids in avoiding local optima, ultimately enhancing the overall performance of the model.

The principal motivation for our research is the need to reduce traffic congestion at intersections. By accurately predicting traffic flow at intersections, our hybrid model can inform real-time traffic management strategies, optimize signal timing and, ultimately, reduce overall journey times for travelers. This application responds directly to the daily challenges faced by city drivers and transport authorities, offering real solutions to improve the efficiency and sustainability of urban mobility systems.

To validate and make our algorithm robust, we continue the validation and updating step continuously using new data to improve the accuracy and make necessary adjustments and change traffic patterns based on this new data. We are currently deploying the model in a real-time environment and comparing its predictions with actual traffic data using computer vision as a technique to collect real-time traffic data at intersections.

TABLE II. THE RMSE AND MAE VALUES OF THE MODELS WERE EVALUATED INDIVIDUALLY FOR EACH OF THE FOUR INTERSECTIONS

		LSTM PSO	LSTM	RFR	KNR	DTR
MAE	Intersection1	**0.0898**	0.1436	0.1766	0.1944	0.2631
	Intersection2	**0.2441**	0.3245	0.3915	0.4577	0.5378
	Intersection3	**0.1672**	0.2217	0.2918	0.32142	0.4405
	Intersection4	**0.4751**	0.6301	0.7508	0.8128	0.9315
RMSE	Intersection1	**0.1525**	0.21	0.2459	0.274	0.3762
	Intersection2	**0.3574**	0.4566	0.5037	0.5869	0.7086
	Intersection3	**0.4227**	0.6012	0.6176	0.6394	0.9027
	Intersection4	**0.6857**	0.8215	1.0722	1.117	1.3212

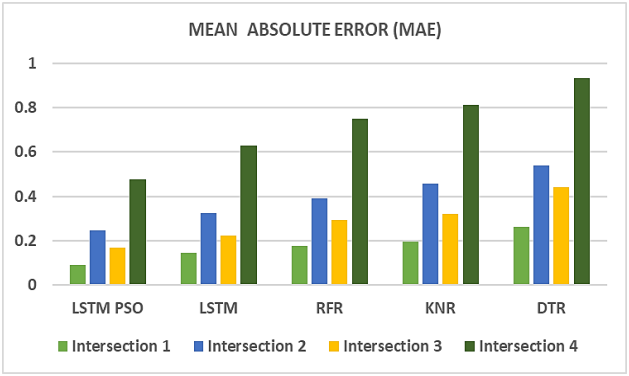

Fig. 8. MAE results according to the four intersections.

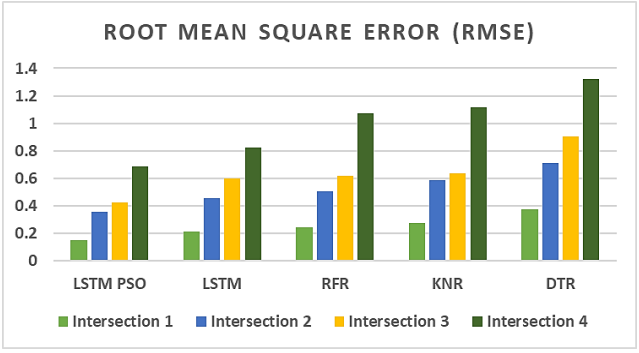

Fig. 9. RMSE results according to the four intersections.

VII. CONCLUSION

The ability to anticipate traffic flow at intersections has emerged as a crucial element in diminishing travel duration on roadways and addressing the escalating predicament of traffic congestion, a challenge of mounting importance in both developed and developing nations.

The primary objective of this research was to evaluate and compare the effectiveness of our hybrid model, whichcombines the LSTM algorithm with PSO, against various alternative models for predicting traffic flow at intersections. To address the temporal fluctuations in traffic data at specific intersections, we initially divided the dataset into four discrete segments, each corresponding to a distinct intersection. This segmentation allowed for independent analysis of each intersection. Subsequently, we normalized the data to ensure uniformity and consistency across the entire dataset. In the final preprocessing phase, we applied data differentiation techniques to remove seasonal patterns and transform the data into a stationary state. These latter two stages were crucial for enhancing the quality of the data and optimizing the performance of the systems used for predicting traffic flow at intersections.

What sets our approach apart is its ability to harness the strengths of both LSTM and PSO. LSTM excels in capturing temporal dependencies in traffic data, while PSO optimizes the hyperparameters of the LSTM model to further enhance its predictive performance. This synergy between LSTM and PSO has proven to be highly effective, resulting in superior predictive capabilities compared to other models. These results underscore the promising potential of employing neural networks trained with particle swarm optimization for traffic flow prediction in general. By leveraging the power of advanced ML techniques, such as LSTM and PSO, we can unlock new possibilities for improving traffic management and enhancing overall transportation efficiency.

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