Multi-Agent Trajectory Prediction for Urban Environments with UAV Data Using Enhanced Temporal Kolmogorov-Arnold Networks with Particle Swarm Optimization

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Abstract: Accurate trajectory prediction for moving agents such as pedestrians and vehicles is essential for autonomous driving, intelligent navigation, and abnormal behavior detection. Real-time prediction of future movements enhances the development of autonomous vehicles and the efficiency of traffic management systems. In this study, a novel trajectory prediction approach based on Temporal Kolmogorov-Arnold Networks (TKAN) is introduced, using the TUMDOT-MUC dataset collected by Unmanned Aerial Vehicles (UAVs) in Munich, Germany, to model large-scale urban scenarios. To improve prediction accuracy, additional features were extracted from the primary dataset and incorporated into the TKAN architecture, demonstrating a marked performance improvement over general machine learning models. The accuracy of predictions is further refined by tuning hyperparameters of TKAN through Particle Swarm Optimization (PSO). The proposed model provides a robust and reliable solution for the trajectory prediction of multi-agents in challenging urban traffic conditions. This research advances intelligent and effective transportation systems by proposing scalable methods for improved traffic management and safety in densely populated urban areas, ultimately contributing to smarter and more efficient transportation networks.

1 INTRODUCTION

Traffic congestion can lead to longer travel times, higher fuel consumption, and air pollution, negatively impacting public health and quality of life for urban residents. In addition, traffic congestion would cause economic losses, disruption of commercial activities, and low productivity levels. These challenges impose costly social and economic pressures on city transport systems, and cannot afford to delay the search for efficient solutions to control and mitigate problems (C. Arti and Kumar, 2022). Urbanization places more pressure on the transportation infrastructure as urban populations continue to grow. The early signs of congestion in most cities around the world begin with specific sections of roads where the number of vehicles traveling through the road is greater than the capacity of the road section, which slows traffic speed and increases travel time. More vehicles mean more fuel consumption and air pollution conditions that adversely affect the health of citizens (R. SenthilPrabha and Harish, 2023).

In recent years, the ability to predict vehicle trajectories has gained attention as a promising approach for traffic optimization in Intelligent Transportation Systems (ITS). Accurate trajectory prediction can also help alleviate congestion and optimize traffic flow. The analysis of the data of moving vehicles enables the system to judge the flow of traffic and provides valuable information to decide in real-time (M. R. Mohebbi and Yamnenko, 2024). Predicting traffic flow can route drivers through detours, reducing air pollution and traffic incidents. Such predictive senses are also of immense importance for urban planners, planning better transportation infrastructure, improving public services, and encouraging the development of smart and sustainable cities (X. Kong and Zhang, 2016). In addition, anticipat-

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ing the next move of dynamic objects is a key to autonomous mobility, with applications such as autonomous vehicles safely interacting in shared infrastructure considering the trajectories of pedestrians and other vehicles (Deo and Trivedi, 2017).

Traditional Machine Learning (ML) models, including Support Vector Machines (SVM), Multilayer Perceptrons (MLP), Random Forest (RF), and early recurrent models, including Long Short-Term Memory (LSTM) networks, have been tried to improve the accuracy of traffic prediction. However, most of these models fail in processing nonlinear, complex traffic data, especially in dynamically changing urban environments (B. Yang and Tian, 2019). The serious limitation of these models is also related to the fact that treating temporal sequences this way, focusing on linearity, might prevent them from capturing complex relationships in urban traffic. Deep Learning (DL) models, especially more advanced Recurrent Neural Networks (RNNs), presented the potential to help with some of those issues by providing proper modeling of complex temporal sequences. More sophisticated models for real-time forecasting by fusing data from multiple sources are needed in the case of urban traffic flow (Y. Lv and Wang, 2014).

This is addressed with the adoption and implementation of a new architecture known as Temporal Kolmogorov-Arnold Networks (TKAN), specially modeled to handle nonlinear complex dependencies in temporal data. The theoretical rationale for the implementation of TKANs lies in the theories by Kolmogorov and Arnold, uniquely and specially fitted for modeling and identification of complex patterns in time-series data. Thus, it has an advanced architecture to handle large-scale and dynamic data more efficiently. TKAN is thus assumed to be proficiently effective in predicting real-time trajectory in an urban environment. Unlike other traditional methods, TKAN considers historical pattern attributes for the generation of more accurate future behavior predictions. Therefore, it considers robust potential for its use within any intelligent traffic management system (Genet and Inzirillo, 2024).

Meanwhile, parallel methodological advances in data collection allow for more accurate and profound inputs of urban traffic flow. Among others, drones or Unmanned Aerial Vehicles (UAVs) have been suggested as an efficient source of data collection on traffic flow and other movements within cities (M. R. Mohebbi and Tavasoli, 2024). UAVs guarantee broad, real-time, and multiangle views often unreachable for ground sources and notably enhance the quality of data collection even for the most densely populated or hard-to-reach areas. Applications involving trajectory prediction benefit from UAVs, which improve accuracy by providing expansive and detailed datasets that often are beyond the reach of ground sensors (A. Kutsch and Bogenberger, 2024). Therefore, enhancing both the quality and quantity of data improves efforts in traffic management and urban planning through the use of UAV technology, which, in turn, provides better insights for researchers and policymakers into the complicated traffic patterns and movement behaviors within cities.

This study addresses the growing complexity of urban traffic and the limitations of standard predictive models by introducing an advanced framework that integrates the Temporal Kolmogorov-Arnold Network with UAV-based data acquisition. The proposed scheme leverages the capability of TKAN for pattern learning of nonlinear variance in time series and high-resolution real-time input provided through UAVs for setting up a more reliable methodology of traffic management in dynamic and high-density urban infrastructure. They address the demand for reliable, efficient, and scalable predictive models with the aim of enabling transportation systems that are safer, more intelligent, and that can learn and adapt to the challenges related to modern urban mobility. To advance the predictive accuracy and scalability of urban traffic models, the following key contributions are introduced:

- **Noise-Reduction Techniques.** Several techniques, such as a moving average filter, have been used to normalize motion data in order to reduce the influence of unreliable points, such as outliers. All of these efforts help maintain the data quality so that model performance and accuracy of predictions can be improved during the training process.
- **TKAN Model.** This model was selected for its efficacy in modeling temporal data by capturing intricate nonlinear features and structures of the traffic pattern. It would improve the capability of the model for scalability in large data and, in essence, a dynamic urban setting with robust trajectory predictions.
- **Particle Swarm Optimization (PSO) for Hyperparameter Tuning.** PSO is applied for hyperparameter optimization to further improve the efficiency and precision of the model. This intelligent parameter search not only accelerates model tuning but also returns a model optimized for effective analysis and prediction.

The remainder of this paper is organized as follows. Section 2 summarizes the related work by situating our approach with respect to the existing methods. Section 3 provides a detailed description of the methodology, covering the data processing pipeline, model architecture, and temporal enhancement techniques. Section 4 presents a full empirical evaluation, and conclusions are given in Section 5.

2 RELATED WORK

Trajectory prediction has been one of the most salient facial features in ITS research and has made sufficient progress along three main lines: vehicle trajectory prediction, human trajectory forecasting, and multi-agent trajectory modeling. These enable improved safety, optimized flow, and better traffic management. The following section tries to identify significant findings and methodological variety in these areas that recent research addresses with evolving challenges for traffic prediction.

2.1 Vehicle Trajectory Prediction

Trajectory prediction has been considered an important task within the scope of ITSs, especially for very dense and complex urban scenarios. Advanced ML and DL models increasingly contribute to the necessary analysis of extensive traffic datasets for the detection of complex traffic movement patterns and the improved prediction of vehicle behavior. For instance, Mohebbi et al. (M. R. Mohebbi and Yamnenko, 2024) presented how the usage of liquid neural networks combined with UAV-derived data significantly improves trajectory predictions in crowded scenarios by offering a wider perspective and enabling the capability to predict urban traffic flow more precisely.

Scalability is an important factor in the predictive models that should be used in handling large datasets of traffic for various instant applications. Another approach has proposed a framework that is efficient in data management for higher volumes of data, enabling the application of such data in various urban contexts with complex adaptive functions that are required by autonomous vehicle systems (P. Rathore and Bezdek, 2019). This makes the frameworks highly effective in dynamic urban environments, as they can manage large volumes of traffic data without losing accuracy. Another research under the objective-oriented approach of prediction demonstrated that the focus on particular traffic prediction goals, such as maintaining the network in a fluid state, considerably improved predictability together with system responsiveness (H. Zhao and Li, 2021).

In the prospect of having more accurate long-term predictions, researchers have turned to using spatio-temporal algorithms, which enable them to forecast more about extended trajectory paths. The strategic benefits are perceived in terms of timely and data-driven decisions for traffic management and urban planning (T. Wu and Chen, 2022). One of the recent effective methods adopted includes the use of Variational Autoencoders (VAEs), which study historical traffic data for patterns that enable highly accurate prediction of vehicle behavior in future scenarios by learning from past trajectories (M. Á. De Miguel and Garcia, 2022).

Recently, hybrid models have gained prominence that try to render the predictive models more amenable to dynamic and fluctuating conditions. For instance, networked traffic data illustrated promising results considering the identification and analysis of dynamic movement patterns by integrating the LSTM network with adaptive chirp mode decomposition. This downloaded hybrid method may improve the extraction of features and improve the precision of prediction in capturing complex temporal structures in urban traffic flow (Z. Wang and Jiang, 2024). In the meantime, some lightweight DL models have been developed to fit the usage demand of applications in dense traffic scenarios in recent years. This is important because both high processing speed and accurate predictions are usually needed for real-time applications (C. Wang and Lu, 2022).

In some research, such as Li et al. (Y. Li and Wu, 2024) focused on the interaction of the vehicle with other urban elements, the results obtained showed that environmental factors and, mainly, the presence of pedestrians and infrastructure played an important role in increasing the accuracy of the prediction results of the methods studied. The following interactions were embedded into predictive models; boosting prediction accuracy increases the robustness of the model for changes in the environment, as shown in recent work about environment-aware prediction approaches. Similarly, social attention mechanisms that are integrated with LSTM networks have also shown how modeling interactions among road users can be used to further refine the prediction results (S. Qiao and Zhao, 2023).

Other techniques incorporated plate recognition data to further improve the accuracy of urban traffic flow forecasts by accurately estimating the tendencies of vehicle motion at busy intersections (X. Shan and Zhang, 2023). Zhou et al. (H. Zhou and Fan, 2023) have combined Conditional VAEs with social awareness models and found substantial improvements in accuracy, particularly in highly populated urban regions where vehicular interactions are even more involved.

This stream of research elicits a continuous shift toward more adaptive and scalable trajectory prediction models that are important to help foster relevant ITS in modern urban environments. These models will grant appropriate flow, safety, and responsiveness of traffic management systems based on new learning techniques, scalability of frameworks, and consideration of the urban context.

2.2 Pedestrian Trajectory Prediction

Pedestrian trajectory prediction has become a focal area in urban traffic management, especially in improving safety and streamlined movement in highly populous settings. This enables accurate trajectory predictions for pedestrians. In this way, proactive interventions in traffic are possible. These would go a long way to improving the safety of pedestrians. Advanced models demonstrate greater accuracy in these predictions, far above what traditional methods are capable of. For instance, the application of diffusion-based autoregressive models has been made in the prediction of complex pedestrian paths, though these have tended to realize a substantial improvement in accuracy due to their ability to model multidimensional aspects of human movement (K. Lv and Ni, 2024).

In a broad examination of human trajectory prediction techniques, research highlights a wide array of approaches that are effective in diverse traffic scenarios. With the incorporation of spatial-temporal interaction, graph-based network models have gained the lead in efficiency for modeling dynamic pedestrian environments. They are able to analyze how pedestrians interact with both people and vehicles, hence obtaining more exact predictions for places with high flow (A. Rudenko and Arras, 2020; R. Wang and Cui, 2022).

In addition, clustering-based methods combined with LSTM networks improve the prediction accuracy by clustering certain groups of pedestrian paths according to their respective shared characteristics; this helps the model cope with large variations in individual behavior (H. Xue and Reynolds, 2020). The challenge of environmental complexity is the core issue in the development of pedestrian movement modeling. Considering genuine complexities from the real world, such as viewpoint distortion, advanced methods have been suggested that will deliver high accuracy even in complicated settings. In one work, the use of spatial distortions to adjust a prediction yields more robust trajectory forecasts, which will be highly useful in urban areas where pedestrian movements are highly variable (S. Gundreddy and Bakshi, 2023).

Another front where developments are being made involves the use of attention mechanisms in sequence prediction for pedestrians. An attention-driven model has shown tendencies to recognize subtle dependencies and time-based sequences of pedestrian paths. This allows for fine-grained improvements in predictions of crowded urban environments, where this attention mechanism acts to give a further added advantage in enhancing the model in capturing intricate movement patterns. (E. Zhang and Malhan, 2022). Moreover, cross-attention-based predictive models have improved multistep human movement predictions for scenarios that involve the interaction of complicated traffic situations where other traditional models struggle to maintain accuracy (W. Zhu and Yi, 2023).

Other recent works further stress the sole importance of multi-modal approaches, as they represent variants of different behavior patterns among individual pedestrians. Such models significantly improve the reliability of prediction. For example, multimodal modeling techniques can be used to account for a wide range of pedestrian behaviors and have better eventual prediction performance (L. Shi and Hua, 2023). More recently, conditional flow normalization has been shown to increase the real-time accuracy of pedestrian trajectory predictions to better meet the specific challenges of urban areas with dynamic pedestrian densities (J. Sun and Lu, 2021).

2.3 Multi-Agent Trajectory Prediction

Trajectory prediction in multi-agent systems is distinctive and challenging due to a multitude of diverse and often unpredictable behaviors among agents. Several recent extensions proposed predictive models incorporating situational awareness and risk assessment, yielding notable improvements in the accuracy of multi-agent trajectory prediction. For example, the Self Attention-LSTM model, designed for dynamic risk and situational context assessment, has been useful in enhancing trajectory forecasts capturing several agent behaviors in uncertain scenarios (Y. Ma and Manocha, 2019). Similarly, DL models in heterogeneous traffic behavior have proven their usefulness while handling diverse agent dynamics within complex urban settings (A. Kutsch and Bogenberger, 2024).

The importance of diverse, high-quality data sources for multi-agent trajectory prediction is also increasingly recognized, as highlighted by the TUMDOT-MUC dataset. This dataset was developed to capture all details of traffic interaction using UAVs and provided comprehensive details on agent movement for training predictive models on more subtle representations of multi-agent interactions (A. Kutsch and Bogenberger, 2024). Such integration of diverse data allows predictive models to better account for and model interactions between agents, mainly when these are in dense urban settings.

It is also underscored by advances in the field of dynamic system modeling that provide the basis for neural networks specifically engineered to manipulate the dynamics of nonlinear interactions. Among these, the TKAN represents yet another big stride, optimized for analyzing intricate behaviors in dynamic environments. Such networks are based on chaos theory and nonlinear dynamics for extracting temporal and spatial patterns in the data of dynamic scenarios. It can be used to simulate complex, nonlinear interactions. The model demonstrates high accuracy in various applications that involve dynamic prediction, movement analysis, and behavioral simulation, which makes it suitable for real-time forecasting tasks (K. Xu and Wang, 2024),(Kashefi, 2024).

One of the studies underlined that TKAN excelled in spatial-temporal integration regarding multi-agent dynamics, while the model considers several agents at once and therefore can ensure higher predictive accuracy compared to traditional models (Genet and Inzirillo, 2024). Furthermore, TKAN has an excellent application for dynamic and high-density environments, such as those generated by the urban traffic system, because it is quite flexible when adaptation speedily copes with complex nonlinear patterns.

In summary, recent multi-agent trajectory prediction contributions have marked a current trend for models that incorporate contextually aware, rich sources of data, and use state-of-the-art neural architectures such as the TKAN. These improvements enable multi-agent predictive models to guarantee much higher accuracy, helping traffic management and safety policing in complex urban settings.

3 DATASET AND METHODOLOGY

This section elaborated on the methodology adopted for trajectory prediction with a discussion on the preparation of the dataset, the extraction of features, and the modeling framework. The proposed model consists of the TKAN optimized with PSO for developing an object trajectory prediction framework.

3.1 Dataset Overview

This work leveraged the rich TUMDOT-MUC dataset for traffic analysis in urban environments. The capture has been performed using 12 UAVs equipped with cameras continuously observing a segment of a 700-meter-long busy urban roadway in Munich, Germany, over two afternoons during peak traffic times on Thursday, October 6th, 2022, and Wednesday, October 12th, 2022. Figure 1 illustrates the specific location of the monitored road segment in Munich, providing context to the high-density traffic dynamics captured in the dataset.

Each recording session captures the road environment and traffic behaviors for several hours, focusing on periods of high traffic density. The first-day recordings were from 15:35 to 18:45, and for the second day from 15:00 to 18:25. This data forms original material with useful insights into traffic dynamics and a wide range of road user behaviors, thus offering strong data material upon which to ground trajectory prediction. The extracted data covers a broad range of road users, including cars, buses, trucks, trams, motorcycles, bicycles, pedestrians, kick scooters, and trailers. It contains detailed information such as the category of each object, its unique identification, its location, its velocity, acceleration, and orientation across consecutive frames.

UAVs positioned to capture the road segment from different heights and angles allow smooth tracking across multiple frames. The interactions between traffic participants in mixed-traffic conditions have varied well, which allows the dataset to contain complex traffic dynamics that are relevant for trajectory prediction models.

3.2 Feature Extraction and Description

This part outlines the primary and derived features that were critical for accurate trajectory prediction, with descriptions of each feature provided in Table 1. The primary features derived from the dataset include the basic data points: stage time, object class, object unique ID, x-spatial and y-spatial coordinates, speed, and acceleration. Our task is to develop further features to add to the model so that it can enhance its performance. Features apart from these basic ones are extracted to derive further insight and improve the accuracy of trajectory prediction. The features that have been extracted, along with their relevance and usefulness in the approach taken to solve the problem, are as follows:

- **Distance Traveled.** The distance traveled by each object, scaled between 0 and 1 based on the minimum and maximum distances within the dataset, is given by:

$$d_{\text{traveled}} = \frac{d_{\text{traveled}} - \min_{\text{traveled}}}{\max_{\text{traveled}} - \min_{\text{traveled}}}, \quad (1)$$

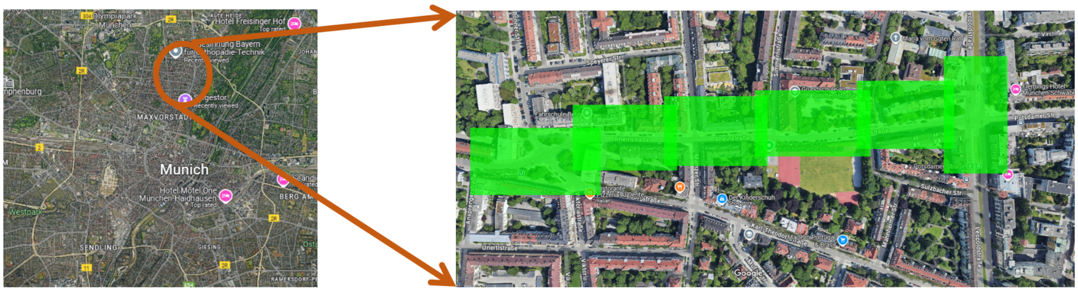

Figure 1: Location of monitored road segment in Munich.

- **Average Velocity (v_{avg}).** The average velocity is calculated as the distance traveled over time, representing the mean velocity of each object:

$$v_{avg} = \frac{d_{traveled}}{time}, \quad (2)$$

- **Manhattan Distance.** The Manhattan distance between two vehicles is the sum of the absolute differences of their coordinates:

$$\text{Manhattan Distance} = |x_1 - x_2| + |y_1 - y_2|, \quad (3)$$

where (x_1, y_1) and (x_2, y_2) represent the coordinates of two vehicles.

- **Manhattan Average Speed.** The Manhattan Average Speed represents the average speed of the surrounding vehicles for each frame, indicating local congestion:

$$\text{Manhattan Average Speed} = \frac{1}{N}\sum_{i=1}^{N} v_i, \quad (4)$$

where N is the number of nearby vehicles and v_i denotes the speed of the i-th nearby vehicle.

- **Yaw Rate.** The yaw rate, representing the angular velocity around the z-axis, is calculated as the rate of change in the z-axis rotation:

$$\text{Yaw Rate} = \frac{\Delta \text{rotation}_z}{\Delta t}, \quad (5)$$

- **Jerk.** Jerk captures sudden changes in acceleration, defined as the time derivative of acceleration:

$$\text{Jerk} = \frac{\Delta \text{acceleration}}{\Delta t}, \quad (6)$$

- **Acceleration Magnitude.** Acceleration Magnitude is the intensity of acceleration, given by the magnitude of the acceleration vector:

$$\text{Acceleration Magnitude} = \sqrt{a_x^2 + a_y^2 + a_z^2}, \quad (7)$$

- **Rotation Magnitude.** Rotation Magnitude captures the total rotation change rate, calculated as the magnitude of the rotation vector:

$$\text{Rotation Magnitude} = \sqrt{r_x^2 + r_y^2 + r_z^2}, \quad (8)$$

- **Heading.** The heading represents the direction of movement of the object, determined using the arctangent of the velocity components:

$$\text{Heading} = \arctan\left(\frac{v_y}{v_x}\right). \quad (9)$$

3.3 TKAN for Trajectory Prediction

The approaches used TKAN since they are capable of capturing the complex, temporal dependencies in such a sequence-based data type, which is best suited for object trajectory prediction. The model utilizes multi-layer neural networks that map dynamic inputs over time, capturing non-linear relationships in the data, hence offering fine-grained, temporal tracking of objects.

TKAN models the complex temporal dependencies of data in a hierarchical neural network layer manner. These layers map object positions across frames and create trajectories with which the model can predict not just the immediate future locations but also the long-term trajectory paths. With each prediction, previous states are considered by the TKAN project's future states, highlighting the essential details in both space and time of motion for applications such as forecasting changes in flow. The TKAN model represents complex functions as:

$$f(x_1, x_2, \ldots, x_n) = \sum_q \Phi_q \left(\sum_p \varphi_{p,q}(x_p)\right). \quad (10)$$

where:

- $\varphi_{p,q}$ are univariate functions mapping each input variable x_p,
- Φ_q aggregates these mappings, facilitating the identification of temporal patterns across data sequences.

3.4 PSO for Model Optimization

To improve TKAN performance, the PSO method was adopted to optimize hyperparameters (layer

Table 1: Extensive feature set of original and extracted features.

Feature	Unit	Symbol	Brief Description	Base Feature	Derived Feature
Timestamp	[s]	t	Frame time	Yes	No
Category	–	cat	Agent type (9 categories)	Yes	No
Track ID	–	ID	Unique agent identifier	Yes	No
Translation	[m]	[x, y, z]	Agent's ground center position	Yes	No
Dimension	[m]	[l, w, h]	Agent's 3D bounding box	Yes	No
Velocity	[m/s]	[vx, vy, vz]	Agent velocity vector	Yes	No
Acceleration	[m/s^2]	[ax, ay, az]	Agent acceleration vector	Yes	No
Distance Traveled	–	d_{travel}	Distance traveled by agents	No	Yes
Average Velocity	[m/s]	v_{avg}	Mean velocity of agent	No	Yes
Manhattan Distance	[m]	d_{man}	Distance between agents	No	Yes
Manhattan Average Speed	[m/s]	v_{man}	Average speed of surrounding agents	No	Yes
Yaw Rate	[rad/s]	ψ	Angular velocity around z-axis	No	Yes
Jerk	[m/s^3]	j	Sudden changes in acceleration	No	Yes
Displacement	[m]	Δd	Agent's movement in 3D space	No	Yes
Acceleration Magnitude	[m/s^2]	a_{mag}	Overall acceleration intensity	No	Yes
Rotation Magnitude	–	r_{mag}	Total rotation change rate	No	Yes
Heading	[rad]	θ	Agent's movement direction	No	Yes

depth, neuron number, and learning rate) by simulating particles moving in the hyperparameter solution space. The particles corresponding to the candidate solutions are defined by a combination of TKAN hyperparameters. The PSO process iterates as follows:

- **Particle Position Representation.** the current position of each particle x_j represents a unique set of TKAN hyperparameters.
- **Velocity Update.** Each particle updates its velocity v_j according to the equation:

$$v_j(k+1) = c_i \cdot v_j(k) + c_c \cdot r_1 \cdot (p_j - x_j) + c_s \cdot r_2 \cdot (p_g - x_j) \quad (11)$$

  Here, c_i is the inertia coefficient that maintains the current momentum of the particle, c_c is the cognitive coefficient that directs the particle towards its best known position p_j (personal best), and c_s is the social coefficient that attracts the particle toward the best global position p_g. The random factors r_1 and r_2 introduce stochasticity, ensuring a diverse exploration of the solution space.
- **Position Update.** Using the updated velocity, the position of each particle is adjusted according to:

$$x_j(k+1) = x_j(k) + v_j(k+1). \quad (12)$$

  This new position corresponds to a revised set of hyperparameters for the TKAN model.

The function repeatedly adjusts velocity and position so that the particles move down to an optimal combination of hyperparameters to reduce the error of the model. This enhances the learning stages of TKAN, which increases predictive accuracy and decreases error rates, allowing for a faster training process. The use of PSO therefore simplifies both TKAN optimization and hyperparameter tuning. Each iteration of this optimization pass is summarized in pseudocode form in Algorithm 1.

Algorithm 1: PSO for TKAN Hyperparameter Tuning.

```
Data: Initialize particles with random positions and
      velocities
Result: Optimal hyperparameters for TKAN
for each particle do
    Set p_best to current position;
    Evaluate fitness (error metric for TKAN);
end
Set g_best as best among all particles;
repeat
    for each particle do
        Update velocity:
            v_j(k+1) = c_i · v_j(k)
                       + c_c · r_1 · (p_best − x_j)
                       + c_s · r_2 · (g_best − x_j)
        Update position:
            x_j(k+1) = x_j(k) + v_j(k+1)
        Evaluate fitness for TKAN model;
        if new fitness < p_best then
            Update p_best;
        end
    end
    if any particle's fitness < g_best then
        Update g_best;
    end
until convergence criteria met;
Return g_best as optimal hyperparameters for TKAN
```

4 EXPERIMENTAL RESULTS

This section describes the results obtained after optimization of the TKAN performance using PSO and further analyzes the results of the trajectory prediction. These findings reveal the improved performance of the model in complex urban conditions in the real world.

4.1 TKAN-PSO Model

The PSO algorithm was used to enhance the precision of the TKAN anchored primitives in predicting trajectories. This was used to fine-tune the crucial hyperparameters of the model for dynamic urban environments where accurate and timely prediction of object trajectories have to be computed in a cluttered scene.

For PSO implementation, each particle represents the position of one TKAN hyperparameter configuration in the swarm of particles. The defined search space was set up in intervals of interest to search for optimal levels that enhance the attention mechanisms and temporal performances of TKAN. These are the most essential parameters of TKAN, which are crucial to handle such complexity of temporal dependencies and are highlighted in Table 2.

Table 2: Hyperparameter ranges for TKAN optimization.

Hyperparameter	Range
Attention Layer Dimension	32 to 128 units
Dropout Rate (Attention Layer)	0.1 to 0.5
Sequence Length	10 to 100 steps
Time-Window Size	5 to 20 steps

To direct PSO toward an effective configuration, the fitness function was designed to minimize the Root Mean Squared Error (RMSE) on the validation dataset. This function reliably assesses model accuracy, guiding PSO to converge on hyperparameter settings that enhance the prediction precision of TKAN. The fitness function used in the optimization is defined as:

$$\text{Fitness} = \frac{1}{\text{RMSE}} \tag{13}$$

The PSO configuration was made up of 30 particles, with each position of the particle being iteratively updated for 100 rounds. The inertia weight w was set to 0.7, while the cognitive and social coefficients (c_1 and c_2) were both set to 1.5. These parameters were tuned to balance the algorithm between exploration and convergence, ultimately contributing to the model's improvement. In Figure 2, the PSO convergence process is visualized over successive iterations, highlighting the steady reduction in RMSE as the optimal performance approaches.

The final optimized configuration, displayed in Table 3, led to a substantial reduction in trajectory prediction error, markedly improving the real-time performance capabilities of the TKAN.

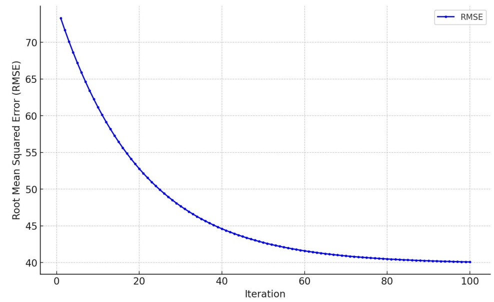

Figure 2: PSO convergence in TKAN hyperparameter optimization.

Table 3: Optimized hyperparameters for TKAN.

Hyperparameter	Optimized Value
Attention Layer Dimension	96 units
Dropout Rate (Attention Layer)	0.3
Sequence Length	40 steps
Time-Window Size	15 steps

Figure 3 presents the optimized TKAN-PSO model, which outperforms the baseline by 10% in RMSE. This configuration enhances TKAN, making it more effective for real-time trajectory prediction in dynamic environments, such as rapidly changing urban settings. The TKAN-PSO model efficiently reduces error rates, well-suited for fast-paced scenarios.

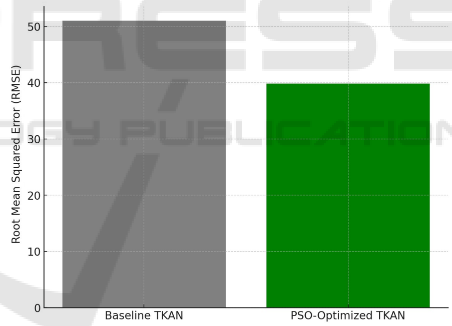

Figure 3: Comparison of RMSE Between Baseline TKAN and TKAN-PSO.

4.2 Visualization of Prediction Results

In this section, the experimental results of the optimized TKAN-PSO model are analyzed and performed within a complex multi-agent urban scenario. In a busy city space monitored by a set of UAVs, different types of entities, from vehicles to pedestrians, are tracked. In these multi-agent settings, the behavior of one entity may influence the other, where vehicles change lanes to avoid pedestrians, and pedestrians are deterred when they see vehicles approaching or other nearby agents. The proficiency and capacity of the model to predict these dynamics driven by interactions between agents is evaluated through these visualizations, demonstrating its effectiveness in predicting trajectories in high-density natural environments.

In Figure 4, a heat map of the test area is presented, where 12 UAVs control vehicles and pedestrians. The movements across multiple lanes and walkways have been captured by each UAV, providing a comprehensive view of high-traffic zones. This heatmap serves to identify areas of increased interaction and potential congestion, which are essential for real-time monitoring and predictive analysis.

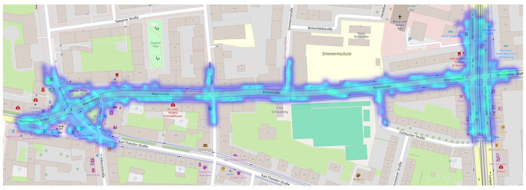

Figure 4: Heatmap of urban monitoring area captured by UAVs.

Figure 5 presents a combined view of predicted versus actual trajectories for all agent classes. The close matching between the predicted and the actual paths within this larger scene underscores the reliability of the model to generate persistent predictions in highly variable urban scenarios. Further, its competencies toward adaptation to various settings and conditions highlight the robustness of the model for accurate predictions of motions in crowded, interacting areas.

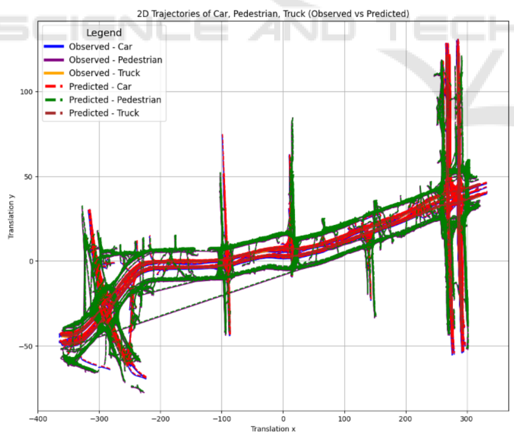

Figure 5: Comparison of predicted and actual trajectories for all agents.

Figure 6 illustrates the 3D visualization and further emphasizes the effectiveness of the model in capturing lateral and vertical movements, crucial in multi-agent scenarios where both dimensions are integral to situational awareness. This three-dimensional view validates the accuracy of the model in spatial tracking, which is essential in scenarios that require real-time positional adjustments.

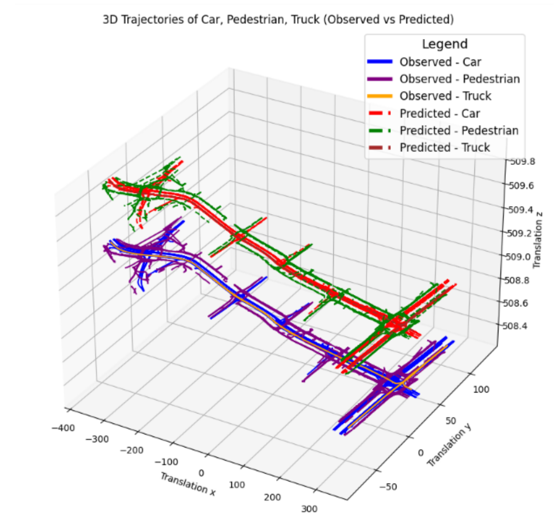

Figure 6: 3D visualization of predicted and actual trajectories across urban terrain.

The predicted trajectories of different agent classes, overlaid against the ground truth trajectories of the model, are shown in Figures 7.a to 7.c. Specifically, predicted trajectories for the car, pedestrian, and truck classes are shown in red, green, and brown, respectively; their ground truth trajectories are shown in the matching colors of blue, purple, and orange, and follow each other nearby. This optimization from PSO tuning reflects in these predictions and points to the precision of the model in high-traffic, dynamic urban settings where accurate real-time adjustments are important for instant decision-making.

Finally, Figure 8 demonstrates how the model is able to avoid collisions in real-time in the reactive path adjustment. The historical data (indicated by red points) aligns closely with the observed movements (blue points), demonstrating how real-time adjustments are predicted by the model. When an object encounters nearby entities, such as another vehicle or a pedestrian, the predictive paths of the model (shown in green) adapt to prevent collisions while accurately projecting future paths. It therefore allows for the capability to make interaction-based adjustments that support suitability in real time for crowded settings where smooth flow and safety are of concern. It should be noted that the representation of the predicted results reflects the accuracy and flexibility achieved by the TKAN-PSO model. The consistent alignment with real-world trajectories in complex urban scenarios illustrates the impact of PSO tuning, which enhances the capacity of the model to handle real-time, multi-agent environments. This precision provides the TKAN-PSO model with considerable use value for application in urban traffic management, autonomous navigation, and multi-agent surveillance

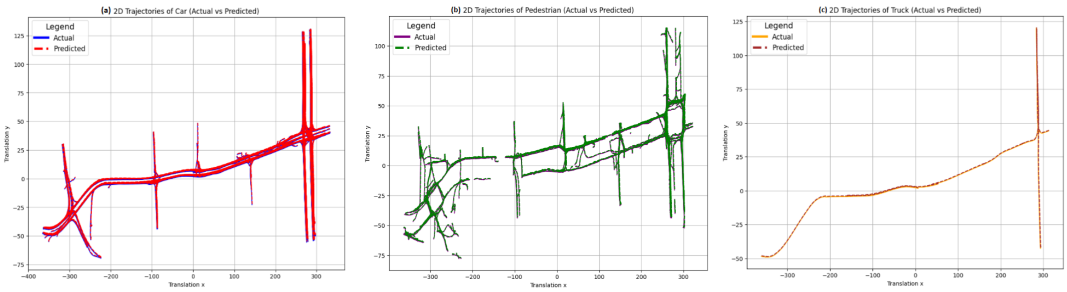

Figure 7: Predicted vs. actual trajectories for multi-agents.

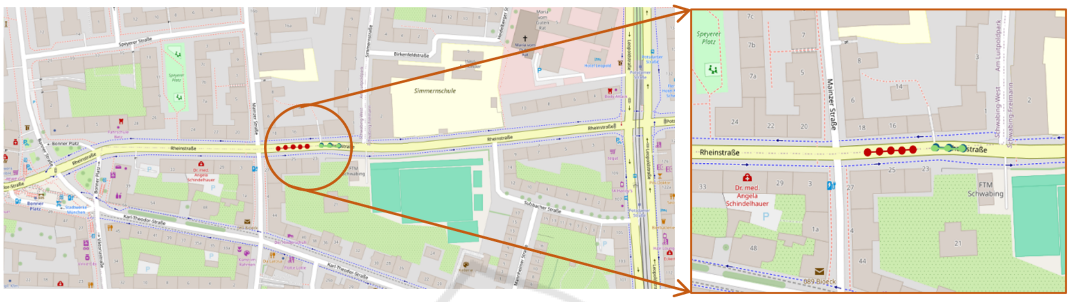

Figure 8: Illustration of historical, real, and predicted trajectories of a car agent.

systems where reliable and efficient decision-making is essential.

4.3 Model Evaluation Metrics

To evaluate the performance of predictive models, key metrics provide information on each accuracy, efficiency, and overall effectiveness of the model (M. R. Mohebbi and Yamnenko,). This section presents the performance of the proposed TKAN-PSO model in comparison with other ML and DL models. Performance evaluation is detailed in essential metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R² score, and Training Time per Epoch, highlighting the strengths and weaknesses of the model for urban trajectory prediction.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |Q_i - A_i|, \tag{14}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (Q_i - A_i)^2, \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (A_i - Q_i)^2}, \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (A_i - Q_i)^2}{\sum_{i=1}^{N} (A_i - \bar{A})^2}, \tag{17}$$

$$\mathrm{MPE} = \frac{1}{N}\sum_{i=1}^{N} \frac{A_i - Q_i}{A_i} \times 100. \tag{18}$$

where O_i denotes the predicted value of i^{th}, A_i represents the actual value of i^{th}, and N signifies the number of test samples, and in R² score formula, $\bar{A}$ is the mean of observed values, and N is the total number of samples.

These metrics collectively offer a comprehensive evaluation framework that balances error magnitude, fit quality, and training efficiency. By analyzing these aspects, practitioners can better understand the strengths and weaknesses of the model, enabling informed decisions for further optimization and improvement.

Table 4 presents the results of each model across these metrics. With an R² score of 0.98, an RMSE of 39.85, and an MSE of 1588.5, the TKAN-PSO model emerged as the most accurate in trajectory prediction. Other models, including LSTM and GRU, performed well, but TKAN-PSO consistently delivered superior results across all metrics, reinforcing its reliability for urban, multi-agent trajectory prediction.

Table 4: Performance comparison of all models on evaluation metrics.

Model	MAE	RMSE	R^2	MPE	Time
TKAN-PSO	**13.75**	**39.85**	**0.98**	**-12.9**	**128**
LSTM	21.3	52.9	0.93	-15.7	152
GRU	22.6	55.3	0.91	-37.4	144
KNN	27.4	67.0	0.85	-21.1	97
RNN	24.9	60.7	0.89	-18.2	125
MLP	26.3	63.5	0.91	-19.9	107
SVR	28.7	69.8	0.83	-49.7	93

Table 5 shows the performance of the TKAN-PSO model when predicting trajectory for specific agent types (cars, pedestrians, and trucks), highlighting an improved accuracy for cars due to the larger dataset for this category. Conversely, pedestrians and trucks show slightly lower R² score values, reflecting data variability and the challenges inherent in predicting these trajectories of agents.

Table 5: Performance of the TKAN-PSO model across various agent types and all agents.

Agent	**MAE**	**RMSE**	R^2	**MPE**	**Time**
Cars	12.6	37.45	0.98	-11.75	122
Pedestrians	19.8	51.6	0.93	-15.68	137
Truck	18.1	50.7	0.93	-14.50	135
All Agents	13.75	39.85	0.98	-13.93	128

Figure 9.a visually compares the MSE-based models, highlighting the clear advantage of the proposed model over the others. In Figure 9.b, the prediction accuracy of the TKAN-PSO model is shown for each agent and the overall accuracy in the urban traffic environment, underlining its effectiveness in predicting urban trajectory. This underlines the effectiveness of the TKAN-PSO model in predicting the trajectory of urban settings viewed in this work. Additionally, this is due to the diversity of data and structural optimization using PSO that enhances the ability of TKAN to make reliable, real-time predictions within complex environmental settings. These analyses help the practitioner find where the best model is strong and where it will need improvement to support decisions toward further optimization and enhancing predictive performance.

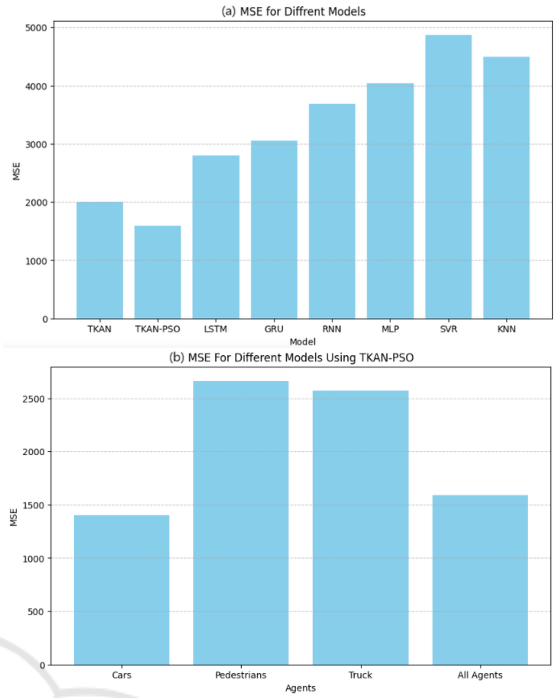

Figure 9: Comparison of model prediction accuracy by MSE and agent type.

5 CONCLUSIONS

The proposed TKAN-PSO model realizes marked improvements in multi-agent trajectory prediction. This proves that the model is able to handle multiple urban agents, such as vehicles, pedestrians, and trucks, with significant accuracy in dynamic and high-density environments. The inclusion of PSO allows for the fine-tuning of hyperparameters and therefore contributes to major improvements in predictive accuracy and error minimization. This optimization strategy enhances the resilience of the proposed model to the varied spatial and temporal dependencies present in urban data, ensuring robust performance across diverse scenarios. Central to the effectiveness of the model is a thoughtful feature extraction process that systematically incorporates critical attributes. These features capture key spatial and temporal patterns that allow TKAN-PSO to predict complex trajectories for individual agents while considering the broader interactions among multiple agents in real-time. The multi-agent predictive ability of TKAN-PSO will have wide implications in the ITS area, which is crucial for real-time decision support, urban traffic management, and object tracking, all key elements in much safer and more efficient mobility. Performing accurate prediction and adaptation to the complex circumstances of urban settings, TKAN-PSO enables intelligent mobility. It provides a key tool that improves flow and safety and reduces congestion in modern cities and towns.

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