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RESEARCH ARTICLE

Filter for Traffic Congestion Prediction: Leveraging Traffic Control Signal Actions for Dynamic State Estimation

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ABSTRACT The field of intelligent transportation systems is rapidly evolving, with increasing focus on addressing traffic congestion, a pervasive problem in urban environments. This study contributes to this domain by enhancing traffic prediction models. Traditional traffic models often fall short in accurately predicting traffic flow, particularly in dynamic urban settings. This limitation necessitates the development of more adaptive and accurate predictive models to manage traffic congestion effectively. In urban environments, traffic estimation at multi-intersection nodes and connecting roadis approached using statistical filters (Kalman or particle filters). The challenge lies in accurately predicting the vehicular traffic state at intersections, considering the dynamic nature of urban traffic and potential communication failures. This study introduces a novel approach in traffic modeling using statistical filters. The method involves the use of dynamically interchangeable state transition matrices, aligned with specific traffic signal control actions. This allows for more precise predictions under varying traffic conditions and control scenarios. The effectiveness of the proposed models is validated across multiple intersections in urban settings. The evaluation focuses on the models' scalability, adaptability to complex traffic networks, and robustness in communication failure scenarios. Our proposed Kalman filter showcased superior performance in traffic prediction with an average RMSE of 12.15975, demonstrating a significant improvement over the average measurement RMSE of 13.996875 and over traditional smooth Kalman filter and traditional particle filter.

INDEX TERMS Road traffic, deep reinforcement learning, Kalman filters, intelligent transportation systems, prediction methods.

I. INTRODUCTION

Traffic congestion, a ubiquitous challenge in modern urban environments, has burgeoned into a global concern with far-reaching impacts [1]. As cities continue to grow in both size and population, the issue of congested roads has escalated, affecting millions of commuters daily [2]. The root of this problem is multifaceted, stemming from urbanization, increased vehicle ownership, and often inadequate public transportation systems [3]. The economic implications of traffic congestion are substantial. In many major cities around the world, countless hours are lost in traffic, translating to significant economic losses. The Texas A&M Transportation Institute reported that in the United States alone, the annual

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cost of traffic congestion exceeded $160 billion, accounting for wasted time and additional fuel consumption [4]. This economic burden is not unique to the U.S.; similar trends are observed globally, where urban centres grapple with the high costs associated with traffic delays and inefficiencies [4]. Environmental concerns are another critical aspect of traffic congestion. Vehicles stuck in traffic emit higher levels of pollutants, contributing to air quality deterioration and increased greenhouse gas emissions [5]. According to the World Health Organization, air pollution is a major environmental risk to health, and by reducing air pollution levels, countries can reduce the burden of disease from stroke, heart disease, lung cancer, and both chronic and acute respiratory diseases [6]. The reduction in vehicle emissions is crucial in combating climate change and protecting public health. Socially, the effects of traffic congestion extend beyond mere inconvenience [7]. Prolonged exposure to traffic congestion can lead to increased stress and decreased quality of life for individuals. It affects the daily routine, reducing the time available for personal and family activities, and can exacerbate societal tensions [8]. These challenges underscore the critical need for effective traffic congestion management and prediction [8]. With urban areas continuing to grow, the ability to predict and manage traffic flow becomes not just a matter of convenience, but a necessity for economic efficiency, environmental sustainability, and social well-being [9]. This global context sets the stage for exploring innovative solutions in traffic congestion prediction, where accuracy and efficiency can make significant contributions to alleviating the multifaceted impacts of traffic congestion [10].

Traffic congestion in urban areas presents one of the most challenging problems of modern times, impacting not only the efficiency of transportation but also the quality of life through increased pollution, wasted time, and heightened stress level [11]. The rapid urbanization and growth in vehicle ownership have exacerbated congestion issues, necessitating innovative solutions to manage and alleviate traffic effectively [12].

The importance of traffic congestion prediction in contemporary urban planning and traffic management cannot be overstated. In the face of escalating urban congestion, accurate and reliable traffic prediction has become a critical tool for city planners, traffic engineers, and policymakers [13]. Effective congestion prediction models serve as the linchpin for developing strategies that enhance traffic flow, mitigate congestion, and improve the overall efficiency of transportation systems. Firstly, accurate traffic congestion prediction enables proactive traffic management [13]. By anticipating congestion patterns, traffic authorities can implement preemptive measures such as dynamic traffic signal timings, optimized routing, and congestion pricing [14]. This proactive approach not only reduces the immediate impacts of congestion but also aids in preventing traffic bottlenecks before they occur [15]. For instance, predictive models can inform the deployment of adaptive traffic signal systems that adjust green and red phases in real-time based on predicted traffic volumes, thereby smoothing traffic flow and reducing stop-and-go conditions. Secondly, effective traffic prediction plays a crucial role in infrastructure planning and development [16]. Long-term traffic congestion forecasts are vital for guiding decisions on infrastructure investments such as road expansions, the construction of new transportation routes, and the development of public transportation systems. Accurate predictions ensure that these costly investments are targeted effectively, addressing current and future congestion issues [17].

Moreover, traffic congestion prediction is integral to enhancing the quality of life for urban residents [18]. Reduced congestion leads to shorter commute times, lower vehicle emissions, and a decrease in fuel consumption [19]. This, in turn, contributes to environmental sustainability, improved air quality, and public health. Furthermore, efficient traffic management driven by accurate predictions can lead to a more pleasant urban living experience, with less time spent in traffic and more time available for personal and community activities [19]. In addition, traffic congestion prediction is increasingly important in the context of smart cities and emerging technologies. The integration of predictive analytics with technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and connected vehicles opens new horizons for real-time data collection and analysis, leading to more dynamic and responsive traffic management systems [20]. The background of traffic congestion control is rooted in the utilization of various technologies and methodologies, ranging from simple timed signals to complex adaptive systems that respond to real-time traffic conditions. Traditional approaches often involve static algorithms that do not account for the unpredictable nature of urban traffic flow. However, with advancements in computing and the proliferation of traffic-related data, there is potential for more dynamic and intelligent traffic management systems [21]. Despite significant progress in this field, there remains a gap in the development of models that can not only predict traffic patterns with high accuracy but also adapt to the constantly changing conditions typical of urban environments. Most existing models fail to integrate real-time traffic control actions and road infrastructure data effectively into their algorithms, which is critical for accurate traffic prediction and management [22].

Statistical filters, particularly Kalman and particle filters, have gained prominence in the realm of predictive analytics due to their effectiveness in processing and interpreting complex, dynamic data [23]. These filters are instrumental in a variety of applications, with traffic congestion prediction being a notable area where their impact is profoundly felt The Kalman filter, renowned for its efficiency in linear dynamic systems, excels in situations where noise and uncertainty are prevalent [24]. It operates by generating estimates of unknown variables, continuously updating them as new data becomes available. This ability to refine predictions in real-time makes the Kalman filter particularly valuable in traffic management, where conditions change rapidly [25]. The particle filter, on the other hand, extends this capability to non-linear and non-Gaussian processes [25]. It utilizes a set of random samples, or particles, to represent probability distributions, allowing for the handling of more complex and diverse data structures. This flexibility is crucial in modelling the unpredictable and often chaotic nature of urban traffic flows. A key factor in the effectiveness of these statistical filters is the process model they are based on [26]. The process model embodies the underlying dynamics of the system being studied, incorporating assumptions and knowledge about how the system evolves over time. In traffic congestion prediction, an accurate and well-defined process model is essential for these filters to yield reliable results [27]. The complexity of urban traffic, characterized by varying patterns, sudden changes, and a multitude of influencing factors, necessitates a robust and comprehensive process model [28]. Incorporating traffic signal information into the process model can significantly enhance its effectiveness. Traffic signals are pivotal in controlling flow and congestion, and their status at any given time can greatly influence traffic conditions. By integrating data such as signal timings, phase durations, and pedestrian crossing information, the process model becomes more representative of the actual traffic environment [29]. This integration enables Kalman and particle filters to predict congestion patterns, adjust to real-time changes, and provide actionable insights for traffic management more accurately. As such, the inclusion of traffic signal information is not just beneficial but perhaps essential for developing a good process model in traffic congestion prediction, leveraging the full potential of these sophisticated statistical filters [30].

This study addresses critical gaps in current traffic congestion prediction methods, including limited real-time adaptability, lack of multi-intersection scalability, and inadequate handling of communication failures. To overcome these challenges, we develop a novel statistical filter that integrates a dynamic traffic process model, extending its application to both Kalman and Particle filters. Our objectives are to validate this approach across multiple intersections, evaluate its robustness in scenarios with communication failures, and provide a comparative analysis against traditional methods. By achieving these goals, this research aims to significantly advance traffic congestion prediction capabilities, contributing to more efficient and responsive urban traffic management systems. Hence, this article aims to address traffic congestion control by introducing an adaptive traffic prediction model that leverages advanced Kalman and Particle filters, incorporating a novel traffic process model to capture the dynamism of urban traffic flow. We propose a framework that not only predicts traffic congestion but also provides actionable insights for traffic control systems. The remainder of the article is structured as follows: we provide a detailed description of the novel process model incorporated into both Kalman and Particle filters, followed by an exposition of the model validation across multiple urban intersections. The results highlight the models' robustness, particularly in scenarios of communication failure, and a comparative analysis elucidates the performance benefits of the proposed models over traditional methods. Finally, we discuss the implications of our findings for intelligent transportation systems and outline future research directions to further refine traffic congestion control algorithms.

II. CONTRIBUTIONS

This article provides key advances in the burgeoning field of intelligent transportation systems, with a focus on the complex problem of traffic congestion prediction and management. The revised contributions are enumerated as follows:

1. Novel Adaptive Kalman Filter Design with Traffic Process Modeling: This study not only introduces an adaptive Kalman filter but goes a step further by integrating a traffic process model into the algorithm. Utilizing different state transition matrices (A) contingent on current traffic control actions, the model is enhanced to better represent real-time traffic conditions at an intersection. The integration of the traffic process model allows for more accurate and reliable predictions, making it a significant advancement over traditional Kalman filter applications.
2. Extension to Particle Filters with Traffic Process Modeling: A notable contribution of this study is the application of a traffic process model to Particle filters, a realm largely untouched by existing studies. The incorporation of the traffic process model augments the Particle filter's capability to estimate system states, particularly under non-linear and non-Gaussian conditions, thus broadening the scope and applicability of congestion prediction techniques.
3. Multi-Intersection Validation: Consistent with previous research, this study further validates the extended Kalman and Particle filters across multiple intersections in an urban setting. This multi-intersection validation serves as a testament to the algorithms' scalability and their ability to adapt to intricate urban traffic networks.
4. Comparative Analysis: As an additional layer of insight, this work offers a comparative evaluation of the Kalman and Particle filters when equipped with a traffic process model. This analysis provides practitioners and policymakers with valuable metrics to choose the best-fit model for specific traffic scenarios and constraints.

III. LITERATURE SURVEY

The foundational approaches in traffic congestion prediction focus on Kalman filter applications and active exploration frameworks. For instance, UAV-based methodologies using dual state ensemble Kalman filters have been pivotal in assessing road network conditions [31]. The integration of Kalman filters with graph neural networks in Dynamic Origin-Destination Matrix Prediction represents a significant advancement in capturing the complexities of road networks [32].Kalman filter algorithms have also been applied for real-time traffic flow prediction in urban arterials [33] and on-board traffic prediction in connected vehicles [34].

Leveraging big data and integrating heterogeneous data sources have become powerful tools in this field. The fusion of quantitative and qualitative data, including social media inputs for comprehensive traffic analysis, demonstrates the potential of data fusion approaches [35]. Data FITS, as an open-source framework, merges various data types to enhance traffic models in Intelligent Transportation Systems [36].

The utilization of real-time data has seen innovative developments, particularly with the use of probe vehicles as sensors [37]. The AKFNN model, combining Adaptive Kalman Filters with neural networks, refines vehicle count estimates, demonstrating the potential of adaptive and learning-based approaches.

Advanced network modelling techniques, such as the Deep Kalman Filtering Network (DKFN) and the Deep Spatial and Temporal Graph Convolutional Network (DSGCN), address spatial-temporal dependencies in traffic prediction [38], [39]. These models effectively capture the complexities of urban and network-wide traffic dynamics.

Emerging technologies, like millimeter-wave radar sensors, play a pivotal role in congestion management. This technology, combined with advanced signal processing and neural networks, offers real-time, accurate data for traffic control [40].

In the era of data privacy concerns, Federated Learning-based approaches, like the Fed-STGRU model, balance the need for accurate traffic flow prediction with privacy preservation [41]. This decentralized learning approach is significant for privacy in Wireless Sensor Networks. The demand for interpretability in traffic prediction models has led to the development of techniques like the Self-Constructed Deep Fuzzy Neural Network (SCDFNN), which combines fuzzy inference with deep learning for insightful traffic pattern analysis [42].

Hybrid learning models, like the Genetic-Algorithm-Improved Kernel Extreme Learning Machine (GA-KELM), blend various methodologies for enhanced performance. This model illustrates how genetic algorithms can optimize learning parameters, resulting in superior prediction accuracy [43]. Comprehensive evaluations of hybrid deep learning models in ITS provide insights into the effectiveness of these advanced approaches [44].

Particle filtering method, Tannoid principles of Emblica officinalis renovate cognitive deficits and attenuate amyloid pathologies against aluminum chloride induced rat model of Alzheimer's disease to predict stream travel times by summing the median of historical travel times, random variations, and a model evolution error, using particle filtering for dynamic mathematical modeling. This approach is tested against actual travel time data, showing satisfactory prediction accuracy.

A notable contribution comes from [45], who introduced a novel approach using Vision Transformers (VTs) in conjunction with Convolutional Neural Networks (CNN) for city-wide traffic congestion prediction. Their method demonstrates superior performance in terms of precision, accuracy, and recall, especially during anomalous traffic situations.

Reference [46] proposed an innovative traffic state prediction method combining improved particle swarm optimization (IPSO) with radial basis function (RBF) and long short-term memory (LSTM)/support vector machine (SVM) feature fusion models. Their approach showed superior performance in predicting urban traffic states and offered a new method for congestion section control based on traffic allocation.

In the realm of large-scale applications, [47] introduced the Congestion Prediction Mixture-of-Experts (CP-MoE) model, developed for DiDi, one of the world's largest ride-hailing platforms. This model addresses the challenges of handling heterogeneous and dynamic spatio-temporal dependencies in traffic data, offering improved accuracy and reliability in travel time estimation systems.

Focusing on areas with limited historical data, [48] evaluated a wide range of models for multi-step traffic congestion forecasting. Their findings indicate that Ensemble Tree-Based (ETB) regressors, particularly the Light Gradient Boosting Machine (LGBM), outperform traditional Deep Learning methods in short-term predictions.

Addressing the computational challenges in traffic forecasting, () [49] proposed a novel AI model combining a Cascaded Transition Recurrent Feature Network (CTRFN) for feature extraction with a Paramount Transfer Learning Network (PTLN) for congestion prediction. Their approach, optimized using a Coherent Lizard Search Optimization (CLSO) algorithm, aims to reduce prediction errors and improve overall performance.

The current research landscape in traffic congestion prediction reveals two notable gaps. First, there is a substantial focus on single-intersection scenarios, with a notable lack of comprehensive evaluations and solutions for multi-intersection environments. This limitation is significant, as the dynamics of urban traffic are heavily influenced by the interplay between multiple intersections, where the complex interactions and dependencies can lead to distinct traffic patterns and congestion dynamics not adequately addressed by single-intersection models. Consequently, there is an essential need for more research aimed at developing models that specifically cater to the intricacies of multi-intersection traffic scenarios. This would ensure that predictions and management strategies are more holistic and reflective of actual urban traffic conditions. Second, many studies in congestion prediction overlook the integration of traffic signal information, a critical aspect of urban traffic management that significantly impacts flow and congestion patterns. The absence of traffic signal data in these predictive models potentially limits their accuracy and applicability. Integrating traffic signal information could enhance these models by providing insights into

TABLE 1. An overview of existing methods in traffic congestion prediction.

Article	Sensors	Prediction	Algorithm	Multi-Intersection Env	Traffic signal incorporation
[31]	UAVs videos	Traffic congestion	EnKF	×	×
[32]	Traffic sensors	Dynamic Origin-Destination Matrix Prediction	Graph neural networks and Kalman filter	√	×
[33]	Connected vehicles	Traffic flow at urban arterials	Kalman filter	√	×
[34]	On-board connected vehicle data	Predicted real-time individualized speed previews	Kalman filter and traffic flow models	×	×
[35]	Multiple modalities (traffic data and twitters)	Traffic congestion	Machine learning methods with Kalman filter	√	×
[37]	Probe vehicles	Predicting signalized approach traffic conditions	Adaptive Kalman Filter (AKF) and AKFNN	√	√
[38]	Traffic sensors and historical data	Network-wide traffic state, specifically speed	Deep Kalman Filtering Network (DKFN)	√	×
[36]	Various sources	Traffic levels and incident classification	k-NN with DTW and Wasserstein	×	×
[39]	Grid-based traffic network	Traffic congestion status	Deep Spatial and Temporal Graph Convolutional Network (DSGCN)	×	×
[40]	Millimeter-wave radar sensors	Predicted urban traffic congestion levels	Spectral clustering and a neural network	√	√
[41]	Wireless Sensor Network (WSN)	Traffic flow prediction	Federated Learning-based spatio-temporal approach (Fed-STGRU) with GCN and GRU	×	×
[42]	×	Traffic flow in intelligent transportation systems	Self-Constructed Deep Fuzzy Neural Network (SCDFNN)	×	×
[43]	×	Short-term traffic flow conditions	Genetic-Algorithm-Improved Kernel Extreme Learning Machine (GA-KELM)	√	×
[44]	Data from large-scale road networks	Short- and long-term traffic conditions	Hybrid deep learning models, including CNN-based, GCN-based, and transformer-based models	√	×
[50]	×	Forecasting pedestrian motion and trajectories	Bayesian methods, neural networks, and a modified particle filter	×	×
[51]	×	Predicted real-time traffic speeds	Deep Graph Neural Networks (DGNNs) with Gated Graph Attention Network (GGAN) blocks	×	×
[52]	Camera	Stream travel time prediction	Particle filtering	×	×
[45]	Traffic images	Traffic congestion	Vision Transformers (VTs) with CNN	√	×
[46]	Regional traffic data	Traffic state and congestion	IPSO-RBF and LSTM/SVM fusion	√	√
[47]	Ride-hailing platform data	Traffic congestion	Congestion Prediction Mixture-of-Experts (CP-MoE)	√	×
[48]	IoT sensor data	Traffic congestion	Ensemble Tree-Based regressors (e.g., LGBM)	√	×
[49]	Traffic dataset	Traffic congestion	CTRFN with PTLN and CLSO optimization	√	×

the timing and phasing of signals, directly affecting traffic flow. Such integration could lead to more dynamic and adaptive traffic management systems, capable of optimizing signal timings based on predictive insights, thus improving traffic efficiency and reducing congestion. Addressing these gaps by focusing on multi-intersection environments and incorporating traffic signal data could greatly enhance the effectiveness and relevance of congestion management strategies in urban traffic networks.

IV. METHODOLOGY

This section presents the developed methodology of this article. It starts with presenting the symbols used. Next, we present the definitions, communication infrastructure, and our proposed Kalman filtering method.

A. SYMBOLS

B. DEFINITIONS

1) INTERSECTION

It is defined by its segments. We assume four segments intersection, namely, north, south, east and west. Each segment has two directions, namely, one inside and one outside. In addition, each direction has three lanes, right only, go-through, and left only [53].

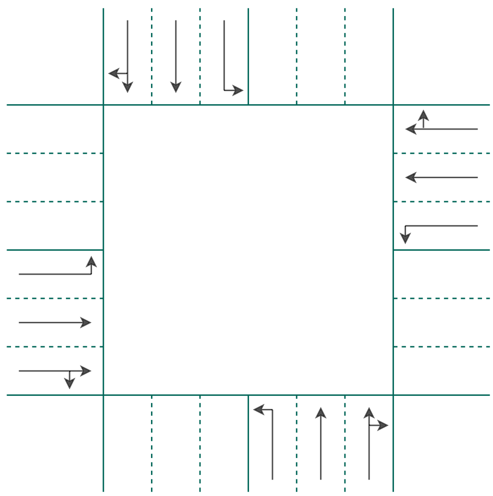

FIGURE 1. From the article of [53].

TABLE 2. Mathematical symbols used in the article and their meaning.

Symbol	Meaning
ITS	Intelligent transportation systems
IoT	Internet of Things
V2X	vehicle-to-everything
ATMS	Advanced Traffic Management Systems
RL	Reinforcement Learning
QT-CDQN	cooperative deep Q-network with Q-value transfer
LSTM	long short-term memory
MARL	multi-agent reinforcement learning
CGB-MATSC	Cooperative Group-Based Multi-Agent reinforcement learning-ATSC
CVIS	Cooperative Vehicle Infrastructure System
TSC	Traffic Signal Control
x_t, x_{t+1}	Number of vehicles in the subject intersection at time steps t and $t+1$ respectively
$A_{in,t}$	A binary vector represents the status of in traffic signal to the intersection from the adjacent intersections
$A_{out,t}$	A binary vector represents the status of out traffic signal from the intersection from the adjacent intersections
u_I is	A vector represents the number of vehicles in each direction leading in to the subject intersection
u_o is	A vector represents the number of vehicles in each direction leading out from the subject intersection
z_t	Represented by the number of vehicles in the intersection at current time step t
x_t^-	Initialize the state estimate
P_t	the error covariance
$x_{t,t}^-$	predicted state estimate
$P_{t+1/t}$	the predicted error covariance
F	*the state transition matrix*
Q	the process noise covariance matrix
H	*the observation matrix*
R	the measurement noise covariance matrix
K_{t+1}	the Kalman gain

2) LEFT-TURN-PERMITTED

Left Turn Permitted refers to a traffic control scenario where vehicles are allowed to make left turns at an intersection during the same green light phase as vehicles going straight through the intersection. In this scenario, left-turning vehicles must yield to oncoming traffic and pedestrians before proceeding with the turn. It is represented by $A = \{a_1, a_2, a_3, a_4\}$. where a_i indicates enabling TSP for vehicles going-through opposite segment with left and right movement allowed. $i \in \{1,2,3,4\}$

A conceptual figure is presented in Figure 2.

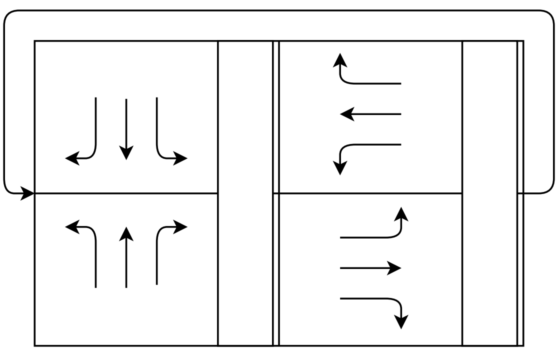

FIGURE 2. Conceptual diagram of left turn permitted [53].

3) LEFT TURN PROTECTED

left turn protected represents scenario where dedicated green arrow signal is provided exclusively for left turning vehicles, allowing them to make the turn without having to yield to oncoming traffic or pedestrians. In this system, the action space can be represented by $A = \{a_5, a_6\}$, where a_j indicates enabling a dedicated protected left turn phase for vehicles $j \in \{5, 6\}$

C. COMMUNICATION INFRASTRUCTURE FOR INTELLIGENT TRANSPORTATION SERVICE

For an intelligent transportation service aiming to control traffic congestion, a robust, resilient, and high-speed communication infrastructure is paramount. The envisioned system requires real-time data acquisition, processing, and communication between vehicles and traffic controllers (TC) positioned at intersections. Therefore, ensuring consistent and fast data transfer rates, minimal latency, and high reliability are key to its successful deployment and operation.

Network Provisioning over Multiple RTAs (Radio Transmission Access): To provide comprehensive coverage and uninterrupted connectivity, the communication infrastructure needs to be provisioned over multiple radio transmission mediums. Leveraging 3G, 4G, and 5G networks can ensure that vehicles, irrespective of their location and the communication technologies they support, remain seamlessly connected to the system.

1. **3G Network:** While considered legacy technology by modern standards, 3G networks can serve as a backup medium, especially in regions or zones where more advanced networks might be temporarily unavailable. Though 3G might not offer the same bandwidth and low latency as 4G and 5G, it provides a safety net to ensure constant communication.
2. **4G Network:** Serving as the mainstream choice for mobile data communication in many regions, 4G can provide high-speed data transfer rates suitable for this application. Its widespread availability ensures that a significant portion of the city or region can be covered, providing the infrastructure for vehicles to communicate their destinations and receive optimized routes in real-time.
3. **5G Network**: As the latest evolution in mobile communication, 5G offers ultra-reliable low latency communication (URLLC) and enhanced mobile broadband (eMBB), which are particularly beneficial for this service. 5G can ensure instantaneous data transfer and communication between vehicles and TCs, allowing for real-time updates and decisions. Furthermore, its increased bandwidth and reduced latency are crucial for facilitating coordination between neighboring TCs, ensuring a holistic approach to traffic management.

To foster optimal communication, vehicles should be equipped with multi-RAT (Radio Access Technology) devices, enabling them to switch between these networks dynamically based on availability and network load. Furthermore, each Traffic Controller (TC) at intersections should also be connected to a high-speed backbone network, preferably fiber-optic, to facilitate rapid data exchange and coordination with neighboring TCs. This would ensure that decisions made are not just localized but are also optimized with a broader, city-wide perspective in mind.

D. KALMAN FILTERING

This section presents an overview of Kalman filter, our proposed problem formulation, and our proposed algorithm.

1) OVERVIEW OF KALMAN

The Kalman [54] is a mathematical algorithm that provides an efficient computational means to estimate the state of a linear dynamic system in the presence of random noise. The underlying mathematical framework for the Kalman filter consists of two sets of equations: the state equations and the observation equations. State equations describe how the state of the system evolves over time. Mathematically, it can be represented as in Equation (1)

$$x_t = A \cdot x_{t-1} + B \cdot u_t + w_{t-1} \tag{1}$$

where x_t is the state vector at time t, A is the state transition matrix, B is the control matrix, u_t is the control vector, and w_{t-1} is the process noise. Observation equations relate the current state of the system to the observed data. It can be described as in Equation (2)

$$z_t = H \cdot x_t + v_t \tag{2}$$

where z_t is the observation at time t, H is the observation matrix, and v_t is the observation noise.

The Kalman filter proceeds through a two-step process at each time step: prediction and update.

The prediction uses state equations. In the prediction, the Kalman filter predicts the state of the system at the next time step and estimates the uncertainty associated with this prediction.

The update uses the observation equations. More specifically, when a new measurement becomes available, the filter uses the observation equations to correct its state estimate. The new state is a weighted combination of the predicted state and the state estimated from the latest measurement, where the weights are determined by the uncertainties in the two estimates. The Kalman filter for predicting the number of vehicles in the intersection is given in Algorithm 1.

To clarify the distinction between the basic Kalman filter and our Adaptive Kalman Filter (AKF) approach, we present Algorithm 2 below, which outlines the key steps of our AKF and highlights its unique features. The key difference in our AKF approach lies in steps 3-4, where we dynamically select the state transition matrix $\boldsymbol{A}_t$ based on the current traffic control action a_t. This allows our filter to adapt to changing traffic conditions and signal timings in real-time, providing more accurate predictions of traffic congestion.

Algorithm 1 Kalman Filter for Predicting the Number of Vehicles in the Intersection

1. **Initialization**: Initialize the state estimate x_t^- and the error covariance P_t You can set an initial guess for x_t^- based on historical data or domain knowledge, and you can initialize P_t as a diagonal matrix with large variances.
2. **Predict step**: Using the state model, compute the predicted state estimate $x_{t+1,t}^-$ and the predicted error covariance $P_{t+1/t}$:
   $x_{t+1,t}^- = A_t x_t^-$
   $P_{t+1,t} = A_t P_t A_t^T + Q$
   where A_t is the state transition matrix (identity matrix in this case, since the state model is a simple linear model), and Q is the process noise covariance matrix.
3. **Update step:** Update the state estimate $x_{t+1,t}^-$ and the error covariance P_{t+1} based on the measurement z_{t+1}:
   - Compute the Kalman gain K_{t+1}:
     $K_{t+1} = P_{t+1} H^T (HP_{t+1} H^T + R)^{-1}$

   where $\boldsymbol{H}$ is the observation matrix (identity matrix in this case, since the measurement is the number of vehicles in the intersection directly), and $\boldsymbol{R}$ is the measurement noise covariance matrix.
   - Update the state estimate:
     $x_{t+1}^- = x_{t+1,t}^- + K_{t+1}(z_{t+1} - Hx_{t+1/t})$
   - Update the error covariance:
     $P_{t+1} = (1 - K_{t+1} H) P_{t+1,t}$
4. **Repeat steps 2 and 3:** Iterate the predict and update steps for each new time step and measurement.

2) OVERVIEW OF PARTICLE FILTER

The filtering approach elucidated here pertains to the utilization of particle filtering, which is a method employed for recursive Bayesian estimation, employing the Sequential Monte Carlo methodology. The fundamental concept underlying this approach involves the representation of a posterior probability density function (PDF) of the state through a collection of particles, each assigned with corresponding weights. The estimation can then be calculated as the anticipated value of this discrete PDF (A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking). This approach relies on the utilization of point mass representations, often referred to as particles, to describe probability densities. It is a versatile technique that can be applied to a wide range of state space models, including those characterized by high non-linearity and non-Gaussian noise densities. The initial step involves the generation of random samples, or particles, for the filter using Monte Carlo methodology. These particles are then systematically advanced and revised in accordance with the dynamics of the system and the characteristics of the measurement models.

The probabilistic state space models that are equivalent, along with the necessity to refresh the information upon

Algorithm 2 Adaptive Kalman Filter for Traffic Congestion Prediction

1: Initialize state estimate x_0 and error covariance P_0.
2: for each time step t do
3: Update traffic control action a_t.
4: Select appropriate state transition matrix A_t: based on:
5: Predict state: $x_{t|t-1} = A_t x_{t-1|t-1}$.
6: Predict error covariance: $P_{t|t-1} = A_t P_{t-1|t-1} A_t^T + Q$.
7: Compute Kalman gain: $K_t = P_{t|t-1} H^T \left(H P_{t|t-1} H^T + R \right)^{-1}$.
8: Update state estimate: $x_{t|t} = x_{t|t-1} + K_t \left(z_t - H z_{t|t-1} \right)$.
9: Update error covariance: $P_{t|t} = (I - K_t H) P_{t|t-1}$.
10: end for

receiving a new set of measurements, align ideally with the Bayesian methodology. In this approach, the objective is to formulate the posterior probability density function (PDF) $p\left(\mathbf{x}_{(k+1)}|\mathbf{Z}_{(k)}\right)$ for the state vector $\mathbf{x}_{(k+1)}$ based on the information that is currently accessible. In this context, $\mathbf{Z}_{(k)}$ denotes the collection of all measurements received up to and including the $\mathbf{z}_{(k)}$ measurement, defined as $\mathrm{Z}_{(k)} = \left\{\mathbf{z}_{(i)}, i = 1, 2, 3, \ldots k\right\}$ The formal recursive Bayesian estimation process encompasses two key operations: prediction and update.

During the prediction phase, the posterior probability density function (PDF) of the state vector is projected from time step k to the subsequent time step $k + 1$. This projection is executed by employing the Chapman–Kolmogorov Equation (Equation 4).

$$\underbrace{p\left(\mathbf{x}_{(k+1)} \mid \mathbf{Z}_{(k)}\right)}_{\text{(Prior at} k+1)} = \int \underbrace{p\left(\mathbf{x}_{(k+1)} \mid \mathbf{x}_{(k)}\right)}_{\text{(Dynamics)}} \underbrace{p\left(\mathbf{x}_{(k)} \mid \mathbf{Z}_{(k)}\right)}_{\text{(Posterior from} k)} dx_{(k)}. \tag{3}$$

The update stage involves the refinement of the prior probability density function (PDF) to account for the newly acquired measurements, resulting in the posterior PDF at time step k. This update process is performed in accordance with Bayes' rule, as illustrated by Equations (5) and (6).

$$\underbrace{p\left(\mathrm{x}_{(k+1)} \mid \mathrm{Z}_{(k+1)}\right)}_{\text{(Posterior at } k+1)} = \underbrace{p\left(\mathrm{Z}_{(k+1)} \mid \mathrm{x}_{(k+1)}\right)}_{\text{(Likelihood)}} \underbrace{p\left(\mathrm{x}_{(k+1)} \mid \mathrm{Z}_{(k)}\right)}_{\text{(Posterior from } k)} / \underbrace{p\left(\mathrm{z}_{(k+1)} \mid \mathrm{Z}_{(k)}\right)}_{\text{Normalising denominator)}}, \tag{4}$$

where

$$p\left(\mathbf{z}_{(k+1)} \mid \mathbf{Z}_{(k)}\right) = \int p\left(\mathbf{z}_{(k+1)} \mid \mathbf{x}_{(k+1)}\right) p\left(\mathbf{x}_{(k+1)} \mid \mathbf{Z}_{(k)}\right) d\mathbf{x}_{(k+1)} \tag{5}$$

The prediction and update steps described above are mathematically challenging to perform analytically, leading to the necessity of resorting to approximate methods such as the Monte Carlo method. The primary objective of the Monte Carlo method is to approximate the probability density function (PDF) by using a collection of random samples, instead of representing it in a functional form. Since this PDF encapsulates all relevant statistical information, this approach can be regarded as a comprehensive solution to the estimation problem.

The particle filtering technique offers an approximate solution to the discrete-time recursive Bayesian estimation problem by continuously updating random samples of the probability density function (PDF). Sampling is a fundamental approach for approximating PDFs and serves as the basis for various Monte Carlo methods. Among these methods, Sequential Importance Sampling (SIS) stands out as the most basic technique employed for this purpose.

Importance sampling becomes necessary when direct sampling from the target distribution is challenging. In such instances, the target distribution is approximated by generating random samples from a proposal distribution. In the context of particle filtering, these random samples are the particles within the filter. These particles are then advanced and adjusted in accordance with the dynamics and measurement model. To ensure consistency between the target and proposal distributions, weights are assigned to the particles (samples) following the prediction stage.

When importance sampling is implemented recursively, the importance weights are updated each time new observations become available. This recursive importance sampling method is known as SIS. As particle filters incorporate SIS, they are also referred to as SIS filters. The assigned weights are subsequently adjusted in a manner that ensures their sum equals one. Following this normalization, all but one particle will essentially carry negligible weight. As particles accumulate these negligible weights, the variance of the importance weights increases over time. This phenomenon is commonly referred to as degeneracy.

The degeneracy problem can substantially raise computational costs since updating particles with nearly zero weights becomes burdensome. This issue stands as one of the significant limitations of particle filtering unless a re-sampling step is introduced at this juncture. Re-sampling involves the removal of particles with insignificant weights.

The final step in the particle filtering process entails computing the mean of the re-sampled particles to derive the ultimate state estimate.

Below, the fundamental stages of the basic particle filter are outlined.

1) The algorithm commences by initializing it with an assumption of the PDF for the initial state, denoted as $p\left(\mathbf{x}_0\right)$, which is assumed to be a normal distribution. Next, N particles are generated randomly using Monte Carlo simulation, labeled as $\mathbf{x}_{0,i}$ for i ranging from $i = 1, 2, 3, 4 \ldots N$.

2) The particles are advanced to the next time step from the current moment using the dynamic model. Following this.
3) The predicted particles are converted into observations according to Equation (5).
4) The weights, representing the relative likelihood (w_i), are computed for the particles, as illustrated in Equation (7). These particles have been predicted and transformed in the preceding two steps, in relation to the corresponding received measurement.

$$w_i = p\left(\mathbf{Z}_{(k)} \mid \mathbf{x}^i_{(k)}\right). \tag{6}$$

If the particles follow a normal distribution, Equation (7) can be represented as depicted in Equation (8).

$$p\left(\mathbf{Z}_{(k)} \mid \mathbf{x}^i_{(k)}\right) = \frac{1}{\sqrt{2\pi \mathrm{R}^{\mathrm{n}}}} e^{-\left(\frac{\left(\mathbf{z}^i_k - \mathbf{z}_k\right)^2}{2\mathrm{R}^n}\right)}, \tag{7}$$

In the context provided, where R^n represents the measurement noise covariance, $\mathbf{Z}^i_k$ is the transformed observation, and $\mathbf{Z}_k$ represents the corresponding received measurement.

Step 5 involves the normalization of the assigned weights, as illustrated in Equation (9), ensuring that the sum of the weights equals unity. That is

$$w_I = \frac{w_i}{\sum_{i=0}^{N} w_i} \tag{8}$$

Here, w_I = represents the normalized weight of an individual particle, w_i = represents the weights of individual particles concerning the most recent update, and $\sum_{i=0}^{N} w_i$ = signifies the sum of weights for all the particles.

5) The particles undergo re-sampling, resulting in the acquisition of N new samples by selecting from the existing N samples. This process involves eliminating those particles from the old set that have negligible weights. Finally, the mean of the re-sampled particles is calculated and regarded as the optimal state estimate.

Particle filtering is a sophisticated computational approach for recursive Bayesian estimation, employing Sequential Monte Carlo methods to represent and estimate the state of a system. The method approximates the posterior probability density function (PDF) using a set of weighted particles, enabling it to handle non-linear and non-Gaussian processes adeptly.

Central to the particle filter is the Sequential Importance Sampling (SIS), which circumvents the challenge of sampling directly from complex probability distributions. The SIS process involves assigning weights to the particles after each prediction step, reflecting the likelihood of each particle given the new data. This weight reflects the importance of each particle in estimating the state. As new observations are incorporated, these weights are updated, ensuring the particles' distribution reflects the updated state estimate. The normalization of weights is crucial, ensuring they sum up to one, maintaining a valid probability distribution.

However, this process encounters a significant challenge known as degeneracy, where after several iterations, some particles may hold negligible weights. This leads to a concentration of the computational effort on a diminishing subset of particles, which increases the variance of importance weights as the algorithm iterates, potentially leading to an ineffective representation of the posterior PDF and an inefficient algorithm.

The mathematical formulation of particle filtering is maintained through equations that describe the prediction and update steps:

Prediction:

$$p\left(x_{k+1} \mid Z_k\right) = \int p\left(x_{k+1} \middle| x_k\right) p\left(Z_k \middle| x_k\right) dx_k \tag{9}$$

Update

$$p\left(x_{k+1} \mid Z_{k+1}\right) = \frac{p\left(Z_{k+1} \mid x_{k+1}\right) p\left(x_{k+1} \mid Z_k\right)}{p\left(Z_{k+1} \middle| Z_k\right)} \tag{10}$$

Integral form of update:

$$p\left(x_{k+1} \mid Z_k\right) = \int p\left(x_{k+1} \middle| x_k\right) p\left(Z_{k+1} \middle| x_{k+1}\right) dx_k \tag{11}$$

These equations underpin the filter's operation, describing the evolution of the system's state through time as new information is acquired and processed. The particle filter's strength lies in its ability to approximate the necessary probability distributions for state estimation in complex, dynamic systems where traditional filtering methods fall short. Despite the challenge of degeneracy, particle filtering remains a robust tool in statistical estimation and prediction in various fields, from robotics and navigation to financial econometrics.

The particle filtering framework continues with the update phase, where the weights of the particles are adjusted in light of new evidence. This step is critical as it refines the state estimate to reflect the most recent observations. The update involves Bayesian inference, utilizing the likelihood of the new measurement given the predicted state and the prior belief about the state's distribution. The process demands the computation of new weights and their normalization to maintain a probabilistic sum of unity.

However, the particle filter's efficacy is challenged by the phenomenon of degeneracy, where over time, particles may end up with extremely low weights, rendering them virtually irrelevant to the state estimation. This situation leads to an increase in the variance of the importance weights, which necessitates a resampling process. Resampling is a technique designed to address degeneracy by focusing computational resources on particles with significant weights, thus ensuring a more efficient and representative particle set for state estimation.

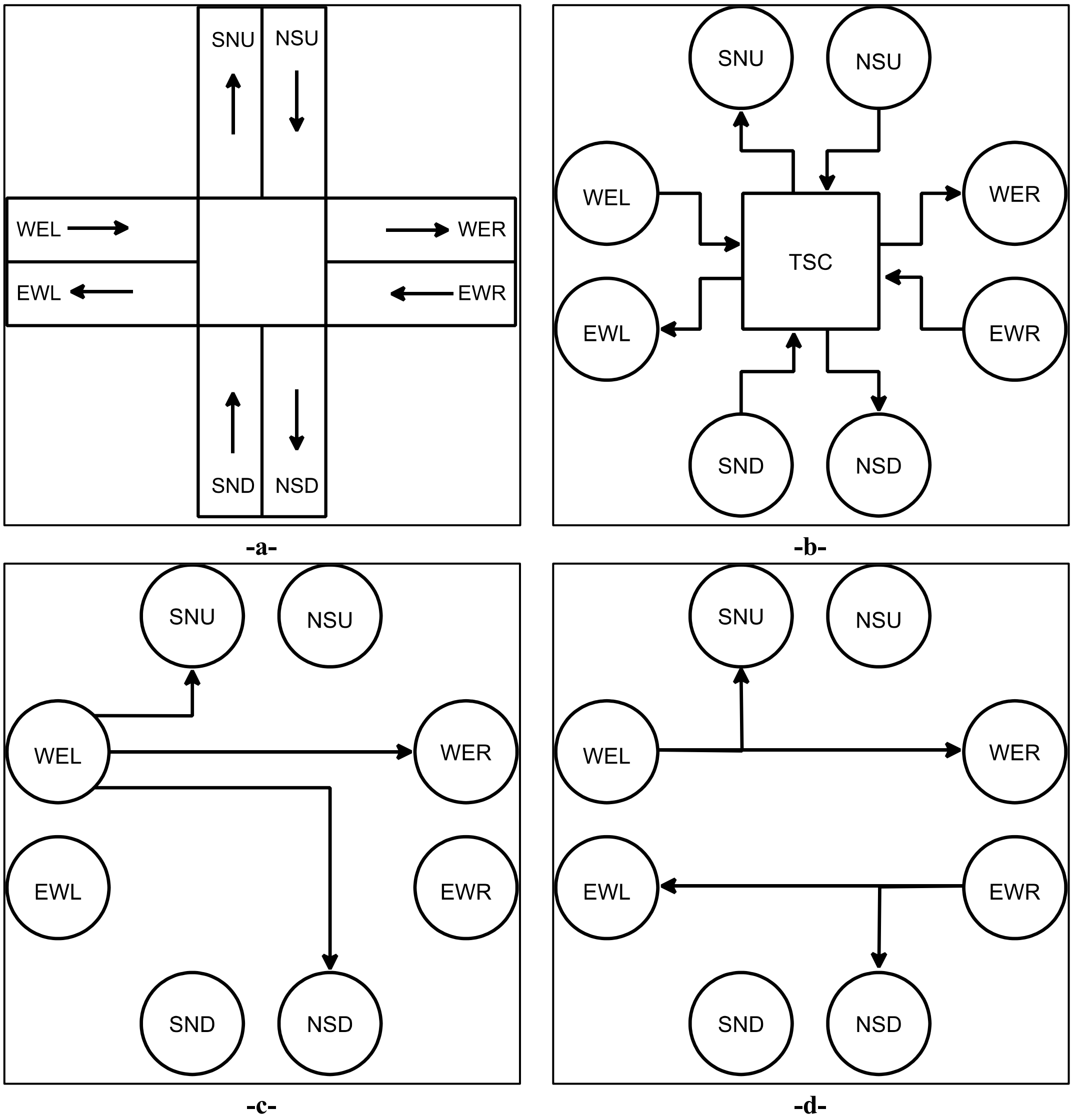

FIGURE 3. **Representation of intersection graph and various action graphs enabled by the controller.**

To circumvent degeneracy, resampling strategies like the Systematic Resampling Algorithm are employed. This algorithm selects a set of particles proportional to their weights, ensuring that particles with higher weights are more likely to be chosen. As a result, the particle set post-resampling represents a probability distribution that is a better approximation of the posterior PDF.

In the realm of particle filtering, a structured approach is taken to address the challenge of state estimation. The process begins with the initialization phase, where an initial probability density function (PDF) is postulated, often assumed to be normal for simplicity. Following this, a set of particles is generated to represent the state space. These particles are then propagated through the system's dynamics to predict their future states.

The predictive step utilizes the dynamic model to advance the particles in time. Subsequently, the predicted particles are mapped to observations using a likelihood equation, which provides weights indicating each particle's relevance given the new data. This weight assignment is crucial as it reflects the adherence of the particle's predicted state to the actual measurement.

Weights are normalized to ensure they sum to unity, maintaining the probabilistic integrity of the model. The normalized weights are crucial for the resampling stage, where particles with negligible impact due to low weights are discarded, and a new set of particles is drawn. The resampling addresses the 'degeneracy' problem, where only a few particles dominate the posterior PDF after several iterations.

Equations governing these steps are fundamental to the particle filtering process, ensuring a robust mathematical underpinning for the algorithm's iterative procedures.

post weight assignment and normalization, resampling is a critical step. This procedure is employed to counteract the issue of degeneracy, where the importance of a majority of particles diminishes over time. Resampling strategically selects a subset of particles based on their normalized weights, essentially duplicating those with higher significance and discarding the less probable ones.

The mathematical expressions involved in this step include the weight of each particle wi being computed as the product of the likelihood of the observed measurement given the particle's state and the particle's previous weight. The likelihood is often assumed to be normally distributed, expressed as:

$$p\left(Z_k \mid x_i^k\right) = \frac{1}{\sqrt{2\pi R}} e^{-\frac{1}{2}\left(Z_k - h\left(x_i^k\right)\right)^T R^{-1}\left(Z_k - h\left(x_i^k\right)\right)} \tag{12}$$

After weights are computed, they are normalized to ensure the sum is one, as shown in:

$$w_i^k = \frac{w_i}{\sum_{j=1}^{N} w_j} \tag{13}$$

Finally, the resampling strategy is implemented, and the set of particles is updated, with the mean of the resampled particles considered the best state estimate. This two-part procedure ensures the particle filter's performance remains robust, providing a reliable estimation of the system's state over time.

3) PROBLEM FORMULATION

In an urban environment U, characterized by a network of multi-intersection roads represented as a graph $G=(N, E)$, where nodes N correspond to intersections and edges E represent connecting roads, the estimation of vehicular traffic is approached through a statistical filter (Kalman or particle filter). A dynamic state transition matrix A_t is employed, wherein each element is interchangeably tailored to specific traffic signal actions - left-protected or left-permitted, leading to six distinct control actions at each intersection. The state of each intersection, defined as the number of vehicles in each direction, is represented by a vector x_t in the filter. The objective is formulated as the prediction of the state x_{t+1} following an action by the traffic signal controller. This prediction is based on a process model developed within the filter framework, which accounts for the dynamic nature of urban traffic flow, particularly during variable conditions such as rush hours or unexpected incidents such as communication failure.

4) PROPOSED ALGORITHM

In traffic modeling for urban environments using statistical filters, be it Kalman or particle filters, the state transition matrix A_t, traditionally static and based on historical data and generalized assumptions about traffic behavior, undergoes a significant transformation. This innovation introduces a set of dynamically interchangeable state transition matrices, each aligned with a specific traffic signal control action. Urban traffic control, predominantly operating under two main modes—left-protected and left-permitted, manifests in a total of six actions that govern vehicular movement at each intersection. The proposed statistical filter model, whether it's a Kalman or a particle filter, intelligently switches between these different A_t matrices in response to real-time actions executed by traffic control signals.

This integration of contextual information into the state estimation process significantly enhances the filter's prediction accuracy, enabling it to robustly accommodate sudden changes in traffic conditions, such as during rush hours or unexpected incidents such as communication failure. The filter's state, defined as the number of vehicles in each direction at an intersection and its connected intersections, is represented by a vector x_t. Each direction is presented as a node in a graph, with intersections serving as controllers that manage connectivity between subsets of these nodes.

For instance, consider an intersection represented in Figure 3, comprising four roads with two directions each, amounting to eight nodes in the graph. The traffic controller *TSC* determines node connectivity, as depicted in figures -b- and -c-. The action controls the directed edges in the graph, such as the set

$$E_1 = \left\{\left(\overrightarrow{WEL, SNU}\right), \left(\overrightarrow{WEL, WER}\right), \left(\overrightarrow{WEL, NSD}\right)\right\} \tag{14}$$

We represent the state of Kalman filter with the number of vehicles in each of the directions as given by the vector $x = [SNU\ NSU\ WER\ EWR\ NSD\ SND\ EWL\ WEL]^T$. This vector is associated with the intersection I. Hence, we add a notation I to the vector x and it becomes as x_I. Furthermore, considering that the control action is related to time t, hence, x_I will change with respect to time with a changing model given by the Equation (4)

$$x_I(t+1) = A_t x_I(t) \tag{15}$$

For example, at moment t when the action corresponding to figure -c- is enabled, then

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & \beta \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \gamma \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Delta \end{bmatrix} \tag{16}$$

Or

$$x_{I,t+1} = \begin{bmatrix} SNU \\ NSU \\ WER \\ EWR \\ NSD \\ SND \\ EWL \\ WEL \end{bmatrix}_{I,t+1}$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & \beta \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \gamma \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Delta \end{bmatrix} \begin{bmatrix} SNU \\ NSU \\ WER \\ EWR \\ NSD \\ SND \\ EWL \\ WEL \end{bmatrix}_{I,t} \tag{17}$$

$$\Delta = 1 - (\alpha + \beta + \gamma) \tag{18}$$

Similarily, when the actions as it is given in figure -d- then the Equation (8) is given as

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & \beta \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & \nabla \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \gamma \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \partial \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Delta \end{bmatrix} \tag{19}$$

Or

$$x_t = \begin{bmatrix} SNU \\ NSU \\ WER \\ EWR \\ NSD \\ SND \\ EWL \\ WEL \end{bmatrix}_{t+1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \alpha \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & \beta \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & \nabla \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \gamma \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \partial \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Delta \end{bmatrix} \begin{bmatrix} SNU \\ NSU \\ WER \\ EWR \\ NSD \\ SND \\ EWL \\ WEL \end{bmatrix}_{t} \tag{20}$$

$$\Delta = 1 - (\alpha + \beta), \nabla = 1 - (\partial + \gamma) \tag{21}$$

We generalize equation -1- from single intersection to multi-intersection in Equation (14)

$$x_{I,i}(t+1) = A_t x_{I,i}(t) \tag{22}$$

where:

i denotes the intersection index $i = 1, 2 \ldots N_I$, N_I denotes the number of intersections

We present a generalizable graph of multi-intersection in Figure 6.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In the conducted simulation for traffic prediction, which utilizes both Kalman and particle filters, a set of specific parameters were employed. The initial values for the process noise covariance matrix (Q) were set at 15, with the measurement noise covariance (R) being equal to Q. The average speed of vehicles was 3 meters per second. A significant amount of simulation time, totaling 720,000-time step, was allocated to ensure comprehensive analysis. The test stage of the simulation was set at 90 units.

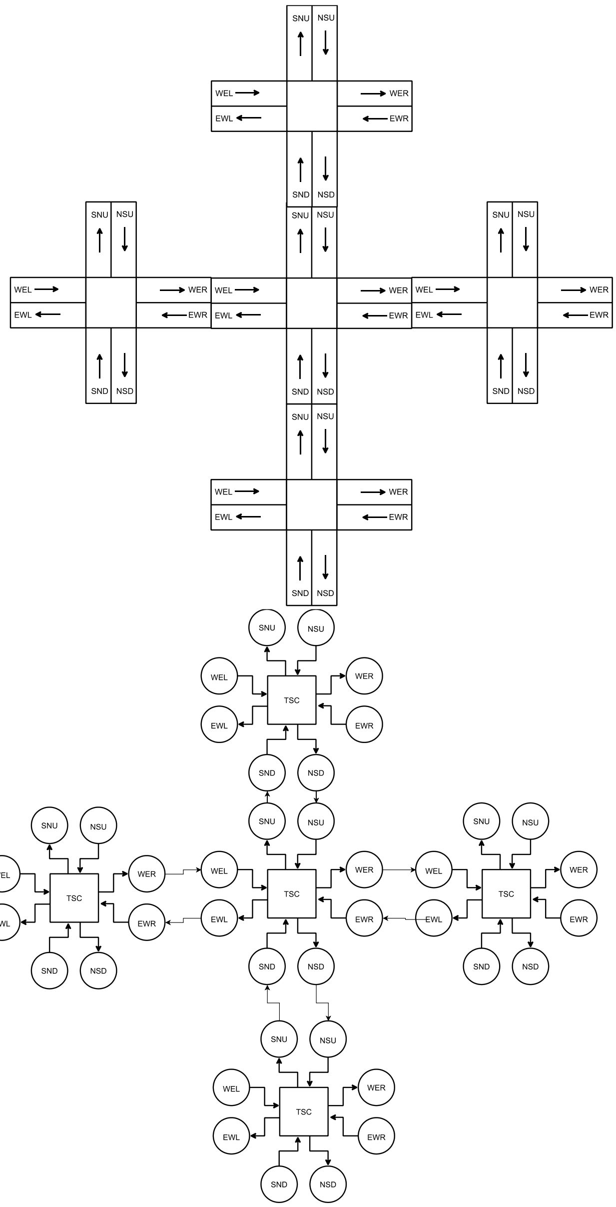

FIGURE 4. **Five intersections with their corresponding traffic graph.**

For the traffic light cycle, a period of 30-time step was established, with the yellow light period lasting for 5 units and the combined green and red-light period extending over 25 units. Vehicle generation in the simulation occurred every 450-time step. The length of each vehicle was taken as 3 meters, with a gap of 0.5 meters maintained between consecutive vehicles. The number of traffic actions was limited

TABLE 3. The parameters.

Parameter name	Parameter value
initial values of Q	15
initial values of R	Q
average speed of vehicles	3 m/s
Simulation Time	720000
TEST_STAGE	90
traffic_light_period	30
Yellow period	5
Green_red_period	25
generation_period	450
Vehicle length	3
Vehicle gap	0.5
NUMBER_OF_ACTION	6
WINDOW_SIZE	15
particle_variance	5
number of particles	100

to six, and a window size of 15 units was utilized for observations. In terms of the particle filter specifics, the variance for each particle was defined at 5 units, with the total number of particles used in the simulation being 100.

This comprehensive set of parameters suggests a detailed approach to traffic simulation, aiming to capture various aspects of urban traffic dynamics using SUMO. Such simulations are crucial for understanding and predicting traffic flow, which has significant implications for urban planning and management.

A. RESULTS ANALYSIS

The proposed novel process-based Kalman filter is observed to closely track the ground truth, with its estimations frequently coinciding with the actual values, especially noticeable at steps where sharp changes occur, such as at step 20 or step 50. Compared to the Smooth Kalman Filter, which represents the traditional approach, the novel Kalman Filter exhibits less deviation from the ground truth throughout the steps, as can be quantified by the smaller gaps between the lines at most of the steps. The alignment of the novel filter's peaks and troughs with the ground truth, for instance around step 40, suggests an enhanced accuracy in prediction.

The superior performance of the novel process-based filters is visually demonstrated in Figures 5 and 6. In Figure 5, the time series of the number of vehicles as predicted by the Kalman filters for the E1 edge is presented, alongside a comparison with the smooth Kalman filter and actual measurements. It can be observed that the novel process-based Kalman filter closely tracks the ground truth, with its estimations frequently coinciding with the actual values, particularly at points of sharp changes. Figure 6 provides a similar visualization for the particle filters, comparing the novel process-based particle filter with the smooth particle filter and measurements. In this graph, the novel particle filter is shown to maintain a good degree of overlap with the ground truth, exhibiting particularly close tracking at various time steps. Both figures illustrate the enhanced predictive capabilities of the proposed filters, highlighting their resilience to abrupt changes and quick adjustments to fluctuations in traffic flow. These visual representations further reinforce the quantitative findings and underscore the significant advantages of employing the novel process model within these filters for traffic control applications.

When considering the particle filter graph, the Particle Filter, indicative of the novel approach, shows a good degree of overlap with the ground truth, with particularly close tracking around step 30. The Smooth Particle Filter, on the other hand, seems to lag, which is especially apparent in its delayed response to changes in the ground truth, such as the peak around step 45. Despite the presence of noise in the estimations from both filters, the novel Particle Filter's trajectory remains closer to that of the ground truth, with smaller deviations than those of the Smooth Particle Filter, for example, at step 35.

Across both graphs, the novel process-based filters demonstrate resilience to abrupt changes in the ground truth, as evidenced by their quick adjustment to the changes, such as those seen around steps 20 and 50. In contrast, the traditional filters present a smoother curve, possibly smoothing out rapid fluctuations in the ground truth, which might reduce their responsiveness to actual changes, such as the ones observed at steps 25 and 60. The enhanced predictive capability of the proposed filters is therefore highlighted, which is a critical attribute for real-time applications in traffic estimation and control, where adapting to sudden changes is of utmost importance.

The overall analysis of the graphs indicates that the novel process-based Kalman and particle filters are more accurately and responsively tracking the direction E1 ground truth when compared to their traditional counterparts. This points to a significant advantage in employing a novel process model within these filters for traffic control applications, as they provide superior adaptability and accuracy, essential for managing the dynamic nature of urban traffic environments.

RMSE indicates to root mean square error which measure the difference between the predicted values of traffic congestion and the ground truth ones. Upon reviewing the RMSE values across different Edge IDs as it is depicted in Table -4-, the performance of the Kalman filter with the novel process model generally exhibits superior accuracy compared to the Particle Filter with the novel process model. For example, on Edge ID E7, the Kalman RMSE registers at 8.808, which is lower than the Particle Filter's RMSE of 9.131, reflecting a more precise estimation. This superiority is consistently observed in several edges, such as Edge ID - E2, where the Kalman filter achieves an RMSE of 10.964, compared to the Particle Filter's slightly higher RMSE of 11.578.

The Smooth Kalman filter, in its best cases, matches the performance of the novel process-based Kalman filter. This is evident in instances like Edge ID E3, where both Kalman variants report an identical RMSE of 11.675, which is better than the Particle Filter's RMSE of 10.767. Such instances suggest that the traditional Kalman filter, when performing

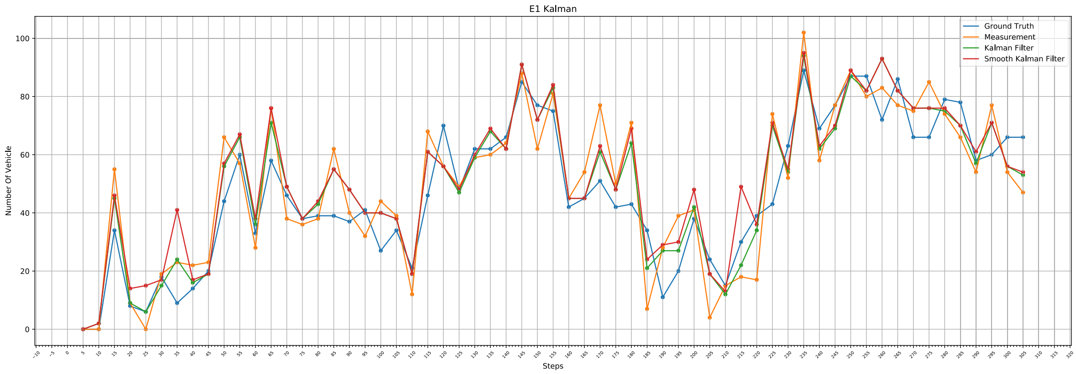

FIGURE 5. Time series of number of vehicles as predicted by the Kalman filters for E1 edge and its comparison with smooth Kalman and measurement.

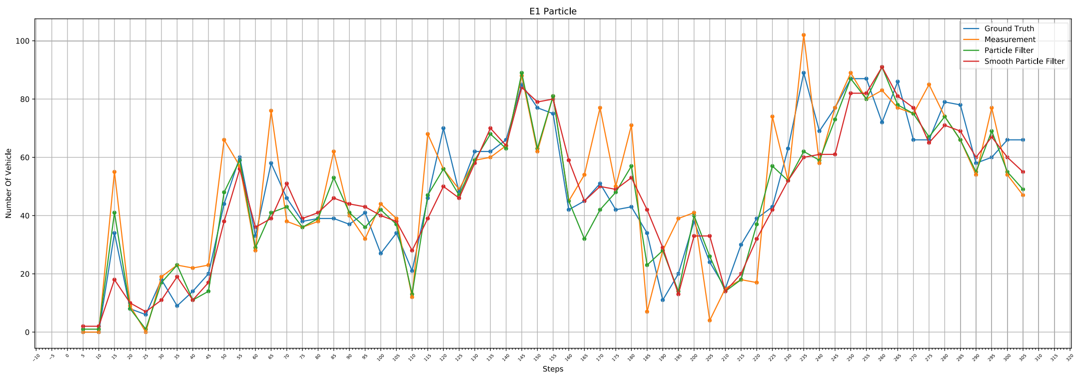

FIGURE 6. Time series of number of vehicles as predicted by the particle filters for E1 edge and its comparison with smooth particle and measurement.

optimally, can achieve estimations equivalent to the novel Kalman filter.

However, the Smooth Particle Filter often demonstrates inferior performance relative to its novel process model counterpart. On Edge ID: E7, the Smooth Particle Filter records a significantly higher RMSE of 22.759, which is substantially poorer than the RMSEs of both the Kalman and Particle filters with the novel process model. This pattern is indicative of the Smooth Particle Filter's reduced efficacy, as seen by the large RMSE of 33.129 on Edge ID E6, which is starkly higher than the RMSE of 9.678 reported by the Particle Filter with the novel process model.

Overall, the lower RMSE values associated with the Kalman filter with the novel process model underscore its enhanced performance in accurately predicting traffic flow, as reflected by the RMSE of 8.953 on Edge ID E5, compared to the Particle Filter's RMSE of 8.765. Even when the Particle Filter outperforms the Kalman filter, the differences in RMSE are generally marginal, suggesting that both filters benefit from the novel process model. However, the Kalman filter's consistently lower RMSE values across a range of edges solidify its superiority in leveraging the process model for traffic estimation. The data indicates that while the Particle Filter with the novel process model remains a competitive approach, the Kalman filter with the novel process model tends to provide a more accurate reflection of the ground truth in urban traffic environments.

B. DISCUSSION

The experimental results and analysis presented in this study provide strong evidence that the outlined objectives have been successfully achieved. The effectiveness of the novel approaches in traffic prediction and management has been demonstrated through rigorous testing and comparative analysis.

1) NOVEL ADAPTIVE KALMAN FILTER WITH TRAFFIC PROCESS MODELING

It has been observed that the proposed novel process-based Kalman filter closely tracks the ground truth, with its estimations frequently coinciding with actual values. This improved accuracy is particularly noticeable at points where sharp changes occur in the traffic flow. When compared to the Smooth Kalman Filter, which represents the traditional approach, the novel Kalman Filter exhibits less deviation from the ground truth throughout the simulation steps. This alignment of the novel filter's predictions with the ground truth suggests that the objective of designing an adaptive Kalman filter with integrated traffic process modeling has been successfully met.

TABLE 4. Comparative analysis of RMSE Values for traffic estimation across various edge ids using novel process-based and traditional filtering approaches.

Edge ID	Measurement RMSE	Kalman RMSE	Smooth_Kalman RMSE	Smooth_Particle_Filter RMSE	Particle_Filter RMSE
ID: E7	10.215	**8.808**	**8.808**	22.759	9.131
ID: E3	16.103	11.675	11.675	12.237	**10.767**
ID: -E9	16.657	**13.993**	15.119	16.951	15.964
ID: -E2	14.702	**10.964**	**10.964**	22.984	11.578
ID: -E1	14.846	**11.088**	**11.088**	23.735	11.658
ID: -E0	13.910	**10.583**	**10.583**	23.099	10.790
ID: -E6	16.908	**14.380**	**14.227**	16.996	16.108
ID: -E12	17.014	27.758	21.249	17.816	**15.343**
ID: E5	10.319	8.953	8.953	15.655	**8.765**
ID: -E7	15.865	13.616	**13.731**	15.740	14.624
ID: E12	12.824	10.944	10.944	16.049	**10.157**
ID: E9	9.643	**8.042**	**8.042**	16.300	8.778
ID: -E11	16.329	**13.630**	13.781	16.630	15.919
ID: E10	11.127	**9.780**	**9.780**	19.249	9.899
ID: E2	14.047	**10.364**	11.520	11.141	10.989
ID: E0	14.791	12.942	11.658	11.399	**10.349**
ID: -E8	17.644	**15.832**	20.221	17.652	16.853
ID: E8	10.711	**8.850**	**8.850**	30.204	10.134
ID: E11	12.202	**10.540**	**10.540**	23.304	11.131
ID: -E5	14.817	**13.337**	19.915	15.833	14.337
ID: E1	13.626	**10.150**	11.245	10.037	10.401
ID: -E10	16.141	**15.000**	20.339	17.492	15.587
ID: E6	10.595	**9.127**	9.127	33.129	9.678
ID: -E3	14.889	11.478	12.036	**10.825**	11.513

2) EXTENSION TO PARTICLE FILTERS WITH TRAFFIC PROCESS MODELING

The application of the traffic process model to Particle filters, a key innovation of this study, has also been validated through the experimental results. It is demonstrated that the Particle Filter incorporating the novel approach shows a good degree of overlap with the ground truth, with particularly close tracking observed at various points in the simulation. The novel Particle Filter's trajectory remains closer to that of the ground truth, with smaller deviations than those of the Smooth Particle Filter. This improved performance indicates that the objective of extending the traffic process model to Particle filters has been accomplished.

3) MULTI-INTERSECTION VALIDATION

The scalability and adaptability of the extended Kalman and Particle filters across multiple intersections in an urban setting have been confirmed. This is evidenced by the comprehensive RMSE values provided for numerous edge IDs, each representing different intersections or road segments within the simulated urban environment. The consistent performance across these varied locations demonstrates that the objective of multi-intersection validation has been successfully achieved.

4) COMPARATIVE ANALYSIS

A thorough comparative evaluation of the Kalman and Particle filters equipped with the traffic process model has been conducted. The detailed analysis of RMSE values across different filtering approaches and various edge IDs provides valuable insights into the relative performance of these filters under different conditions. This comprehensive comparison fulfills the objective of offering practitioners and policymakers the necessary metrics to select the most appropriate model for specific traffic scenarios and constraints.

VI. CONCLUSION AND FUTURE WORKS

This article marks a substantial stride in the domain of intelligent transportation systems, particularly addressing the intricate challenge of forecasting and managing traffic congestion. The study's foremost accomplishment is the innovative design of an Adaptive Kalman Filter that incorporates a traffic process model, substantially enhancing the filter's ability to reflect real-time traffic dynamics at intersections. This advancement is critical for making more accurate predictions and outperforms traditional Kalman filter applications by responding more adeptly to the variable nature of traffic flows.

Moreover, the study breaks new ground by extending traffic process modeling to Particle filters. This extension is particularly significant because it empowers Particle filters to handle complex, non-linear, and non-Gaussian traffic conditions effectively, thereby expanding the methodologies available for traffic congestion prediction.

A key aspect of this research is the multi-intersection validation approach, confirming the scalability and adaptability of the extended Kalman and Particle filters in a realistic urban traffic network. This validation is crucial for demonstrating the practicality of these algorithms in expansive and complex traffic systems.

The study also explores the robustness of the proposed models against communication failures, which are prevalent in real-world scenarios. The findings reveal that both the Kalman and Particle filters, when integrated with the traffic process model, exhibit remarkable resilience, ensuring reliable performance even when vehicle count data transmission is disrupted.

Finally, the article provides a comprehensive comparative analysis, juxtaposing the performance of Kalman and Particle filters equipped with the traffic process model. This comparative study yields valuable insights and offers a metric-based framework to assist practitioners and policymakers in selecting the most appropriate model for specific traffic conditions.

Through these contributions, the research not only advances the theoretical framework for traffic estimation and control but also offers practical algorithms that are robust, scalable, and adaptable to the unpredictable nature of urban traffic, paving the way for more responsive and intelligent transportation systems.

The development of advanced traffic congestion control algorithms faces interconnected challenges that needs to be stated. Data quality and availability form the foundation, as accurate predictions rely on robust, real-time information. This links to the computational complexity of implementing adaptive filters and predictive models, potentially straining resources in real-time applications.

Adaptability presents another hurdle, as algorithms must handle diverse urban layouts, time periods, and unforeseen events without frequent recalibration. This adaptability challenge extends to scalability issues when managing large urban areas with complex traffic interdependencies.

Practical implementation concerns include integration with existing infrastructure and ensuring interoperability with current systems and emerging technologies. The algorithms must also demonstrate robustness to anomalies like accidents or extreme weather, while balancing multiple, sometimes conflicting objectives.

Thorough real-world testing is crucial but challenging to conduct without disrupting existing traffic flows. Finally, the use of detailed traffic data raises privacy concerns that must be addressed for public acceptance and regulatory compliance.

These interlinked limitations underscore the complexity of transitioning from theoretical models to practical, large-scale implementations, requiring interdisciplinary collaboration and innovative approaches as research progresses.

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