Optimizing Urban Traffic Control with Particle Swarm Optimization: A Case Study on Cumberland Ave, Knoxville, TN

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***Abstract*—In urban areas worldwide, traffic congestion remains a prevalent issue, leading to wasted time for commuters and significant challenges for energy consumption and environmental sustainability. Traditional traffic control methods often fall short in adapting to the dynamic nature of urban traffic patterns, provoking congestion and inefficiencies in transport systems. To address these challenges, this research proposes a Particle Swarm Optimization (PSO) approach for traffic signal optimization, focusing on Cumberland Ave in Knoxville, TN, as a case study. Utilizing Simulation of Urban MObility (SUMO) and PSO algorithm, specific vehicle metrics such as total travel time and waiting time at red lights are tracked and optimized. Results demonstrate notable improvements, with approximately a 4% reduction in total travel times and a 30% decrease in waiting times. Hyper-parameter tuning further emphasizes the significance of selecting appropriate values for optimal performance. This study contributes to the discourse on traffic management strategies by providing a practical and effective solution for alleviating congestion and enhancing the efficiency of urban transport systems.**

***Index Terms*—Traffic congestion, Particle Swarm Optimization (PSO), Traffic signal optimization, wait times, Cumberland Ave, Knoxville, TN**

I. Introduction and Motivation

Urban areas around the globe are facing a common problem: traffic congestion. This issue not only causes frustration and wasted time for commuters but also has broader implications for energy consumption and environmental sustainability. Despite efforts to manage traffic through traditional methods, such as fixed signal timings, these approaches often struggle to keep pace with ever-changing dynamics of urban traffic patterns. As a result, congestion persists, leading to significant inefficiencies in transport systems.

The motivation behind our research stems from the pressing need to address these challenges and improve the overall efficiency of traffic flow in urban management. By focusing on Cumberland Ave in Knoxville, TN, we aim to tackle congestion issues in a specific locality while also contributing to broader insights into traffic management strategies.

Traditional traffic control methods have limitations in their ability to adapt to the dynamic nature of urban traffic. Fixed signal timings, for example, may not account for variations in traffic volume throughout the day or respond effectively to unexpected events such as accidents or road closures. As a result, congestion tends to build up at certain times, leading to delays, frustration, and increased fuel consumption.

To overcome these limitations, our research proposes the utilization of Particle Swarm Optimization (PSO), a meta-heuristic algorithm inspired by the collective behavior of swarms in nature. PSO offers a dynamic and adaptive approach to optimizing traffic signal timings by iteratively adjusting signal phasing based on real-time traffic conditions.

By leveraging PSO, we seek to achieve two primary objectives: minimizing congestion and enhancing the overall efficiency of traffic flow. By dynamically optimizing signal timings in response to changing traffic patterns, we aim to reduce wait times at intersections and improve the overall travel experience for commuters.

Our focus on Cumberland Ave in Knoxville, TN, provides a practical context for our research. Cumberland Ave serves as a vital artery in the city's transportation network, experiencing significant traffic volumes throughout the day. By implementing and evaluating PSO-based traffic control optimization on Cumberland Ave, we aim to demonstrate the efficacy of our approach in a real-world urban setting.

II. Related Work

In the realm of optimizing traffic light timings, various academic works provide valuable insights and methodologies. These studies often focus on optimizing traffic light cycles and signal timings using heuristic algorithms and optimization techniques. One such paper, "Optimal Cycle Program of Traffic Lights With Particle Swarm Optimization," underscores the importance of optimizing traffic light cycle programs for improving energy consumption, traffic flow management, and environmental sustainability [3]. While existing literature tends to concentrate on limited areas with elementary traffic light schedules, our research extends the application of Particle Swarm Optimization (PSO) to a specific urban locality, Cumberland Ave in Knoxville, TN, aiming to address congestion issues and enhance traffic efficiency in a localized context.

Additionally, our methodology shares similarities with a related work on time optimization for traffic signal control using genetic algorithms [9]. Both studies focus on optimizing traffic signal timings in real-time to improve traffic performance. However, while the referenced work utilizes genetic algorithms to dynamically adjust signal timings based on real-time traffic conditions, our research employs PSO to iteratively optimize signal timings and minimize congestion on a specific urban road network.

Furthermore, the related work ”From cellular attractor selection to adaptive signal control for traffic networks” explores the utilization of a biological mechanism inspired by cellular attractor selection to design adaptive signal control for traffic networks [10]. While both our methodology and the related work aim to optimize traffic signal timings to manage varying traffic flows, we approach this task differently by employing PSO and focusing on dynamically adapting signal operations at individual intersections based on real-time traffic conditions. Additionally, our research integrates PSO-based optimization with simulation-based evaluation, offering a practical approach to traffic signal optimization in a specific urban context.

Similarly, our methodology, which involves running SUMO simulations with traffic light timings, tracking specific vehicles, and utilizing PSO for traffic signal optimization, shares similarities with the related work on ant colony algorithm (ACA) for traffic signal timing optimization [5]. However, unlike the ACA approach that focuses on performance indexes such as time delay, number of stops, and traffic capacity, our research prioritizes metrics like total travel time and waiting time at red lights. Additionally, while ACA is evaluated against Webster algorithm and genetic algorithm in the related work, our study uniquely applies PSO for traffic signal optimization on Cumberland Ave in Knoxville, TN.

Moreover, our methodology shares similarities with a related work on multiple intersections traffic signal timing optimization with a genetic algorithm [2], as both studies aim to optimize traffic signal timings to alleviate traffic congestion and improve urban traffic flow. However, while the related work utilizes a genetic algorithm for optimization, our research employs a Particle Swarm Optimization (PSO) approach. Additionally, we track specific vehicle movement and save total travel time and waiting time at red lights, providing a more granular assessment of traffic signal optimization effectiveness compared to the broader network-level approach in the related work.

Furthermore, our methodology shares similarities with the related work in ”Urban Traffic Flow Optimization using Intelligent Techniques” [1], as both involve the optimization of traffic flow in urban areas through intelligent algorithms. However, while the related work focuses on optimizing traffic flow by computing the best routes for vehicles using techniques like Evolutionary Algorithm (EA) and Simulated Annealing (SA), our approach specifically targets the optimization of traffic signal timings using Particle Swarm Optimization (PSO), thereby directly influencing traffic flow dynamics at intersections. Additionally, our methodology tracks specific vehicles in the simulation to measure total travel time and waiting time at red lights, providing a more detailed evaluation of traffic control strategies compared to the route optimization approach described in the related work.

In our methodology, we employ SUMO simulation to evaluate traffic light timings and track specific vehicle metrics, such as total travel time and waiting time at red lights. Unlike the hierarchical strategy proposed in the related work ”Adaptive collaborative optimization of traffic network signal timing based on immune-fireworks algorithm and hierarchical strategy”, which focuses on offset conflicts and configuration, our approach centers on utilizing Particle Swarm Optimization (PSO) to dynamically update traffic light timings based on real-time traffic conditions, ultimately aiming to minimize congestion and improve traffic flow [8].

The related work in the paper ”Traffic light optimization using non-dominated sorting genetic algorithm (NSGA2)” underscores the significance of computational intelligence (CI) in addressing urban traffic congestion by optimizing traffic light programming [6]. While both our methodology and the related work focus on optimizing traffic signal timings to alleviate congestion, our approach utilizes Particle Swarm Optimization (PSO) instead of NSGA2 and employs a simulation environment (SUMO) to evaluate and update traffic light configurations in real-time based on specific metrics such as total travel time and waiting time at red lights. Additionally, our research emphasizes the importance of real-time optimization and considers the dynamic behavior of traffic flow in a localized urban setting, contributing to the broader understanding of traffic management strategies.

Moreover, in relation to the paper on real-time optimization of traffic signals to prioritize public transport [11], our methodology shares a common objective of optimizing traffic signal timings. However, while the referenced paper focuses on prioritizing public transportation, our approach aims to minimize congestion and improve traffic flow in urban areas using Particle Swarm Optimization (PSO). What sets our methodology apart is the utilization of PSO to dynamically optimize traffic signal timings based on real-time traffic conditions, contributing to more efficient traffic management in urban environments.

Finally, our methodology shares similarities with the related work on traffic signal optimization using Particle Swarm Optimization (PSO) for signalized roundabouts [4]. Both studies employ PSO to optimize traffic signal timings in order to alleviate congestion and improve traffic flow. However, while the related work focuses on optimizing signal timings at complex roundabouts using a microscopic traffic simulation model, our research applies a similar approach to optimize traffic signal timings at intersections, specifically focusing on the Cumberland Ave locality in Knoxville, TN, using SUMO simulation.

III. Methodology

Our method for optimizing traffic signal timings along Cumberland Ave involved integrating our PSO algorithm with an existing traffic simulator. We chose to do this to enhance the realism of our experiment and simulate real-world traffic conditions as closely as possible. Through optimizing the traffic signal timings, our goal was to reduce the total travel time and total time spent waiting at red lights, along with obtaining realistic results that could be applied to the real world.

A. Simulation of Urban MObility (SUMO)

We decided to use the Simulation of Urban MObility software for the traffic simulator, or SUMO for short. SUMO is a highly portable traffic simulator that allows for the creation of complex road networks and supports traffic light signal configurations [7].

To define our road network, we used OpenStreetMap to select a portion of Cumberland Ave in Knoxville and export it to an OSM file. The file was then used to generate a SUMO network configuration file, thus creating the roads and their traffic lights within the simulator. The figure below visualizes part of the generated network that represents a portion of Cumberland Ave.

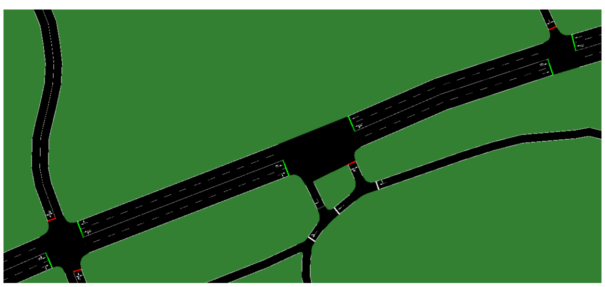

Fig. 1. SUMO Network (Cumberland Ave.)

Next, we used one of the built-in Python scripts provided by SUMO to generate various vehicles and trips throughout the network. The vehicles would each have a trip defining where it starts and where it needs to get to. We generated ten different vehicles and trips which would then be scaled up to a factor of five when running the simulator. This was done to simulate realistic traffic along Cumberland Ave. Our particular vehicle and trip of interest was a vehicle going from the West side of Cumberland Ave to the East side. Along this portion of the road, the vehicle would need to pass through five different intersections providing us with ample opportunities to optimize the traffic light timings. All of the trip information, like the total travel time and total time spent waiting, would then be exported to a results file, enabling easy access for our PSO algorithm.

While SUMO provides an extensive set of options for configuring realistic traffic scenarios, we found that the configuration for traffic signal timings and durations was difficult to work with. All traffic lights are configured the same way and are only different depending on the number of lights in the intersection. Below, Figure 2 shows how the traffic lights were configured for a four-way intersection.

```xml
<tlLogic id="202880757" type="static" programID="0" offset="0">
    <phase duration="10" state="GGGggrrrrGGGggrrrr" />
    <phase duration="5" state="yyyyyrrrryyyyyrrrr" />
    <phase duration="10" state="rrrrrGGggrrrrrGGgg" />
    <phase duration="5" state="rrrrryyyyrrrrryyyy" />
</tlLogic>
```

Fig. 2. Default SUMO Traffic Light Configuration

Here, this particular intersection defines that for 10 seconds, the lights going from East to West and West to East will be green. After that 10 seconds, they will then turn yellow for 5 seconds. Once the yellow duration is up, it will then turn red and the other two lights will turn green. We found this configuration very odd, as it becomes difficult to define static times for each individual light phase. While green and yellow durations can, in a way, be explicitly set for all intersections, red light phases cannot. In fact, the red light durations end up being the sum of the green and yellow light durations. So, while we could not specifically define a global red light time, we were still able to define green and yellow which would be the timings our PSO algorithm would optimize. In turn, this would still try to minimize the overall red light time for the intersections.

B. Particle Swarm Optimization (PSO) Algorithm

Our PSO algorithm was designed to optimize the durations of green and yellow traffic lights across all five intersections within our network. The red light durations would then be the sum of these two values. The fitness values we were looking to minimize were the total travel time of a vehicle, or the total time it took for a vehicle to complete its trip, and the total time spent waiting at red lights in seconds.

When defining our PSO algorithm, we ended up having to constrain the minimum and maximum values that it could generate for the traffic light durations. If the values were anything below five seconds, it would often crash the SUMO simulator when run with those durations. Alongside this, we found that if any values generated were above thirty, PSO would find that it could set all of the lights on our specific vehicle path to green long enough that it never had to stop at a red light. So, to keep it as realistic as possible and avoid crashing, we limited these values to between 5 and 30 seconds.

Next, when running the PSO, we integrated support to update the SUMO network and run the simulator with newly generated traffic light durations. This will be discussed further below.

Lastly, we also decided to test five different values for four different hyperparameters. We wanted to see how these different hyperparameters affected the optimization and whether we could find better results. These are displayed in Figure 3 below.

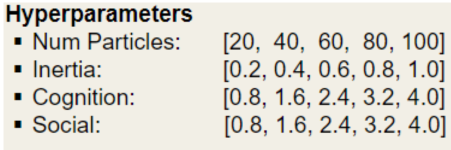

Fig. 3. Hyperparameter Values

C. Combining SUMO & PSO

Finally, we combined SUMO with our PSO algorithm to get a continuous feedback loop to optimize the traffic light durations. Figure 4 visualizes this loop.

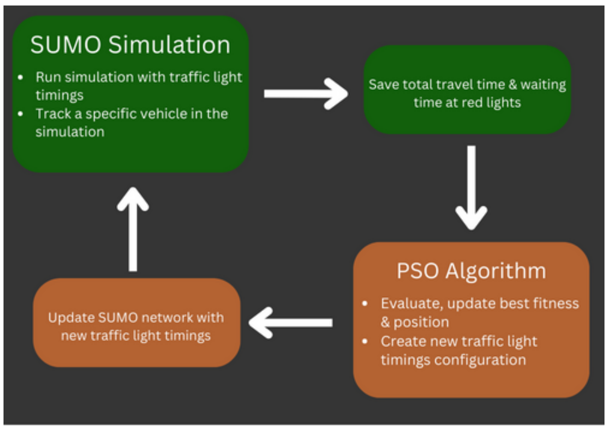

Fig. 4. SUMO & PSO Experimental Loop

Firstly, we run the SUMO simulation with the default traffic light timings of 10 seconds for green and 5 seconds for yellow. During the runs, we always track the same vehicle going from one end of Cumberland Ave to the other. Once the simulation has finished, we save the results to our results file so it's accessible for our PSO algorithm.

Then, our PSO algorithm will get the user-defined fitness value, either the total travel time or time spent waiting at red lights from the results file. Once it has this value, it will then evaluate the fitness, update the best position and value if needed, and generate two new traffic light timings for green and yellow lights.

After generating these values, our algorithm will then update the SUMO network configuration file. Within this file, it will change all of the traffic light durations to the newly generated values. Doing this essentially standardizes the light timings across all intersections. Once this is done, it will re-run the simulation with the new durations and start the loop over again.

Using this combination proved to be very effective and allowed us to automate the entire process of testing the newly generated, optimized traffic light durations.

IV. Results

Our experiments were set up to optimize the total travel and waiting times to optimize the flow of traffic. The simulator used for this experiment was set up with a route a car will follow to gather relevant data. Also, both of the fitness values were optimized independently of each other. After applying the Particle Swarm Optimization (PSO) algorithm and conducting various tests for 80 iterations, we saw significant improvements in traffic flow efficiency on our test area of Cumberland Avenue in Knoxville, TN.

TABLE I
DEFAULT VS. BEST HYPERPARAMETERS

Hyperparameter	**Default Value**	**Best Value**
Number of Particles	60	80
Inertia	0.6	0.2
Cognition	1.6	3.2
Social	1.6	4.0

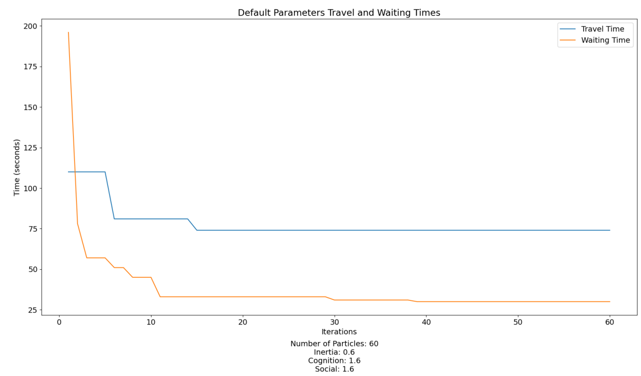

Fig. 5. Default Hyper-Parameters Travel and Waiting Times

Before the application of the PSO algorithm and using default hyper-parameters where the number of particles = 60, inertia = 0.6, cognition = 1.6, and social = 1.6, the minimum travel time was recorded to be 74 seconds with signal timings set at [green: 30 s, yellow: 5 s, red: 35 s]. Also for the same set of hyper-parameters, the minimum waiting was recorded to be 30 seconds with signal timings set at [green: 28 s, yellow: 5 s, red: 33 s]. We can see this in Figure 1, where the waiting time starts well over 180 seconds, almost encroaching 200 seconds, and travel times start around 120 seconds with significantly less traffic.

After applying optimizations with the adjusted hyper-parameters where the number of particles = 80, inertia = 0.2, cognition = 3.2, and social = 4.0, we saw substantial improvements in the total travel and waiting times and their respective signal timings. The minimum travel time was decreased to 71 seconds with the signal timings set at [green: 27 s, yellow: 5 s, red: 32 s]. Moreover, the minimum waiting time saw a notable reduction with a recorded value of 21 seconds with signal timings set at [green: 21 s, yellow: 5 s, red: 26 s], indicative of improved traffic flow dynamics. Looking at Figure 2, which was generated after the PSO optimization, we see a significant improvement in travel and waiting times with very little traffic. These results underscore the efficacy of our PSO-based approach in minimizing congestion and enhancing

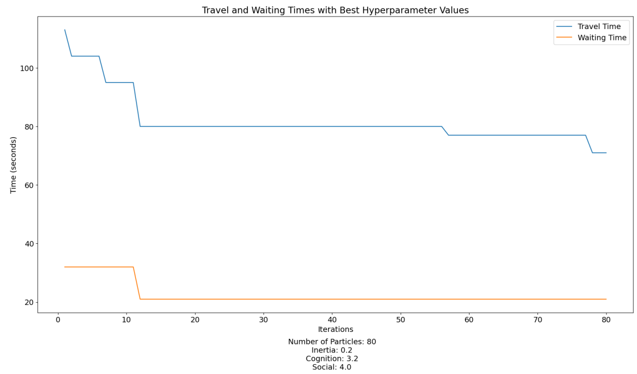

Fig. 6. Best Hyper-Parameters Travel and Waiting Times

overall traffic efficacy, demonstrating its potential for real-world application in urban traffic management scenarios.

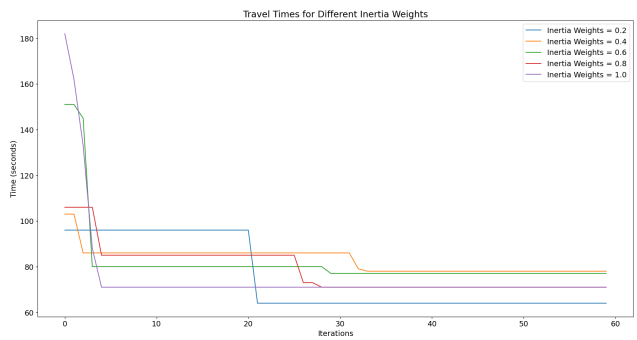

Fig. 7. Travel times for the inertia hyper-parameter

Fig. 8. Waiting times for the inertia hyper-parameter

Talking about choosing the optimal values for the hyper-parameters, we chose them after conducting multiple test runs with a combination of different hyper-parameters. Our approach to determining the optimal values for each hyper-parameter was to change the hyper-parameter under testing while keeping values of other hyper-parameters to the respective defaults.

Upon examining the inertia plots depicting travel and waiting times (refer to Fig. 3 and Fig. 4), which were generated during the hyper-parameter tuning phase, we identified the optimal value to be 0.2. This conclusion was drawn from its consistently low initial values for both travel and waiting times. Although other values exhibit superior performance individually in each graph, 0.2 emerges as the standout choice due to its consistent behavior across both plots.

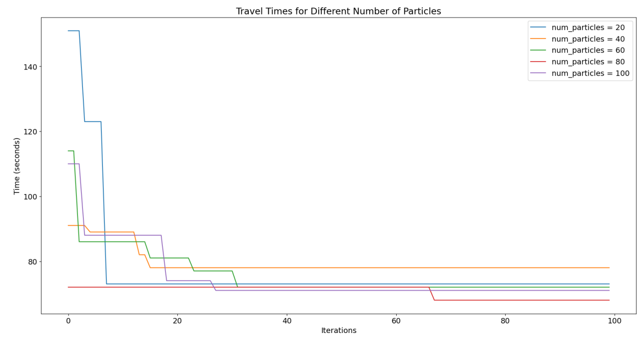

Fig. 9. Travel times for the Number of Particles hyper-parameter

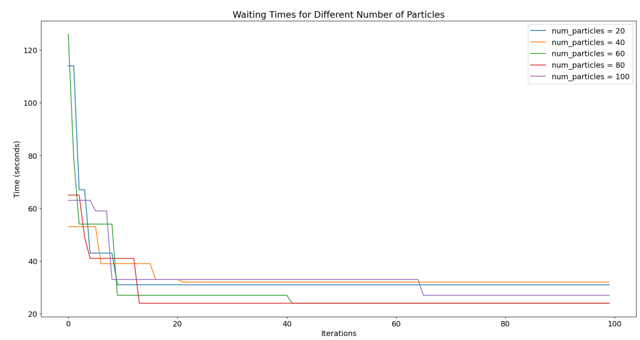

Fig. 10. Waiting times for the Number of Particles hyper-parameter

Upon analyzing the travel and waiting time plots of the hyper-parameter ”number of particles” (refer to Fig. 5 and Fig. 6), it becomes evident that the optimal value is 80. This value consistently yields the shortest travel and waiting times throughout our testing period. While alternative values occasionally show superior performance in either plot, we opt for 80 for the sake of consistency, as it consistently demonstrates favorable results across both graphs.

Upon examining the plot for the best social and cognition parameter values (Fig. 7), we see that it minimum waiting time of 64 seconds and a minimum waiting time of 25 seconds. The specific values of social and cognition parameters were chosen by plotting graphs for each combination of social and cognition values.

The utilization of PSO allowed for a dynamic adjustment of signal timings in response to real-time traffic conditions, enabling a more adaptive and efficient traffic control strategy. By optimizing the hyper-parameters of the PSO algorithm, we were able to achieve better convergence towards optimal signal timings, resulting in reduced travel times and waiting times for commuters on Cumberland Avenue. This approach not only addresses immediate challenges in traffic congestion but also contributes to the broader goal of sustainable urban

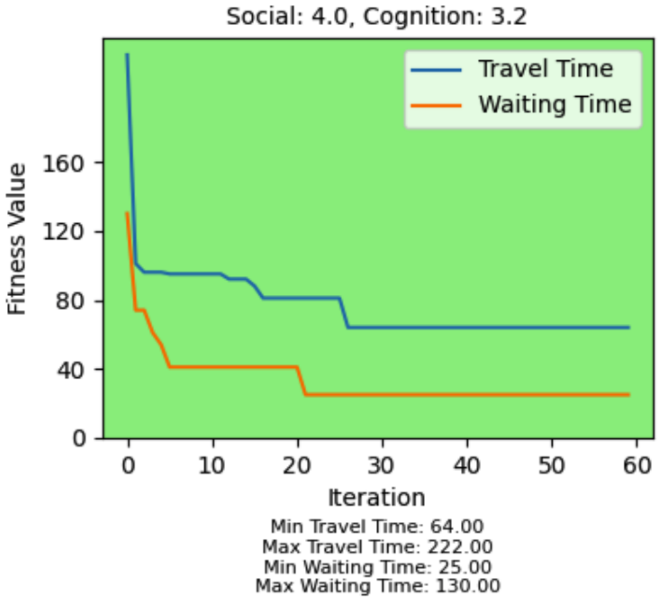

Fig. 11. Travel and Waiting Times for the best social and cognition parameters

transportation systems by reducing fuel consumption and emissions associated with prolonged idling at intersections.

V. Discussion

After our testing, we found that combining the individual, best-performing values for each hyperparameter produces overall better optimizations for the traffic light timings when compared to using the default values. Furthermore, these better traffic light signals reduced both fitness values, showing improvements in total travel time and time spent waiting at red lights.

While these were great results, there are a few additional concerns to consider. Firstly, when adjusting these traffic light durations, we standardized them across all traffic lights. Doing so does not account for any sensors that may be used in the real world that change phases depending on the traffic flow. Alongside this, having to limit the minimum and maximum duration of each traffic light duration is also not incredibly realistic. This was done to prevent the SUMO simulator from crashing along with attempting to make it realistic by forcing the vehicles to stop at a red light at some point, rather than PSO optimizing it so that our particular vehicle never has to stop. Lastly, our research only considered a small section of Cumberland Avenue that contained various intersections. We decided to limit the experiment to this due to the complexity of large networks in SUMO and the inability to run the simulation without the program crashing almost immediately.

Limitations aside, we would consider this experiment an overall success. Utilizing PSO, along with the SUMO simulator, proved to be a valuable combination that resulted in lower travel times and waiting times at red lights.

VI. Conclusion

In conclusion, our research endeavors to address the challenge of traffic congestion in urban areas by leveraging Particle Swarm Optimization (PSO) as a dynamic adaptive approach to traffic flow optimization. The escalating issue of traffic congestion not only results in frustration and wasted time for commuters but also poses significant challenges to energy consumption and environmental sustainability. Traditional traffic control methods often struggle to keep pace with the ever-changing dynamics of urban traffic patterns, leading to persistent inefficiencies in transport systems.

Through a focused study on Cumberland Avenue in Knoxville, TN, we demonstrated the efficacy of our PSO-based approach in optimizing total travel and waiting times with traffic signal timings. By fine-tuning the hyper-parameters of the PSO algorithm and conducting thorough testing, we observed substantial improvements in both travel and waiting times. Our results indicate about a 4% improvement in total travel times and about 30% improvement in waiting times and also prove the significance of adaptive optimization techniques in addressing the complexities of urban traffic management.

Furthermore, our analysis of hyper-parameter tuning highlighted the importance of selecting appropriate values to achieve optimal performance. From the determination of the optimal number of particles to the identification of the ideal inertia value, our findings underscore the necessity of careful parameter selection in optimizing traffic control strategies.

Overall, our study contributes to the ongoing discourse on traffic management strategies by offering a practical and effective solution for mitigating congestion and enhancing the efficiency of urban transport systems.

VII. Future Work

1) **Integration of Sidewalks and Pedestrian Crosswalks:** Incorporating pedestrian infrastructure into the traffic control optimization framework presents an avenue for enhancing safety and accessibility for pedestrians. Future work could explore the integration of sidewalks and pedestrian crosswalks into the simulation model to evaluate their impact on traffic flow and pedestrian safety.
2) **Expansion to more Complex Network:** While our research focused on optimizing traffic flow on Cumberland Ave, future work could involve scaling up the simulation to encompass larger and more intricate urban networks with numerous traffic lights and intersections. This expansion would provide insights into the scalability and applicability of the proposed PSO-based optimization approach in more complex urban environments.
3) **Exploration of Hyperparameter Combinations:** Further experimentation with a wider range of hyperparameter combinations for the PSO algorithm could yield additional insights into its performance and robustness. Testing various combinations of parameters such as swarm size, inertia weight, and acceleration coefficients

could help identify optimal configurations for different traffic scenarios.

4) **Optimization for Environmental Factors:** In addition to minimizing congestion and improving traffic flow, future research could extend the application of PSO to optimize environmental factors such as fuel efficiency and pollution reduction. By incorporating environmental objectives into the optimization framework, we can work towards creating more sustainable and eco-friendly transportation systems.
5) **Integration of Multi-Objective Optimization:** Considering the diverse objectives and constraints involved in urban traffic management, future work could explore the adoption of multi-objective optimization techniques. By simultaneously optimizing for multiple objectives such as travel time, congestion, environmental impact, and pedestrian safety, we can strive to achieve more holistic and balanced solutions.
6) **Real-world implementation and Validation:** Finally, future research should aim to validate the effectiveness of the proposed approaches through real-world implementation and testing. Collaborating with transportation authorities and urban planners to deploy the optimized traffic control strategies in actual urban settings would provide valuable insights into their practical feasibility and impact on traffic operations.

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