Optimizing Traffic Adaptive Signal Control: A Multi-Objective Simulation-Based Approach for Enhanced Transportation Efficiency

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Keywords: Multi-Objective Optimization, Simulation-Based Optimization, Traffic Signal Control.

Abstract: This research aims to improve traffic flow efficiency, reduce congestion, and enhance the overall performance of the transportation system for different road users, while keeping in mind the ease of implementation of the provided approach. That is achieved by optimizing the stage length parameter in the VAP files for VISSIM using ParMOO, a powerful optimization tool. The VAP files contain crucial information about traffic signal control logic, including signal timings, stage durations, and cycle lengths. The maximum stage length parameter within VAP files represents the maximum allowable time for a particular traffic signal stage before transitioning to the next stage. Optimizing this parameter can significantly impact traffic performance by reducing delays and improving overall traffic flow efficiency. Average delays for passenger cars and pedestrians are chosen as objective functions to be minimized. Sensitivity analysis is employed to validate the optimized solutions. Comparing the traffic performance measures using the optimized VAP files with the base case, we found that the optimized solutions consistently outperformed the observed performance. The research contributes by utilizing the ParMOO algorithm and integrating it within VISSIM software, enabling researchers to readily apply the methodology and advance the field of traffic signal control with practical and industry-relevant solutions.

1 INTRODUCTION

The increasing demand for urban mobility underscores the necessity of improving transportation networks. However, congestion in urban areas impedes efficiency, causing delays, increased fuel consumption, and pollution. Construction of new roads in densely populated urban areas is challenging due to space constraints and environmental concerns. Moreover, improving roads may exacerbate traffic by attracting more vehicles. Innovative solutions focusing on current infrastructure and efficient transportation policies are essential to tackle these challenges. Expanding road infrastructure is impractical due to limited land resources and socioeconomic factors. Research efforts now prioritize effective traffic management, transportation facility enhancements, and meeting escalating traffic demands. Developing efficient traffic management solutions offers a cost-effective approach to alleviate congestion and address optimization challenges in cities by enhancing network performance.

Upgrading transportation systems to enhance intelligence is a significant focus in transportation research. The Intelligent Transportation System (ITS) integrates technology into infrastructure to enhance performance, efficiency, and safety. ITS targets transportation issues such as safety, congestion, efficiency, and environmental protection through smarter highways and innovative technologies. Traffic signal control systems play a crucial role in urban traffic management and are a key area of study in ITS. They regulate traffic at intersections, ensuring the safety of all road users. Efficient operation of these systems is vital for network performance and is integral to ITS.

Two main strategies for optimizing traffic signal timing exist: mathematical programming and simulation-based methods. Mathematical programming utilizes mathematical models to optimize traffic management goals. However, these

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Salem, S. and Leonhardt, A.
Optimizing Traffic Adaptive Signal Control: A Multi-Objective Simulation-Based Approach for Enhanced Transportation Efficiency.
DOI: 10.5220/0012682100003702

In *Proceedings of the 10th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2024)*, pages 344-351
ISBN: 978-989-758-703-0; ISSN: 2184-495X

models often entail complex computations, limiting their real-time usability and accuracy in depicting detailed traffic dynamics. Simulation-based methods strive to accurately model interactions among various traffic characteristics. Recent studies favor simulation-based techniques, employing microscopic traffic simulators to illustrate complex traffic patterns in cities. Nevertheless, scarcity of simulation resources presents a challenge for addressing large-scale urban traffic management problems. Advanced simulation models require further development to tackle high-dimensional optimization challenges in large metropolitan networks (Chen & Chang, 2014; P. T. M. Nguyen, 2020; Papatzikou & Stathopoulos, 2015; Poole & Kotsialos, 2016).

Improvements in traffic signal management systems have targeted multiple goals, including reducing queue lengths, delays, travel time, enhancing traffic flow, and minimizing traffic exhaust emissions. Optimizing traffic signals can achieve these goals simultaneously, leading to reduced travel times and improved traffic flow. However, optimization for different road users and environmental goals may conflict with other priorities and receive limited consideration. Transportation management studies often focus on single-goal issues, despite real-world situations involving multiple objectives (Chen & Chang, 2014; P. T. M. Nguyen, 2020; Papatzikou & Stathopoulos, 2015; Poole & Kotsialos, 2016).

2 LITERATURE REVIEW

Traffic simulation models are classified into macroscopic, microscopic, and mesoscopic models based on their level of detail. Macroscopic models represent traffic flow using aggregate measures, while microscopic models simulate individual vehicles in detail. Mesoscopic models strike a balance between detail and efficiency. This study focuses on microscopic and mesoscopic simulators like VISSIM due to their ability to handle complex traffic scenarios. Microscopic simulators offer detailed modeling capabilities, while mesoscopic simulators compromise between detail and computational efficiency. They utilize driver behavior models to simulate vehicle interactions based on perception and response thresholds. (Qadri et al., 2020).

Multi-objective optimization problems (MOOPs) are prevalent across scientific and engineering domains, including product design and model fitting, where multiple performance criteria must be considered. The main goal of MOOPs is to identify solutions that balance conflicting objectives, resulting in a range of achievable values for each objective. This range of solutions, known as the Pareto front or tradeoff curve, illustrates inherent trade-offs within the problem. Real-world MOOPs often include additional constraints or rules that solutions must adhere to. In multi-objective simulation-based optimization, objectives are typically derived from costly simulations, providing data to evaluate different designs or strategies. By optimizing these objectives, a set of Pareto-optimal solutions is revealed, offering various trade-offs between conflicting objectives. In essence, MOOPs provide a framework for decision-making amid conflicting goals, facilitating the exploration of trade-offs and the identification of optimal solutions that align with specific requirements and priorities (Červeňanská et al., 2020; Chang & Wild, 2023; P. T. M. Nguyen, 2020).

There appears to be a research gap in implementing multi-objective simulation-based optimization for the traffic signal control problem (Qadri et al., 2020). Most transportation management optimization studies and implementations focus on issues with a single goal; real-world situations, on the other hand, frequently entail many goals. Optimization for other road users such as transit vehicles or pedestrians or optimization for environmental goals sometimes clash with other priorities, and as a result, they are given little consideration. P. H. Nguyen et al. (2016), Hatri and Boumhidi (2016), Zheng et al. (2019), and Zhang et al. (2022) have been among the few researchers to employ a multi-objective simulation-optimization approach. Although this approach is relevant, there appears to be a research gap when it comes to implementing multi-objective Simulation Optimization for the traffic signal control problem.

Nguyen et al. proposed a multi-objective simulation-optimization approach for urban traffic signal control. Their approach integrated a local search algorithm with NSGA-II, outperforming other algorithms and achieving good simulation results during the optimization process. The study demonstrated the effectiveness of the approach in balancing multiple objectives and improving traffic flow (P. H. Nguyen et al., 2016). Hatri et al. focused on bi-objective optimization of traffic signal timings using the NSGA-II algorithm with the Enhanced Archive Memory (EAM) technique. The goal was to find optimal signal timings that strike a balance between traffic flow and delay. The results indicate that the proposed approach effectively manages the trade-off between these two objectives and achieves improved performance compared to other methods.

By utilizing the EAM technique, the algorithm can efficiently handle the optimization process (Hatri & Boumhidi, 2016). Another study by Zheng et al. presented a bi-objective stochastic simulation-optimization approach for traffic signal optimization. They incorporated surrogate models to capture the mapping relationship between decision variables and objectives, resulting in improved performance compared to other approaches. The use of surrogate models also enhanced the efficiency of the optimization process (Zheng et al., 2019). Zhang et al. utilized a multi-objective evolutionary algorithm for the optimization of signal timing at intersections. The algorithm addressed the challenge of coordinating traffic signals to improve traffic flow and reduce congestion. By simultaneously optimizing multiple objectives, the algorithm identified a set of Pareto-optimal solutions offering different trade-offs between objectives. This approach provides decision-makers with a range of options based on their priorities (Zheng et al., 2019).

The research introduces a significant advancement by utilizing ParMOO, an open-source algorithm, for multi-objective optimization in traffic signal control. This approach ensures accessibility and ease of implementation for researchers, industry experts, and municipalities involved in traffic management. Additionally, the study incorporates modifications within the VAP file of VISSIM, a widely recognized software in transportation and municipal planning. These modifications align the proposed methodology with existing practices and enable seamless integration into real-world traffic management systems.

3 METHODOLOGY

This research utilizes VISSIM, a popular microscopic traffic simulation software, and the ParMOO algorithm for multi-objective optimization to tackle the challenge of optimizing traffic signal timings. VISSIM provides a realistic platform for modelling and simulating complex traffic scenarios, allowing researchers and practitioners to assess various traffic management strategies' performance. Meanwhile, ParMOO offers a comprehensive framework for multi-objective optimization, facilitating simultaneous optimization of conflicting objectives. In the following section, we delve into the functionalities and methodologies of VISSIM and ParMOO, highlighting how their capabilities are leveraged to enhance traffic flow and alleviate congestion through signal timing optimization.

3.1 Traffic Simulation and VISSIM

VISSIM, developed by Company PTV AG, is the chosen traffic modelling tool for this paper. Widely used by traffic engineers and researchers, VISSIM offers an intuitive graphical user interface (GUI) for designing road networks and running simulations. Additionally, the VISSIM-COM interface allows programmers to control simulator functions and parameters through various programming languages like Matlab and Python. (*PTV Vissim VisVAP User Manual*, 2021; *VISSIM: Microscopic Multi-modal Traffic Flow Simulation*, 2021; Tettamanti & Horváth, 2020; Yan et al., 2013).

The Vissig module of VISSIM determines signal data, including stage and interstage definitions. Control logic, governing traffic signal operations, is defined using VAP (Vehicle Actuated Programming), with VisVAP serving as a GUI to create flowchart-based control logic stored in a .vap file. Static signal base data can be defined in VISSIG, stored in a .pua file, serving as main inputs for the VISSIM simulation environment. (Figure 1).

Parameterizing maximum stage durations in VAP files and simulating signal control schemes lets you evaluate their effects. This iterative method explores and optimizes traffic signal layouts to improve system performance, lowering delays, boosting traffic flow efficiency, and improving road user experiences.

3.2 Multi-Objective Optimization with ParMOO

ParMOO, a strong multi-objective optimization toolkit, is used in this section. Multi-objective optimization is crucial to traffic signal timing optimization, and ParMOO's features and capabilities help (Chang & Wild, 2023). ParMOO is designed for simulation-based multiobjective optimization. The difference between simulations and objectives is crucial to ParMOO. Simulations with ParMOO require a lot of processing power and time. ParMOO uses response surface methodology to solve this. This method fits computationally simpler surrogate models to simulation outputs. ParMOO optimizes problem scalarizations using surrogate models instead of expensive simulations. This method efficiently explores and optimises the multiobjective problem space while lowering computational costs and execution time (Chang & Wild, 2023; ParMOO Documentation, 2022). Main components of ParMOO (Parallel Multi-Objective Optimization) (ParMOO Documentation, 2022):

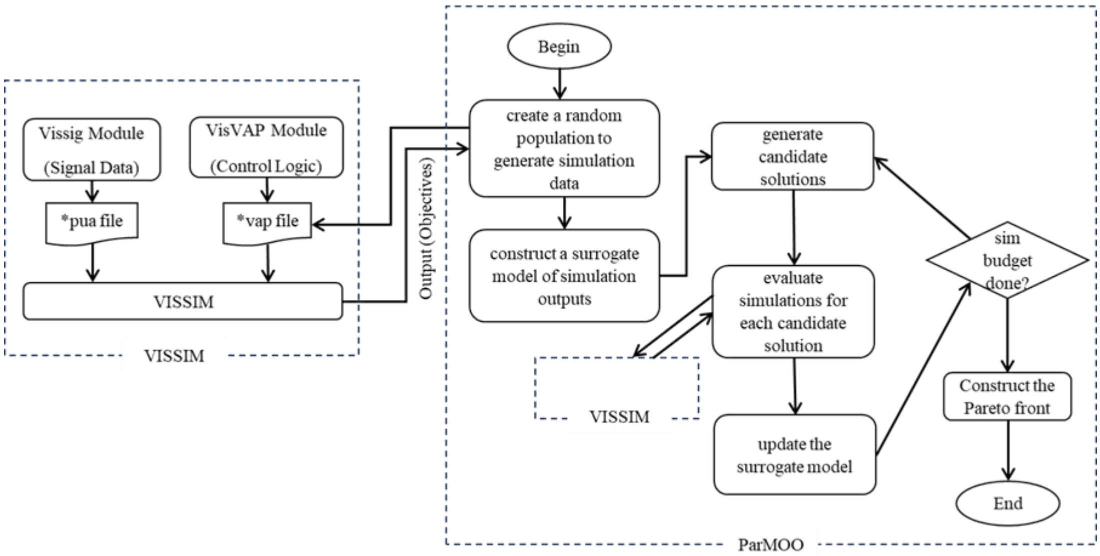

Figure 1: Framework of ParMOO and VISSIM Integration (*Parmoo Documentation*, 2022; *VISSIM: Microscopic Multi-modal Traffic Flow Simulation*, 2021).

A MOOP object is a data structure that contains essential information for a multi-objective optimization problem. The problem is solved using a multi-objective optimization technique.

Objective Functions. With ParMOO, define one or more functions to represent the performance measures to optimize. These functions measure optimization aims. Traffic signal optimization objectives may include decreasing delays, maximizing throughput, reducing emissions, or minimizing user class conflicts.

Decision Variables. Adjustable parameters or variables that can be optimized to meet desired outcomes. ParMOO can optimize traffic signal decision variables like maximum stage length.

Pareto Front. ParMOO uses the concept of the Pareto front, which represents the set of non-dominated solutions in the multi-objective optimization problem. The Pareto front consists of solutions that cannot be improved in one objective without worsening another objective.

Surrogate Functions. Incorporating a simulation dictionary links each simulation in the MOOP object to a surrogate model. This relationship uses solution data to approximate the simulation's response surface. The surrogate model estimates simulation behavior and outcomes more efficiently and cheaply than the actual simulation.

Search Techniques. Each simulation in the MOOP object has a unique search technique assigned upon inclusion. This method generates simulation data before ParMOO's first iteration to fit initial surrogate models.

Figure 1 demonstrates the ParMOO algorithm and its components. More information on ParMOO can be found at (Chang & Wild, 2023; *ParMOO Documentation*, 2022).

3.3 Methodology for Traffic Signal Timing Optimization

This section outlines the methodology for traffic signal timing optimization. It provides a detailed step-by-step explanation of how VISSIM and ParMOO are integrated and employed to optimize traffic signal timings. The methodology employed in this study follows a scientific approach to optimize the maximum stage length parameter using ParMOO and subsequently incorporating the optimized values into the VISSIM simulation environment. Figure 1 shows how VISSIM and ParMOO interact.

The methodology begins by defining the design variables that represent the maximum lengths of different stages in the traffic signal cycle. These design variables are carefully selected to capture the key parameters that influence traffic flow and congestion. The lower and upper limits are chosen as 5 and 40 seconds, respectively, for a three-stage signal plan. To begin, the code implemented three design variables representing the lengths of different stages in the traffic signal cycle. These variables are set within predefined ranges, allowing for flexibility in optimizing signal timings while keeping the allowable minimum and maximum stage lengths.

A simulation function is developed to simulate the traffic scenario using VISSIM. This function takes the design variables as input and modifies the VAP file accordingly to update the maximum stage lengths. The simulation function then runs the VISSIM simulation and calculates the average delay for passenger cars and pedestrians.

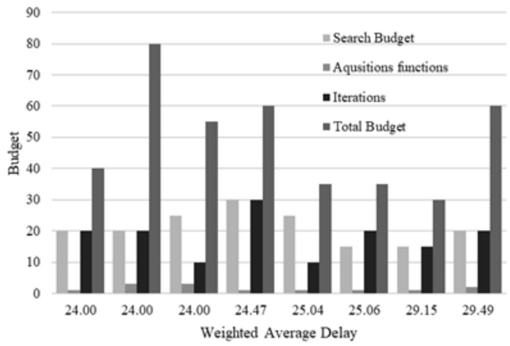

Figure 2: Different Budget Configurations with Corresponding Weighted Average Delay Values.

The ParMOO algorithm is employed to search the design space and identify Pareto-front solutions. The algorithm iteratively explores different combinations of the design variables to find optimal signal timings that balance the conflicting objectives. A range of budgets were tested, and ultimately, a budget configuration of 20, 1, and 20 was selected (Figure 2). This configuration represents the search budget, number of acquisition functions, and maximum iterations, respectively. By combining these values, the final budget totalled 40 (Equation 1). The surrogate model used is gaussian RBF, and the acquisition function type is uniform weights. The execution time of the algorithm ranges between 400 and 700 seconds using a PC with an 11th Gen Intel (R) Core (TM) i7-1165G7 @ 2.80 GHz. These results suggest that for practical applications and larger-scale optimization problems, cloud computing or more powerful processors may be necessary to achieve acceptable processing times.

$$\mathrm{Budget}_{\mathrm{Total}} = \mathrm{Budget}_{\mathrm{Search}} + \mathrm{N}_{\mathrm{Aquistion\ Functions}} \ \mathrm{x}\ \mathrm{N}_{\mathrm{Iterations}} \quad (1)$$

As mentioned before, ParMOO provides multiple optimal solutions, known as the Pareto front, it presents decision-makers with a range of alternatives to choose from (Figure 3). Ultimately, the choice of the optimal solution depends on a careful balance of technical analysis, stakeholder input, and informed decision-making. By considering multiple factors, objectives, and perspectives, the solution that best aligns with predefined goals and maximizes the desired outcomes for your transportation system can be selected. In our research, a weighted objective approach is chosen as a decision criterion. The weight assigned to each objective is 0.5. This approach allows you to prioritize certain objectives over others and select the solution with the minimum weighted sum. The optimized maximum stage lengths are then incorporated into the VAP files, which contain the traffic signal control logic for the VISSIM simulation. The necessary modifications are made to ensure that the optimized values are used during the simulation runs.

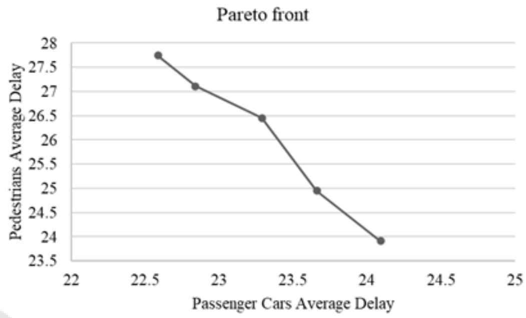

Figure 3: Pareto front for one of the scenarios.

3.4 Experimental Setup

To evaluate the proposed methodology's effectiveness and robustness, a simple four-legged intersection is chosen from VISSIM examples. Examples of three-stage fixed-time control and three-stage vehicle actuated control are provided with the VISSIM installation, along with control logic files created with VisVAP for reference, incorporating pedestrian demands. Each scenario consists of three stages (Figure 4), with lane widths ranging from 2.75 to 3.50 m and a vehicle composition of 5% heavy goods vehicles (HGV) and 95% passenger cars, with an average speed of 50 km/hr.

The proposed methodology is applied to each traffic scenario by configuring design variables and executing the optimization process using the ParMOO algorithm. The objective is to identify optimal signal timings minimizing average delay for both passenger cars and pedestrians, accounting for each scenario's specific characteristics and demands.

After the optimization process, resulting Pareto front solutions are obtained for both traffic scenarios. These solutions represent trade-offs between average delays for different vehicle types, offering a comprehensive view of achievable performance improvements in each scenario. To assess the methodology's performance, optimized signal timings from Pareto front solutions are implemented in respective traffic scenarios. Subsequently, VISSIM simulations are conducted using updated signal timings to evaluate the optimization process's effectiveness.

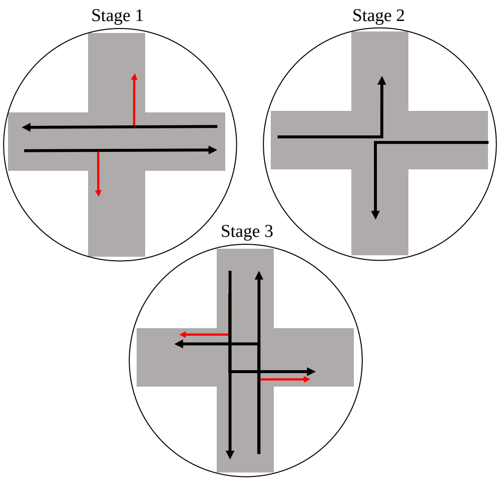

Figure 4: Traffic Stages.

4 RESULTS AND ANALYSIS

This section of the paper contains two components: validation and sensitivity analysis. These analytical approaches are employed to evaluate and validate the optimized solutions obtained through the optimization process.

4.1 Validation Analysis

In the validation analysis, the optimization algorithm is tested by varying parameters to be optimized, ensuring it can identify values leading to reduced delays. Systematically varying these parameters, we compare resulting objective values with optimized solutions to evaluate effectiveness and robustness.

Table 1 presents the validation results of scenario 2 (actuated). The table provides the average delay values (in seconds) for passenger cars and pedestrians under different cases. For the fixed control scenario, the optimization algorithm was highly effective in finding the most optimized values for the three parameters, specifically the maximum stage length, which resulted in substantial reductions in delays. This success in optimizing the parameters indicates the algorithm's ability to efficiently balance the trade-offs and find signal timings that significantly enhance traffic performance in the fixed control setting (the validation results for scenario 1(fixed) is not presented because of space limitation).

On the other hand, in the vehicle actuated control scenario, the optimization process also led to reductions in delays. However, the validation analysis revealed that only the maximum gap parameter exhibited a strong response to optimization efforts. This means that optimizing the maximum gap had a substantial impact on reducing average delays in the vehicle actuated control scenario.

These findings suggest that the vehicle actuated control system already exhibits a higher level of adaptability and responsiveness to changing traffic conditions, making the optimization process less influential for other parameters. Nevertheless, the optimization of the maximum gap parameter showcased the algorithm's capability to identify critical adjustments that improve traffic performance in this scenario.

Overall, the validation analysis provides valuable insights into the performance of the optimization algorithm in both control scenarios. It demonstrates the algorithm's success in finding optimized parameter values that effectively reduce delays in the fixed control scenario. In the vehicle actuated control scenario, the analysis highlights the significance of the maximum gap parameter and its sensitivity to optimization efforts, further solidifying the algorithm's capability to fine-tune signal timings for improved traffic flow.

Table 1: Validation Results of Traffic Scenario 2 (Vehicle Actuated Control).

	Max stage length (sec.)			Max Gap	Average Delay (sec.)	
	St. 1	St. 2	St.3		*Passenger Cars*	*Pedestrians*
Base Values	20	5	10	3	16.75	19.90
Optimal values	11	7	10	1	15.50	17.26
Random Values	5	5	5	1	17.15	17.56
	7	5	5	1	15.95	17.47
	7	5	5	2	16.15	19.14
	20	20	20	1	15.96	17.62
	20	20	20	1	17.14	20.15
	11	10	7	1	15.47	17.79
	19	20	11	1	15.44	17.34
	19	20	11	2	16.67	19.69
	8	8	8	2	16.97	18.71
	8	8	8	1	15.50	17.52
	8	8	8	3	16.84	19.97
	11	7	11	1	15.50	17.31
	12	6	11	1	15.49	17.34
	11	7	10	2	16.63	19.84
	11	8	10	1	15.50	17.26
	10	7	10	1	15.56	17.29
	9	7	10	1	15.57	17.33
	9	7	9	1	15.52	17.40

4.2 Sensitivity Analysis

In the sensitivity analysis, the demands of vehicles and pedestrians are systematically varied to evaluate the robustness of the optimized solutions obtained through traffic signal optimization. By modifying the input parameters related to traffic demand, we aim to examine the performance of the optimized solutions under different scenarios. Several simulations are conducted, each representing a specific variation in the demand for vehicles (Table 2). Average delays for personal cars and pedestrians are collected and compared to those of the base case, where no optimization was applied.

Table 2: Demand Variations for Sensitivity Analysis.

	North-bound	East-bound	South-bound	West-bound
Base	140	244	248	500
Case 1	1000	244	248	500
Case 2	140	1500	248	500
Case 3	140	244	248	2000
Case 4	1000	244	1200	500
Case 5	140	244	1200	500
Case 6	140	244	248	500

The results indicated that simulations with optimized values significantly reduced the average delay for both personal cars and pedestrians compared to simulations with base values. These outcomes highlight the effectiveness of the optimized solutions in adapting to varying traffic demands, leading to more efficient traffic flow and reduced congestion. This finding underscores the importance and benefits of conducting sensitivity analysis to evaluate the impact of optimized values on traffic flow and overall efficiency.

Table 3 shows the performance gain for different scenarios and cases. The Performance Gain is determined by comparing the reduction in average delay achieved in the optimized scenario with respect to the base case. This reduction is calculated as a percentage of the average delay in the base case. The table presents the average delay reduction percentage for passenger cars and pedestrians in Scenario 1 and Scenario 2. Each row represents a specific scenario, and the corresponding values indicate the percentage reduction in average delay for the given case and scenario.

Furthermore, as a step towards real-world applicability, our plan is to implement the approach at an actual intersection. By deploying the optimized signal timings in a live traffic environment, we can assess the effectiveness and feasibility of our methodology in a practical setting. This real-world implementation will provide valuable insights into the challenges and considerations involved in translating optimization results into tangible improvements in traffic operations. Additionally, it will allow us to validate the performance of our approach and gather empirical evidence of its impact on various road users and the overall traffic system.

Table 3: Performance Gain.

Cases	Scenario 1 (Fixed-Time)		Scenario 2 (Vehicle-Actuated)	
	Passenger Cars	Pedestrians	Passenger Cars	Pedestrians
1	13.78%	34.11%	7.44%	13.02%
2	14.77%	33.53%	14.89%	10.30%
3	6.88%	14.60%	5.24%	12.96%
4	5.41%	11.38%	1.42%	24.19%
5	3.12%	26.00%	3.06%	9.06%
6	22.27%	20.69%	28.93%	14.00%

5 CONCLUSIONS

Overall, the assessment of the methodology in the two selected traffic scenarios (fixed-time control and vehicle actuated control) has provided valuable insights into its effectiveness in optimizing signal timings and improving traffic performance. The analysis of the results has allowed us to evaluate the methodology's applicability in diverse traffic settings and its potential for practical implementation in real-world traffic management scenarios. ParMOO has proven to be a valuable tool, facilitating the identification of efficient and effective traffic signal plans that enhance overall transportation system performance.

In future work, our aim is to extend the optimization approach to include the needs and priorities of additional road users, such as cyclists and public transit vehicles. We can work toward a more comprehensive and all-inclusive approach to traffic signal timing optimization by including these modes of transportation in our framework. This expansion will enable us to develop signal timings that enhance the safety, efficiency, and overall travel experience of cyclists and public transit users.

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at an actual intersection. By deploying the optimized signal timings in a live traffic environment, we can assess the effectiveness and feasibility of our methodology in a practical setting. This real-world implementation will provide valuable insights into the challenges and considerations involved in translating optimization results into tangible improvements in traffic operations. Additionally, it will allow us to validate the performance of our approach and gather empirical evidence of its impact on various road users and the overall traffic system.

ACKNOWLEDGMENTS

This research is part of the project MORE – Munich Mobility Research Campus. The project is funded by dtec.bw – Digitalization and Technology Research Center of the Bundeswehr. dtec.bw is funded by the European Union – NextGenerationEU.

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