Chapter

Metaheuristics for Traffic Control and Optimization: Current Challenges and Prospects

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Abstract

Intelligent traffic control at signalized intersections in urban areas is vital for mitigating congestion and ensuring sustainable traffic operations. Poor traffic management at road intersections may lead to numerous issues such as increased fuel consumption, high emissions, low travel speeds, excessive delays, and vehicular stops. The methods employed for traffic signal control play a crucial role in evaluating the quality of traffic operations. Existing literature is abundant, with studies focusing on applying regression and probability-based methods for traffic light control. However, these methods have several shortcomings and can not be relied on for heterogeneous traffic conditions in complex urban networks. With rapid advances in communication and information technologies in recent years, various metaheuristics-based techniques have emerged on the horizon of signal control optimization for real-time intelligent traffic management. This study critically reviews the latest advancements in swarm intelligence and evolutionary techniques applied to traffic control and optimization in urban networks. The surveyed literature is classified according to the nature of the metaheuristic used, considered optimization objectives, and signal control parameters. The pros and cons of each method are also highlighted. The study provides current challenges, prospects, and outlook for future research based on gaps identified through a comprehensive literature review.

Keywords: metaheuristics, intelligent traffic control, signal optimization, swarm intelligence, evolutionary computation, transport networks

1. Introduction

1.1 Traffic congestion: a challenging front

Recent decades have witnessed a rapid surge in population growth. Consequently, a high concentration of social and economic activities in urban metropolitans has led to the emergence of various transportation modes and services. Urban traffic congestion has become a daunting challenge in cities around the world. Excessive delay, low traveling speeds, increased travel costs, elevated drivers' anxiety and frustrations, high fuel consumption, and vehicular emissions are the few consequences of traffic congestion. It also poses a threat to a stable urban economy [1, 2]. Traffic demands fluctuate significantly during the day (TOD), especially during rush hours, which is one of the main causes of congestion buildup. Congestion may be recurrent, arising from routine cyclic fluctuations in traffic volumes, or it may be non-recurrent produced due to unforeseen events such as traffic incidents, unpredictable weather conditions. Existing transport infrastructure cannot withstand the ever-growing traffic demands, while the inappropriate allocation of temporal and spatial resources further exacerbates the problems [3, 4]. An effective solution to mitigate traffic congestion is to embed intelligent transportation system (ITS) technologies in existing transport infrastructure for efficient and sustainable operations. Researchers and practitioners have proposed various strategies such as signal control optimization and dynamic lane grouping to address the issue in recent years.

1.2 Traffic signal control (TSC)

Signalized intersections are a vital component of urban traffic networks and play a pivotal role in traffic control and management strategies. Over the years, they have been the primary focus of traffic improvement efforts since they are representative of frequent and restrictive bottlenecks. Poor traffic management at urban intersections leads to traffic jams and unsustainable travel patterns network-wide. Alternatively, intelligent traffic control and better management at these critical locations could result in smooth, safe, cheap, and sustainable operations. Traffic Signal Control (TSC) is an integral part of ITS. TSC is an important operation that can tackle various urban traffic issues such as congestion, fuel consumption and exhaust emission, and inefficient resource utilization. TSC involves determining appropriate signal timings parameters to improve various traffic performance measures like average vehicle delay, travel time, maximizing throughput, and reducing queue lengths and vehicular emissions. One of the main objectives of traffic signal control is to facilitate the safe and efficient movement of people through a road network. Achieving this goal warrant establishment of an accommodation plan that ensures appropriate assignment of right-of-way (ROW) to different users.

1.3 Classical methods for TSC

Over the years, different strategies have been proposed to address the TSC problem. A fixed-time signal control scheme has been widely used for managing traffic lights in urban areas. This strategy requires the determination of optimum TOD breakpoints for establishing TOD intervals, which are subsequently used for obtaining the predefined green splits for each split (green times) using Webster's formula or some other optimization tools [5]. However, the fixed-time signal control strategy is suitable for stable and nearly homogenous traffic patterns. Alternatively, studies have focused on actuated and traffic responsive TSC schemes for dynamic traffic control and management. In such traffic control schemes, signal cycle length and green splits are adjusted according to real-time traffic data collected from sensors installed on each approach. Though actuated TSC strategies overcome some limitations of the former methods, they do not work well under all traffic and adverse conditions. TSC problem was initially addressed using various probability and regression-based methods [6, 7]. However, for oversaturated and undersaturated traffic conditions, such methods do not provide reliable solutions. Few notable classic TSC strategies proposed during the last few decades include: SCOOT [8], SCAT [9], MAXBAND [10], CRONOS, PRODYN [11], TRANSYT [12], RHODES [13], OPAC [14], and FUZZY LOGIC [15]. Few other methods recently used for traffic light setting are ARRB [16], TRRL [8], and HCM [17]. In addition, to signal control strategies, traffic light design could be isolated intersection based or coordinated. Isolated intersections signal schemes have limited benefits compared to coordinated strategies that consider the network of intersections.

1.4 Limitations of classical TSC strategies

The timing of traffic signals significantly influences the performance of the transportation system. Obtaining the optimal signal timing plan for a network in its entirety is challenging due to the stochastic and non-linear characteristics of the traffic system. From a computational perspective, the signal control optimization problem under the influence of several constraints is a highly non-linear and non-convex problem. To reduce the complexity of problem, studies have assumed partial convexification for obtaining the optimal signal plans [18, 19]. It has been shown that traffic light optimization belongs to the family of NP-complete problems whose complexity increases dramatically for real-world and more extensive transportation networks with prolonged study periods. Classical optimization methods used in this regard are not suitable for a variety of reasons. For example, they are sensitive to initial estimates of solution vector and require gradient computation of constraints and the objective functions. Further, the discrete nature of signal timing plan and phasing sequence limit the application of traditional optimization approaches. Similarly, classical signal control optimization techniques are usually more suited to isolated intersections. They are not scalable for large urban transport networks where the interdependence of traffic signals across multiple intersections may be explored. Hence, such methods do not consider the interdependencies and connectivity of traffic signals vital for large-scale urban transport networks.

1.5 Metaheuristics for TSC: the new frontier

Metaheuristics techniques, including and swarm intelligence and evolutionary algorithms, have emerged as appealing alternatives to classical optimization methods for addressing signal control problems. They can be easily adapted for solving signal optimization problems with mixed types of continuous and discrete variables on large-scale transportation systems. Metaheuristics are based on approximate random methods and involve an iterative master process that can efficiently provide high-quality, acceptable solutions with relatively low computational efforts [20]. No prior information regarding the search space characteristics is required. In addition, metaheuristics do not rely on gradient information of the objective functions and the associated constraints with reference to signal timing variables. Further, the process of finding the optimal solution is simple and straightforward. Entailing less complexity than exact methods means that metaheuristics could be easily implemented to solve non-linear complex optimization problems. Furthermore, for many large-scale engineering problems that involve uncertainties (such as traffic flow), obtaining near-optimal solutions within a reasonable time is acceptable. Owing to these benefits, several metaheuristics techniques have been successfully applied for solving TSC optimization problems. Metaheuristics aim at obtaining the optimal values/ranges for various signal parameters that influence the performance of signalized intersections and include variables such as cycle length, green splits, phase sequence, offsets, change interval, etc. These parameters of interest are also known as decision variables. Constraints conditions for signal optimization include lower and upper cycle length, green splits thresholds, etc.

Metaheuristics have been widely applied to solve the TSC problems under a single objective framework known as mono-objective optimization. The single objective optimization can be classified into four main types: i) travel time minimization, ii) delay minimization, iii) throughput maximization, and iv) fuel consumption and exhaust emissions (*CO*, CO_2, NO_x, HC_s) minimization. Mono-objective optimization of traffic signals has some benefits; however, field traffic is highly complex, non-linear, and stochastic in nature, and quite often, the application of multi-objective optimization becomes inevitable. In the process of finding the optimal signal control parameters, traffic engineers usually deal with multiple conflicting objectives. They are seldom interested in knowing the single-objective-based best solution without considering the other objectives. It is quite possible that an indented improvement in one of the objectives may lead to the deterioration of others. Therefore, it is essential to obtain a reasonable trade-off among various clashing objectives while optimizing the signal timing parameters. To address this issue, researchers have proposed bi-objective or multi-objective metaheuristic frameworks which involve more than one objective function to be optimized concurrently. Adoption of multi-criteria/objectives metaheuristics for signal optimization is rational as well as more beneficial.

1.6 Study objectives

This study provides a comprehensive review of metaheuristics techniques applied to signal control optimization. The surveyed literature is categorized based on the types of metaheuristics used, i.e., evolutionary algorithms and swarm intelligence techniques. A total of over 15 metaheuristics optimization techniques in traffic signal control and optimization are presented. Literature is summarized based on classification of techniques, considered optimization objectives, decision variables, and constraints conditions. Finally, based on the identified literature gaps, major challenges and prospects for future research are also proposed.

1.7 Paper organization

The remainder of this work is organized as follows. Section 2 provides research methods and publication analysis of signal control optimization using metaheuristics. Section 3 reviews evolutionary algorithms' metaheuristics for signal optimization. Section 4 provides a summary of swarm intelligence techniques in the context of the subject domain. Section 5 and 6 presents surveys of trajectory-based metaheuristics and few others for TSC optimization. Finally, Section 7 presents the review conclusions and outlines the current challenges and recommendations for future research.

2. Methodology

The relevant literature on TSC was searched (in May 2021) using a detailed systematic review (SR). SR is a formal and standard protocol for performing a review study. To ensure that findings were reached in a valid and reliable manner, the study adopted a three-staged approach, i.e., i) planning, ii) execution, and iii) analysis. The planning stage involved defining the research scope and aims, setting the inclusion and exclusion criteria, and developing the review protocols. The execution stage involved a systematic search using relevant search strings. The relevant publications were meticulously selected by browsing through different electronic databases such as "Google Scholar," Science Direct," Wiley Online Library," "Scopus," "Web of Science," and "IEEE Xplore." To explore these databases, the following "Keywords" were used: "signalized intersections," "traffic congestion," "traffic signal control," "traffic signal timing optimization," "traffic control through metaheuristics," "intelligent traffic control," "dynamic traffic management," "traffic simulation and optimization," "multi-objective traffic control," etc. Titles, keywords, and abstracts of all the downloaded documents were reviewed to determine the appropriate selection of articles for the current study. Additional appropriate publications were added to the list by looking at the references selected

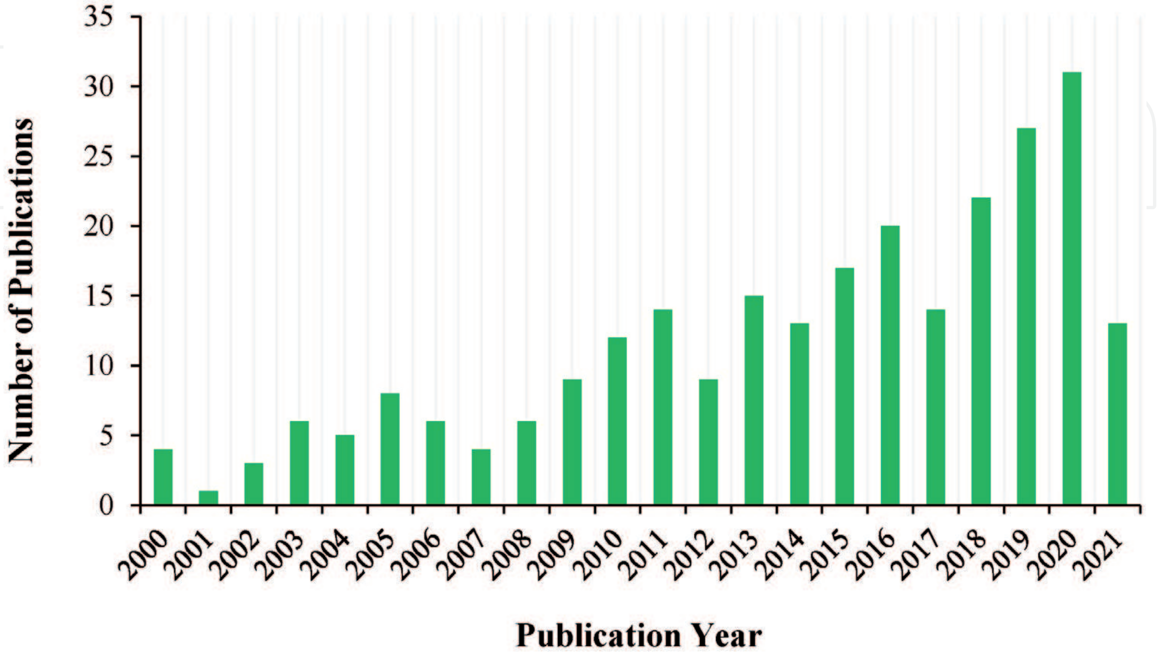

Figure 1.
Chronological distribution of indexed publications on traffic signal optimization using swarm intelligence and evolutionary computation techniques (period 2000–2021).

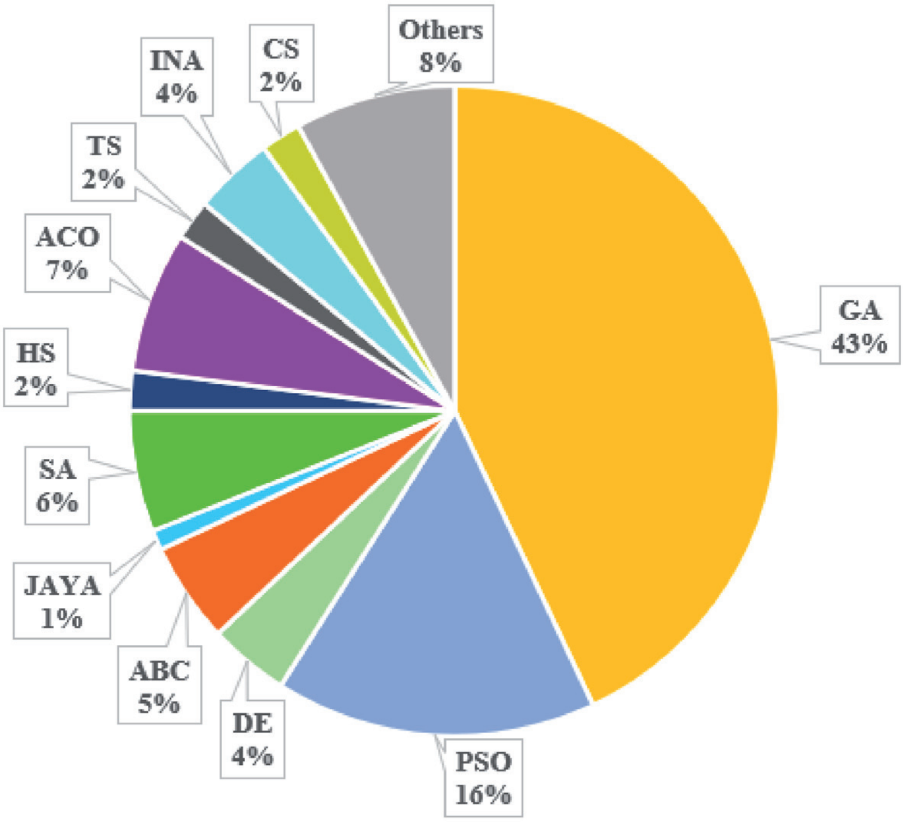

Figure 2.
Percentage distribution of indexed publications on traffic signal optimization based on metaheuristic type.

publications. Publications were searched irrespective of publication year and the number of citations to have the maximum number for initial consideration. Duplicate articles found in various databases were also identified and removed. Non-academic publications, such as magazine articles, company reports, newspapers, presentations, and interview transcripts, were excluded. Finally, the analysis stage involved the classification, categorization, and summarization of the main theme of selected articles.

Figure 1 presents the chronological distributions of shortlisted publications in which metaheuristics are used for solving traffic signal control optimization. It may be observed from the publications reporting in **Figure 1** that is there is a growing trend in the application of metaheuristics in the subject domain. **Figure 2** shows the percentage distribution of published studies in the area of traffic control optimization based on the type of metaheuristic applied. It may be observed from the Figure that the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been widely used for signal optimization.

3. Review of evolutionary algorithms (EAs) for TSC

This section reviews the previous studies in the literature that applied evolutionary algorithms (EAs) for traffic signal control and optimization. EAs are the most widely used metaheuristics optimization techniques across diverse fields of science and engineering. EAs are population-based random search techniques and are inspired by Darwin's theory of natural theory of evolution. The EAs contain a population of individuals, each symbolizing a search point in the feasible solution space exposed to a common learning process while proceeding among different generations. EAs begins with the initialization of random population, which are then subjected to selection, crossover, mutation through various generations so that offsprings generated evolve toward more favorable regions in the search space. At each generation, the fitness of the population is evaluated, and those with better fitness values are selected and recombined that have an increased probability of improved fitness. The program is iteratively repeated until it converges to the best (or near-optimal) solutions. The basic structure of EAs remains similar for all the algorithms under its family. **Figure 3** presents the sample structure of EAs and their working principle. The following passages provide a brief explanation of

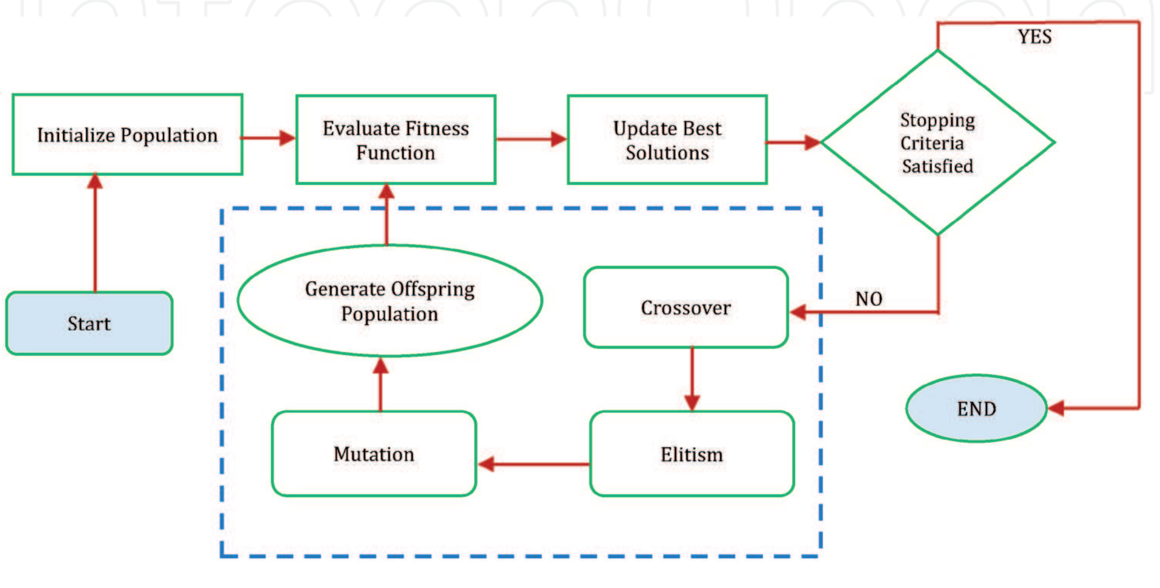

Figure 3.
General flow depicting the search mechanism of EAs.

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S.No	Metaheuristic Used	Optimization Objectives							Reference
		Delay	Stops	throughput	Travel time	Queue	Emissions	Fuel Consumption	
1	GA	✓							[21]
2	GA	✓	✓						[22]
3	DE						✓	✓	[23]
4	GA	✓							[24]
5	DE	✓		✓					[25]
6	DE	✓							[26]
7	GA	✓					✓		[27]
8	GA	✓					✓		[28]
9	GA and DE	✓							[29]
10	GA	✓					✓	✓	[30]
11	DE	✓				✓			[31]
12	GA						✓	✓	[32]
13	GA	✓							[33]
14	NSGA			✓		✓			[34]
15	NSGA-II	✓	✓				✓	✓	[35]
16	GA	✓							[36]
17	DE	✓		✓					[37]
18	GP	✓							[38]

Table 1.
Summary of previous studies on traffic signal optimization using EAs.

various EAs employed in the field of traffic signal optimization. **Table 1** presents a summary of previous studies that have applied EAs for traffic signal control and optimization.

3.1 Genetic algorithm

Genetic algorithm is the most widely used method for traffic light optimization. John Holland initially proposed the GA metaheuristic in 1975 [39]. GA search mechanism for finding the optimal solution of an objective function mimics the natural selection process of the evolutionary theory of nature, which supports the "survival of the fittest" concept. It is a population-based technique that involves the ranking of individual members of the population according to their fitness.

The search process of the optimal solution begins with the initialization of a random population of solutions. The offspring population is created by iteratively applying various genetic operators such as crossover, mutation, elitism, etc. until the stopping criteria are satisfied. In literature, many studies have demonstrated the robustness of GA for adaptive traffic signal control. For example, Foy et al. utilized GA for traffic light optimization, considering delay time minimization as the objective function [36]. The number of initial GA generations was varied over five GA traffic runs. The optimal fitness value was achieved for populations ranging between the 20th to 30th generations with an average vehicle waiting time of around 40 seconds. GA was noted to yield rational signal timing plans reducing the timing delay significantly compared to the existing traffic control scheme. In their study, Rahbari et al., studied that traffic control at the signalized intersection with GA could reduce the congestion [40]. Yang and Luo adopted a hybrid GA simulated annealing (GA-SA) for signal control optimization at isolated signalized intersections considering delay as the objective function [41]. Empirical results showed that GA produced a rational signal timing plan compared to fixed control scenarios. A study conducted by Mingwei et al. proposed the application of multi-objective for intelligent traffic management at an isolated signalized intersection for a case study in China [42]. The considered optimization objectives included; average vehicle delay, vehicular stops, and fuel consumption. It was found that the optimized signal timing plan from GA significantly improved the considered traffic performance measures.

In another study, Turki et al. proposed a multi-objective NSGA-II to optimize various measures of effectiveness (such as delay, stops, fuel consumption, and emissions) at isolated signalized intersections in the city of Dhahran, Saudi Arabia [35]. Study results were compared with Synchro traffic simulation and optimization tool, and the results for a typical intersection are shown in **Figures 4** and 5. All the performance measures witnessed considerable improvement for the optimized signal timing plan obtained using an NSGA-II optimizer. **Figure 4 (a–d)** depicts the evolution of the four selected performance measures (delay, stops, fuel consumption, and emissions) against the number of iterations for three random initial populations. It may be noted that all the algorithms converged to their respective objective functions at approximately 70 to 100 generations. Comparing the random initial populations, population size 30 for all cases yielded the best results.

Figure 5 shows the performance comparison of NSGA-II and Synchro signal control strategies for the selected measures of effectiveness (delay, stops, fuel consumption, and emissions). It may be noted from the Figure that the NSGA-II optimizer outperformed the Synchro results for all the performance measures.

Li et al. also investigated the applicability of NSGA-II for solving signal control optimization problems [34]. Average queue ratio and vehicle throughput were the objective functions. The algorithm's results were validated on a microscopic traffic

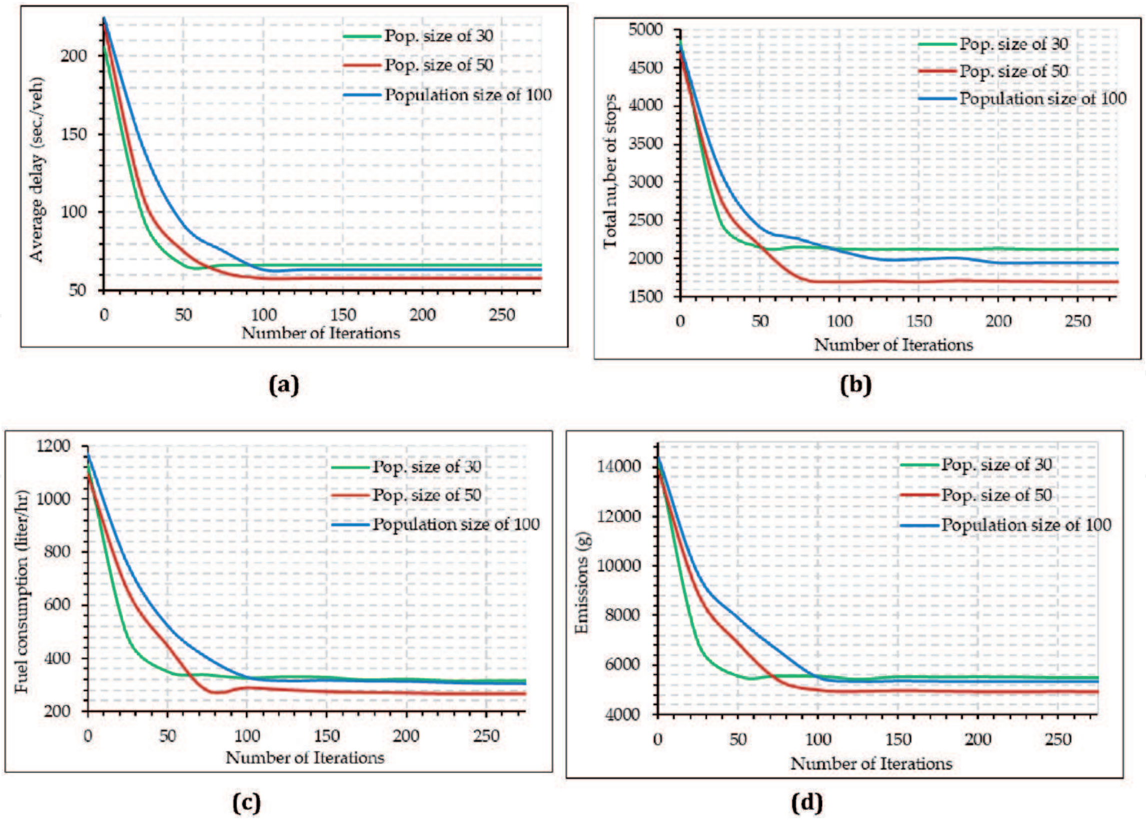

Figure 4.
Evolution of different performance measures against NSGA-II iterations; (a) delay evolution, (b) number of vehicle stops evolution, (c) fuel consumption evolution, (d) emission evolution. Reprinted with permission from Ref. [35] copyright (2021), MDPI.

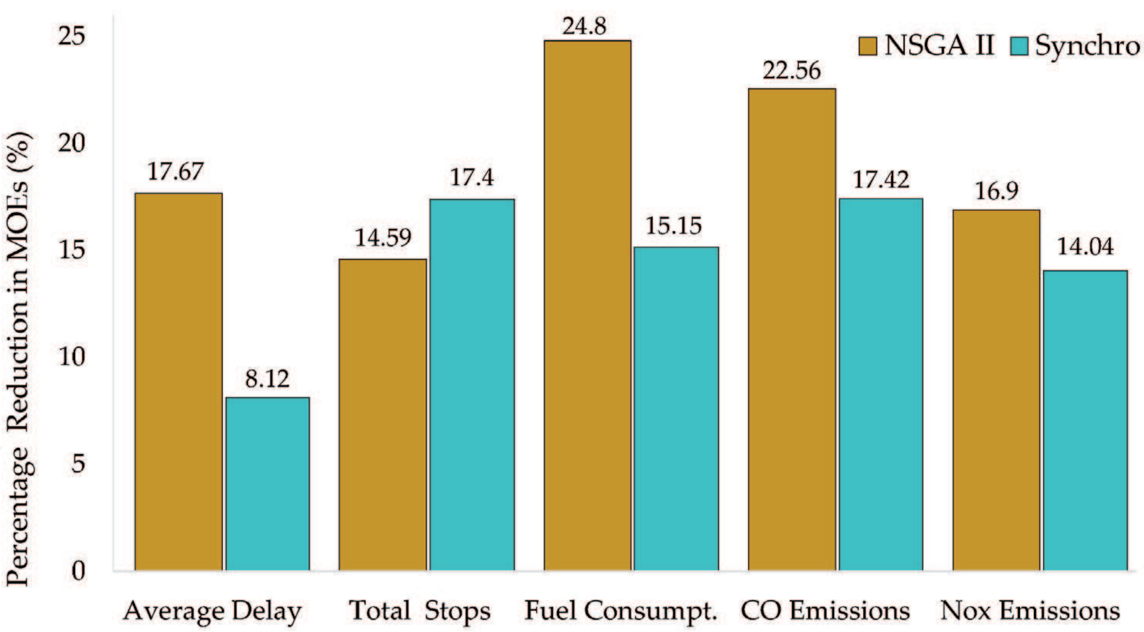

Figure 5.
Comparison of NSGA-II and synchro optimizers for various traffic performance measures. Reprinted with permission from Ref. [35] copyright (2021), MDPI.

simulation tool, VISSIM. Kwak et al. developed a GA traffic optimizer to evaluate the influence of traffic light setting on vehicle fuel consumption and emissions [32]. Model results were compared with TRANSIM, a microscopic traffic simulator. It was observed that the proposed GA traffic optimizer could reduce exhaust emissions by approximately 20% and fuel consumption in the range of 8–20%. In another study, Kou et al. employed multi-criteria GA for optimizing the signal timing plan of signalized junctions and compared the results with the highway capacity manual (HCM) method [28]. The study considered several optimization objectives such as stops, delays, and emissions. A reasonable trade-off established an optimal Pareto front among different conflicting objectives. Study results demonstrated the superior performance of the proposed GA traffic control scheme compared to the HCM method in terms of all the optimization objectives. Guo et al. developed a model for area-wide intersection traffic control in the central business district (CBD) area of Nanjing, China [43]. Capacity ratio, turning movement delay, and travel time was the three chosen objective functions. Computational experiments results showed significant mobility improvement compared to existing conditions. Study results were also validated in PARAMICS traffic simulation tool. In their study, Dezani et al. have shown that simultaneous optimization of traffic lights via GA and vehicle routes could significantly reduce the vehicle travel time compared to optimization considering only routes [44]. In another study, Tan et al. proposed a new Decentralized Genetic Algorithm (DGA) for signal timing optimization of traffic networks under oversaturated traffic conditions [45]. Average vehicle delay was used as the performance metric to evalauate the performance of proposed algorithm. Simulation results showed that DGA could effectively optimize the traffic light setting and reduced the average network delay.

3.2 Differential evolution (DE)

Differential evolution is another population-based metaheuristic technique initially proposed by K.V. Pricein 1995 [46]. DE is characterized by its robustness, fast convergence to the objective function, and simplicity. Though the method has been successfully used for numerous applications across different disciplines, only a few studies have adopted DE for urban traffic control and management [25–29]. For example, in their recent study, Jamal et al. compared the performance of GA and DE for optimizing traffic lights at isolated signalized intersections in the city of Dhahran, Saudi Arabia [29]. Average delay time minimization was the objective function. The study concluded that both GA and DE could yield intelligent and rational signal timing plans, reducing the intersection average delay between 15 and 35%. DE was noted to converge to objective function faster than DA over several simulation runs. Similarly, in another study, Liu et al. proposed bacterial foraging optimization-based DE algorithm for optimizing delay at signalized intersections [37]. To improve convergence precision, DE was utilized for updating the bacteria position during the chemotaxis process. The proposed scheme yielded very promising results, reducing the intersection delay by over 28% compared to only 5% obtained by GA optimization. In their study, Korkmaz et al. suggested three different types of delay differential evolution-based delay estimation models (DEDEM), i.e., linear, quadratic, and exponential [47]. The researchers reported that all the proposed models effectively predicted the vehicle delay estimates in terms of relative errors between estimated and simulated values; however, quadratic DEDEM methods outperformed other models. Ceylan also approached the signal control optimization problem using the metaheuristic DE and Harmony-Search (HS) for network-wide traffic control and optimization [48]. Study results showed that DE algorithms yielded better results compared to HS.

In another research study, Yunrui et al. proposed multi-agent fuzzy logic control based on DE to optimize delay and queue length through a network of eleven intersections in the urban traffic context [31]. DE was used to decide and optimize the parameters of the fuzzy systems because it is easy to understand and implement.

Empirical results revealed that the proposed method could substantially improve the network performance measures such as average vehicle delay, traffic throughput, and queue length. In a recent study, Liu et al. have proposed an improved adaptive differential evolution (ADE)-based evolvable traffic signal control (EvoTSC) scheme for global optimization of different traffic performance measures on large scale urban transportation networks [49]. The proposed TSC method was compared with a conventional TSC scheme on two practical and three synthetic transportation networks with varying traffic flow demands and different physical scales. Comparison results indicated that the DE-based EvoTSC method significantly outperformed its counterpart under all the considered scenarios. Zhang et al. also applied an online intelligent urban traffic signal control approach using multi-objective DE for real-time traffic control and optimization [50]. Experimental results showed that the proposed approach provides a more robust configuration of traffic signal phases and has relatively better real-time performance than the traditional traffic control scheme.

3.3 Genetic programming (GP)

Genetic programming (GP) is another population-based metaheuristic technique that belongs to the family of evolutionary algorithms [51]. GP is an extension of GAs that allows for deep exploration of space on computer programs. GP starts with a population of random programs (candidate solutions) that are fit for applying evolutionary operators similar to genetic processes, thereby simulating the fundamental principles of Darwin's evolution theory [52]. GP follows an iterative process to breed the solutions to problems using the probabilistic selection procedure for the carryover of fittest solutions to the offerings by applying genetic operators such as crossover and mutation. In literature, not many studies have focused on applications of GP for traffic analysis and management in urban transport networks. Montana and Czerwinski used a hybrid GA with strongly typed GP (STGP) for intelligent control and optimization of evolving traffic signals on a small-scale transport network [53]. Numerical simulation results showed that the proposed hybrid STGP model could effectively improve network performance under varying traffic demands.

A study conducted by González also proposed the application of GP for solving signal control problems [54]. This study considered four different traffic scenarios with properties and traffic conditions in a previous study [55]. Study results were also validated using the microscopic traffic simulator tool SUMO. Findings showed that GP could provide competitive and robust results for all the tested scenarios. However, the highway/network scenario had a more pronounced performance improvement (having an improvement of 10.34%) than the isolated intersection scenario (with an improvement of 4.24%). In another study, Ricalde and Banzhaf adopted an improved GP with epigenetic modifications for traffic light scheduling and optimization under dynamic traffic conditions [56]. Extensive simulation analysis revealed that the proposed model improved the network performance compared to standard GP and other previously used methods. This study, however, did not use any real-world data for validation purposes. In another study, the authors used a similar GP approach with epigenetic modifications (EpiGP) to design and evolve traffic signals using real-time field traffic data [38]. Results indicated significant improvement in network performance compared to conventional methods, including standard GP, static, and actuated traffic control techniques.. Over 12% improvement in average delay was reported under high-density traffic conditions.

4. Review of swarm intelligence (SI) techniques for TSC

This section reviews the previous studies in the literature that applied swarm intelligence (SIs) techniques for traffic signal control and optimization. SI is another class metaheuristics that are increasingly used for various engineering and industrial applications. The search mechanisms of SI are believed to be inspired by human cognition representing the individual's interaction in a social environment. For this reason, SI techniques are also sometimes called "behaviorally inspired algorithms." In SI algorithms, each swarm member has a stochastic behavior due to their perception of the neighborhood and acts without supervision. By collective group intelligence, swarm utilizes their resources and environment effectively. The primary attribute of a swarm system is self-organization, which assists in evolving and obtaining the desired global level response by effective interactions at the local level. Just like EAs, SIs are population-based iterative procedures. After randomly initializing the population, individuals are evolved across different generations by mimicking the social behavior of animals or insects to reach the optimal solutions. However, SIs do not involve the use of evolutionary operators like crossover and mutation like EAs. Instead, a potential solution modifies itself based on its relationship with the environment and other individuals in the population as it flies through the search space. The following passages provide a brief explanation of various swarm intelligence techniques employed for solving signal control optimization problems. **Table 2** presents a summary of previous studies that have applied SIs for traffic signal control and optimization.

4.1 Particle swarm optimization (PSO)

Particle swarm optimization is a population-based swarm intelligence technique that was first introduced in 1995 by Eberhart and Kennedy. In the PSO algorithm, every potential solution is referred to as a particle representing a location in the problem space. The entire population of potential solutions (particles) is called the swarm. PSO search mechanism for global optima is inspired by birds in which each particle can update its velocity and position by using local and global best values. PSO is yet another widely used optimization algorithm for signal control problems. For example, Celtek applied PSO for real-time traffic control and management in the city of Kilis city in Turkey [77]. Algorithm performance was investigated in real-time using the SUMO traffic simulator. Social Learning-PSO was introduced as an optimizer for the traffic light. Empirical results obtained using the proposed PSO architecture resulted in travel time by 28%. The algorithms performed well both for undersaturated and oversaturated traffic conditions. Gokcxe and Isxık proposed a microscopic traffic simulator VISSIM-based PSO model for optimizing vehicle delay and traffic throughput using field data from28 signalized roundabout in Izmir, Turkey [64]. The simulation tool was used to evaluate the solutions obtained by PSO. Optimization of traffic signal head reduced the average delay time per vehicle by approximately 56% and increased the number of passing vehicles by 9.3%. In their study, Jia et al. employed multi-objective optimization of TSC using PSO [72]. The optimization objectives included average vehicle delay, traffic capacity, and vehicle exhaust emissions. The validity of the algorithm was examined by applying it to the real-time signal timing problem. The suggested algorithm provided competitive performance for all the MOEs compared to other efficient algorithms such as NSGA-II, IPSO, and GADST.

Abushehab et al. compared PSO and GA techniques for signal control optimization on a network of 13 traffic lights [78]. SUMO was used as a simulator tool for the network. Both the algorithms yielded systematic and rational signal timing plans;

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S.No	**Metaheuristic Used**	**Optimization Objectives**							**Reference**
		Delay	**Stops**	**throughput**	**Travel time**	**Queue**	**Emissions**	**Fuel Consumption**	
1	ACO	✓	✓	✓					[57]
2	AIS			✓		✓			[58]
3	GWO					✓			[59]
4	ABC	✓	✓						[60]
5	ACO	✓	✓						[61]
6	BA				✓	✓			[62]
7	CS	✓							[63]
8	PSO	✓			✓				[64]
9	PSO	✓	✓						[65]
10	BA				✓				[66]
11	PSO	✓							[33]
12	PSO						✓	✓	[67]
13	ABC	✓							[68]
14	ABC	✓	✓						[60]
15	PSO	✓				✓	✓		[40]
16	ACO	✓							[69]
17	CS	✓							[70]
18	ACO			✓	✓				[71]
19	PSO	✓		✓			✓		[72]

S.No	Metaheuristic Used	Optimization Objectives							Reference
		Delay	Stops	throughput	Travel time	Queue	Emissions	Fuel Consumption	
20	PSO					✓			[73]
21	PSO	✓							[74]
22	INA	✓		✓					[75]
23	FFA					✓			[76]

Table 2.
Summary of previous studies on traffic signal optimization using SI techniques.

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however, some algorithm variants were found to be more efficient than the others. In their study, Angraeni et al. proposed a modified PSO (MSPO) and fuzzy neural network (FNN) for optimizing signal cycle length at an isolated intersection [79]. Simulation results using PSO led to a reduction in MSE value from 6.3299 to 2.065, while network performance was improved by 4.26%. The accuracy of the training process using MPSO was higher than FNN. Chuo et al. reported a significant decrease in vehicle queue length by using PSO as a traffic signal optimizer [73]. In another study, Garcıa-Nieto et al. applied PSO to optimize the cycle program of 126 traffic signals located in two large and heterogenous metropolitans of cities of Bahıa Blanca in Argentina and Malaga in Spain [80]. The Obtained solutions were validated using the traffic simulation package SUMO.

In comparison to the existing pre-defined traffic control schemes, PSO achieved significant quantitative improvement for both the objectives, i.e., overall journey time (74% improvement) and the number of vehicles reaching their destinations (31.66%) improvement). In another study, a researcher proposed an improved PSO architecture by combining traditional PSO with GA for multi-objective traffic light optimization. The selected performance indexes included vehicular emissions, vehicle delay, and queue length [40]. The authors reported that the improved PSO method has a quick response and higher self-organization ability which is beneficial for improving the efficiency of traffic signal control.

Olivera et al. investigated the applicability of PSO to reduce vehicular exhaust emissions (CO and NOx) and fuel consumption considering large-scale heterogeneous urban scenarios in the cities of Seville and Malaga in Spain [67]. Study results showed that the proposed signal control strategy could significantly reduce the exhaust emission (CO by 3.3% and NOx by29.3%) compared and fuel consumption (by 18.2%) compared to signals designed by human experts. In their study, Qian et al. designed a simulation protocol for traffic different signal parameters such as cycle, green signal ratio, and phase difference using three Swarms Cooperative-PSO algorithms [74]. The considered optimization objectives included average vehicle delay and average parking number per vehicle. Algorithm simulation results were validated using traffic simulator CORSIM. Lo and Tung compared the performance of PSO and GA-based signal control along four intersections on an urban arterial and noted that the PSO algorithm outperformed GA both in terms of speed convergence and accuracy of search [81]. A couple of other recent studies also demonstrated the adequacy and robust performance of PSO for TSC and optimization [82, 83].

4.2 Ant colony optimization (ACO)

Ant Colony optimization is a swarm intelligence method-based optimization technique that mimics the natural behavior of ants in finding the shortest path from an origin to a food source [84]. In ACO, the path of every ant from origin to destination is considered as a possible solution. ACO has been widely used for traffic signal optimization. In their study, Putha et al. used ACO for traffic signal coordination and optimization in the context of an oversaturated urban transport network [85]. The authors reported that ACO could provide reliable solutions of optimal signal timing plan compared to GA. Yu et al. also applied ACO for intelligent traffic control at signalized intersections considering vehicle waiting time as the optimization objective [86]. The authors reported that ACO outperformed the traditional traffic actuated scheme, predominantly during traffic flow periods. He and Hou also proposed the application of a multi-objective ACO algorithm for the timing optimization of traffic signals [57]. Several parameters such as vehicle delay, number of stops, and traffic capacity performance indices were chosen as performance indexes. Numerical simulation results demonstrated that ACO is a simple and robust technique for signal control optimization problems. The proposed ACO technique significantly improved the selected performance indicators compared to Webstar and GA algorithms.

In another study, ACO optimized the timing plan for traffic lights at isolated signalized intersections [61]. All the selected intersection measures of effectiveness (MOEs), including vehicle delay, parking rate, and the number of stops, were improved by a fair margin. Sankar and Chandra proposed a multi-agent ACO for effective traffic management on a network level [69]. The authors concluded that the method could be pretty useful in reducing average vehicle delays and traffic congestion under varying traffic conditions. Haldenbilen et al. developed an ACO-based TRANSYT (ACOTRANS) model for area traffic control (ATC) through a coordinated signalized intersection networks under different traffic demands [87]. A total of 23 links were considered for the analysis, and the network Disutility Index (DI) was chosen as the primary performance index. A comparative analysis of the network's PI obtained using TRANSYT-7F with hill-climbing (HC) optimization and TRANSYT-7F with GA was also performed. Study results showed that the proposed ACOTRANS improved the network's PI by 13.9% and 11.7% compared to its counterparts TRANSYT-7F optimization with HC and GA. Li et al. compared ACO and Fuzzy Logic for optimizing traffic signal timing in a simulated environment [88]. Traffic capacity and vehicular delay were considered as the objective functions and did not consider pedestrian traffic. The validity of proposed algorithms was tested using actual time-period and conventional algorithms. Jabbarpour et al. conducted a detailed review of the literature focused on applying ACO evolutionary algorithms for the optimization of vehicular traffic systems [89].

Rida et al. proposed ACO for real-time traffic light optimization problems at isolated signalized intersections [71]. Objective functions include minimizing the vehicle waiting time and increasing the traffic flow. The proposed model yielded robust performance compared to fixed time signal controller and other dynamic signal control strategies. Renfrew and Yu, in their studies, also reported that ACO demonstrated robust performance compared to actuated control in optimizing signal timing plan, particularly under high traffic demand [90, 91]. Srivastava and Sahana proposed a novel hybrid nested ACO model intending to reduce the vehicle waiting time at signalized intersections [92]. The proposed model was also compared with the hybrid nested GA model. Results showed that nested hybrid models outperformed traditional ACO and GA-based traffic control.

4.3 Artificial bee colony (ABC)

The traditional algorithms used for training carry some drawbacks of getting stuck in computational complexity and local minima. The artificial bee colony (ABC) algorithm is a revolutionary approach developed by Karaboga et al. [93]. ABC has good exploration capabilities in finding optimal weights during the training process [94]. ABC algorithm operates on the principle of foraging behavior of honeybees in seeking quality food. Each cycle of the search comprising three steps: sending employed bees onto the food source to measure nectar amount; selecting food source by onlookers once the information is shared by employed bees, and sending the scouts for discovering new food source [95].

ABC algorithm is widely used in optimizing traffic-related problems by previous researchers [60, 68, 96]. Zhao et al. investigated a typical intersection as a case study at Lanzhou city [60]. The green time length of each phase of the signal cycle and signal cycle were considered as decision variables. Favorable convergence was achieved using different setting parameters of the algorithm. The effect of signal cycle on control targets resulted that vehicle delays will increase with the signal cycle; however, the stops will decrease. In comparison to non-dominating sorting genetic algorithm and webster timing algorithm, ABC manifested better convergence. In another study, Dell'Orco et al. developed TRANSYT-7F to investigate network performance index (PI) for optimizing signal timing [96]. Results revealed that PI's of the network in the case of ABC improved by 2.4 and 2.7% compared to genetic algorithm and hill-climbing method.

4.4 Cuckoo search (CS)

Cuckoo search (CS) is a recently developed metaheuristic algorithm developed by Yang and Deb [97], inspired by the natural breed parasitism of the cuckoo species. For understanding its working principle, consider that each bird lays one egg at a time and dumps it in a random nest which represents a single solution. The nest with high-quality eggs will be moved to the next generation. The number of host nests is fixed, and the egg laid by the cuckoo is discovered by the host bird. In this situation, the host bird either gets rid of the egg or abandons the nest by developing a new nest [98]. Few studies interpret CS as more efficient than PSO and GA [97].

Araghi et al. employed neural networks (NN) and adaptive neuro-fuzzy inference system (ANFIS) to optimize the results of CS in the case of intelligent traffic control [63]. The results were compared to that of the fixed time controller. It was revealed that the CS-NN and SC-ANFIS showed 44% and 39% improved performance against the fixed-time controller. Similarly, in another study, the authors evaluated the performance of ANFIS using CS for optimization of controlling traffic signals for an isolated intersection [70]. Improved performance of ANFIS-CS was obtained against fixed-time controller.

4.5 Bat algorithm (BA)

Bat algorithm (BA), initially developed by Xin-she yang in 2010, is inspired by the echolocation of microbats [99]. The working principle of BA encompasses three basic steps: bats use echolocation to sense the distance bifurcating the food and barrier; bats randomly fly with variable loudness and wavelength.; bats automatically adjust their wavelength and pulse depending upon the proximity of food/prey [100].

Srivastava, Sahana used BA to determine the wait time at a traffic signal for the discrete microscopic model [66]. The study was based on 12 nodes and four intersections. The results were compared to GA. Relatively higher performance was obtained for BA algorithm as compared to GA. Jintamuttha et al. carried experimental simulation for the green time of intersection for ten cycles per run [62]. The results of the experiment were optimized using BA. The average queue length and waiting time improved due to optimization.

4.6 Artificial immune system (AIS)/immune network algorithm (INA)

The immune network algorithm (INA) or artificial immune system (AIS) is another useful optimization algorithm recently practiced for signal control optimization problems. As its name suggests, the working mechanism of this algorithm is inspired by the biological immune system. Immune cells have receptors that can detect harmful pathogens and activate antibodies to fight them, leading to their elimination [101]. Louati et al. applied INA to optimize queue, delay, and traffic throughput at signalized intersections under varying traffic demands [75]. It was found that INA outperformed traditional fixed-time adaptive traffic control strategies and validated the study results through VISSIM, a microscopic traffic simulation platform. In another study, Trabelsi et al. evaluated the performance of AIS to detect and rationally control anomalous traffic conditions through a network of signalized intersections [58]. Simulation results proved the adequacy and robustness of the proposed AIS-based signal control method.

Darmoul et al. employed multi-agent immune network (INAMAS) for optimal control and management of interrupted traffic flow at signalized intersections [102]. The proposed INAMAS models offered an intelligent mechanism that could explicitly capture the disturbance-related knowledge of traffic fluctuations. To demonstrate the efficacy of the proposed model, the authors compared its performance against two widely used signal control strategies, namely fixed-time control and LQF-MWM (longest queue first –maximal weight matching) algorithm. The suggested INAMAS scheme provided a competitive performance in terms of chosen performance indicators, i.e., vehicle queue and waiting times under extreme traffic conditions involving high traffic volume and block approaches. **Figure 6a** plots the average vehicle delay for all the three signal control strategies under various traffic scenarios [102]. For scenario 1 (moderate traffic congestion), the INAMAS algorithm produces approximately a 24% reduction in average delay values compared to the LQF-MWM strategy. For scenario 2 (high-density traffic), the proposed INAMAS optimizer decreased the average delay by nearly 32%. For scenario 3 (extreme congestion), the corresponding improvement by the INAMAS algorithm is about 28%. **Figure 6b** depicts the relationship between the total network delay and simulation time (in minutes) for all three signal optimization strategies [102]. It is evident from the results in **Figure 6b** that during the first 5 minutes, all the controllers have comparable performance. At the end of simulation analysis (after 5 hours), when the traffic density reaches 9600 vehicles per hour, the INAMAS controller achieved better performance compared to others, showing its superior capability to manage large and complex traffic networks.

Moalla et al., in their study, also demonstrated the robustness of AIS for controlling traffic at isolated signalized intersections [103]. However, the authors also emphasized that validation of the proposed AIS scheme is challenging and should be handled carefully. In another study, the author highlighted AIS-based traffic control's significance for network-wide traffic management [104]. Comparative results with TRANSYT 7F showed the superior performance of AIS approach. Galvan-Correa et al. proposed a new metaheuristic known as the micro artificial

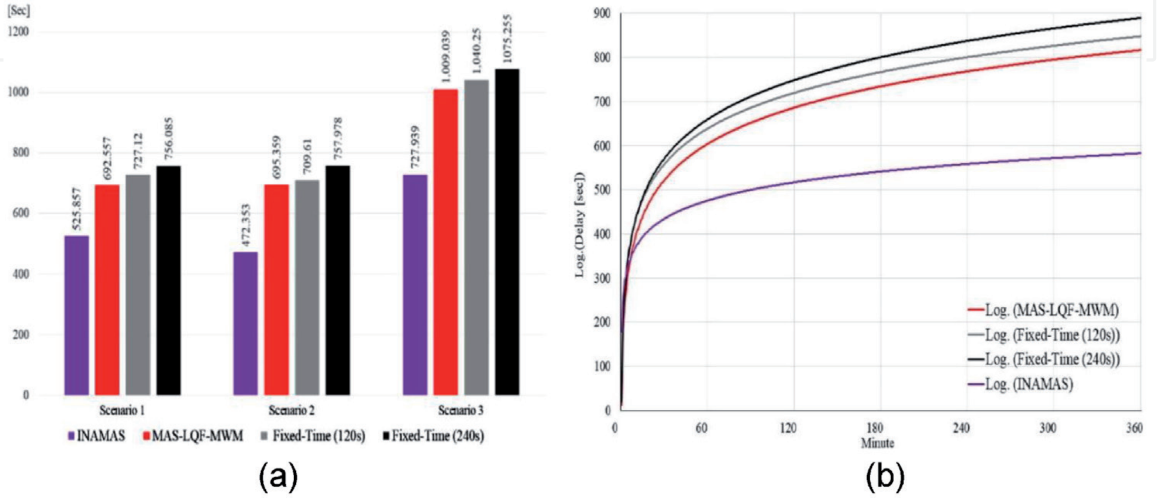

Figure 6.
(a) Comparison of average total delay per vehicle from various optimizers (b) cumulative network delay for scenario 1 for various optimizers Ref. [102].

immune systems (MAIS) to optimize vehicular emission and traffic flow in the city of Mexico [105]. The performance of the suggested MAIS technique was compared with several other metaheuristics, including GA, DE, SA, PSO. Results showed that MAIS achieved better results compared to most of the other metaheuristics. In a recent study, Qiao et al. proposed a novel hybrid algorithm, known as the Immune-Fireworks algorithm (IM-FWA) for effective traffic management on large-scale urban transportation networks [106]. The proposed hybrid algorithm was developed based on fireworks and artificial immune algorithms. A hierarchical strategy was proposed in the framework to avoid possible offsets conflicts and reasonable configuration of intersection offsets. Simulation results showed that the proposed IM-FWA could successfully overcome the shortcomings of FWA and AIS algorithms by providing a better and more rational signal timing plan to effectively reduce traffic flow delays.

4.7 Firefly algorithm (FA)

The characteristic behavior of fireflies is animated by Yang [107] into a nature-inspired meta-heuristic swarm intelligent method called Bat Algorithm. In BA, all fireflies are assumed unisex, and attractiveness is proportional to their brightness, which in turn depends on the distance. Thus, the brightness can be considered a cost function, which is maximized in optimization.

Kwiecień, Filipowicz [studied optimizing costs controlled by queue capacity, maximal wait, and servers [76]. It was deduced that the use of FA could maximize the value of the objective function, and FA converges toward the optimal solution very quickly. Goudarzi et al. [108] investigated traffic flow volume by a probabilistic neural network method called deep belief network (DBN). FA was used to optimize the learning parameters of DBN. As a result, the proposed model predicted the traffic flow with higher accuracy compared to traditional models.

4.8 Gray wolf optimizer (GWO)

Gray wolf optimizer (GWO) is a new metaheuristic technique recently proposed by Mirjalili in 2014 [109]. GWO is inspired by the social hierarchy and hunting behavior of gray wolves. In GWO optimization, the wolves represent a solution set of candidate solutions. The hunting cycle in the GWO commences with the acquisition of a random population of candidate solutions (wolves) followed by identifying optimal prey's locations using a cyclic process. GWO has several advantages compared with evolutionary approaches, easy programming and implementation, algorithm simplicity, no need for algorithm-specific parameters, and lower computational complexity [110]. In recent years, GWO has been increasingly used in diverse disciplines. However, studies on its applications in transportation and traffic engineering in general and traffic control and optimization in particular are very few.

Teng et al. were the first to use a hybrid gray wolf and grasshopper algorithm (GWGHA) algorithm for timing optimization of traffic lights [111]. The obtained solutions were simulated in a microscopic traffic simulator package SUMO. The performance of the proposed GWGHA hybrid algorithm was compared with other metaheuristics like GWO, GOA, PSO, and SPSO2011. Results indicated that the proposed hybrid algorithm provided better solutions than its counterparts because it utilizes the feature of GWO for accelerating the convergence speed while using GOA to diversify the population. In another recent study, Sabry and Kaittan proposed a novel hybrid algorithm consisting of gray wolf and fuzzy proportional-integral (GW-FPI) for active vehicle queue management in an urban context [59].

The proposed traffic controller was compared with PI through repeated MATLAB simulations. Study results indicated the stable and robust performance of the proposed hybrid controller for queue management in a dynamic transport network with varying traffic flow demands.

5. Review of trajectory-based metaheuristics for TSC

This section surveys the previous works that applied trajectory-based metaheuristics techniques) for traffic signal control and optimization. As the name suggests, these algorithms form search trajectories in solution space and iteratively improve the single solution in its neighborhood. Their exploration process starts from a random initial solution generated by another algorithm. At each stage, the current solution is replaced by a better offspring population. Trajector-based metaheuristics are mainly characterized by their internal memory sorting the state of search, candidate solution generator, and selection policy for candidate movement through generations. **Table 3** summarizes the previous works that applied trajectory-based search metaheuristics, hybrid metaheuristics, and others for traffic signal control and optimization.

5.1 Tabu search for signal control optimization

Tabu Search (TS) is a metaheuristic introduced by Fred Glover in 1986 to overcome the local search (LS) problem of existing methods [123]. TS allows the LS heuristic to diversify the search for solution space outside the local optima [124]. One of the important features of TS is its memory function, which can restrict few search directions for a more detailed LS, thereby making it easier to avoid local optimum solutions. By combining the greedy concept and randomization, the TS algorithm could provide an efficient solution to many optimization problems. In literature, only a few studies have focused on the application of Tabu search for signal control optimization. Hu and Chen proposed traffic signal control based on a novel greedy randomized tabu search (GRTS) algorithm considering travel time as the primary optimization objective [118]. GRTS results were compared with a GA-based traffic control scheme using data from a real city network to demonstrate the benefits of the proposed method. Numerical simulation results revealed that over 25% reduction in travel time might be achieved under medium to high traffic demands. In another study, Karoonsoontawong and Woller applied reactive tabu search (RTS) for simultaneous solutions of traffic signal optimization and dynamic user equilibrium problems on two transport networks in a simulated environment [119]. Three different variants of RTS were investigated based on deterministic or probabilistic neighborhood definitions. The performance of all the RTS variants was evaluated using three criteria such as solution quality, CPU time, and convergence speed. Simulation results showed that the RTS approach could provide promising results in terms of improving the overall network performance.

In a recent study, Hao et al. proposed a hybrid tabu search-artificial bee colony (TS-ABC) algorithm for robust optimization of signal control parameters in undersaturated traffic conditions at isolated signalized intersections [68]. This study considered two performance indexes such as average delay and mean-square error of average delay. The proposed signal control optimizer was validated using field data from an intersection in the city of Zhangye, China. Numerical simulation results compared with GA showed that the proposed TS-ABC is better in reducing the traffic delay under varying and heterogeneous traffic conditions. Chentoufi and Ellaia also proposed a hybrid particle swarm and tabu search (PSO-TS) for adaptive

S.No	Metaheuristic Used	Optimization Objectives							Reference
		Delay	Stops	throughput	Travel time	Queue	Emissions	Fuel Consumption	
1	SA-GA	✓							[112]
2	IM-FWA	✓							[106]
3	ISA-GA						✓		[113]
4	SA	✓	✓						[114]
5	HS	✓							[115]
6	HS	✓	✓	✓					[116]
7	JAYA	✓							[117]
8	TS				✓				[118]
9	TS-ABC	✓							[68]
10	TS				✓				[119]
11	PSO-TS	✓							[120]
12	WCO	✓							[121]
13	GHW-GHA	✓		✓					[111]
14	JAYA	✓							[122]
15	GW-FPI					✓			[59]

Table 3.
Summary of previous studies on traffic signal optimization using trajectory-based metaheuristics, hybrid metaheuristics, and others.

traffic lights timing optimization on real-time isolated signalized intersections in the context of Moroccan cities [120]. The authors also highlighted the significance of integrating the proposed PSO-TS model and VISSIM to achieve optimum average delay estimates. Simulation results demonstrated the superior efficiency of the PSO-TS technique against the traditional static models under oversaturated traffic conditions.

5.2 Simulated annealing (SA)

Simulated Annealing (SA), developed by Kirkpatrick et al. is inspired by the statistical mechanics of annealing in solids [125]. For understanding, consider a change in temperature, which causes a change in energy and movement of particles in solids. There is a sequence of decreasing temperature in annealing until criteria are met [126].

Li, Schonfeld [112] reported traffic signal time optimization using metaheuristic capabilities of SA with GA. It was concluded that SA-GA models outperform in optimization compared to individual SA and GA models. Similar results were reported by Song et al. in evaluating the optimized model for reducing traffic emissions on arterial roads [113]. Oda et al. [114] employed SA to optimize traffic signal timing and reported its improved performance as compared to traditional models.

6. Other metaheuristics for TSC

This section reviews the previous works that applied some other metaheuristics for traffic signal control and optimization. These include the harmony search algorithm, water cycle algorithm, and Jaya algorithm. **Table 3** summarizes the previous works that applied trajectory-based search metaheuristics, hybrid metaheuristics, and others for traffic signal control and optimization.

6.1 Harmony search (HS)

The metaheuristic harmony search (HS) algorithm simulates the natural musical improvisation process where the musicians aim to achieve a near-perfect state of harmony [127]. In the HS algorithm, the candidate solution population is known as harmony memory (HM), where every single solution in solution space is referred to as "harmony," which belongs to the "n"-dimensional vector. Though HS has been successfully used for numerous applications across diverse domains, its applications for signal control optimization are limited. In a recent study, Gao et al. applied to HS in addition to four others metaheuristics for traffic signal scheduling (TSS) problems [121]. Experiments were conducted on real-time data from signalized intersections in Singapore to examine the performance of proposed metaheuristics. The authors considered heterogeneous traffic conditions. Simulation results proved the adequacy of all algorithms; however, the hybrid algorithm (ABC-LS) outperformed other techniques in terms of solution quality.

In another study, Ceylan and Ceylan adopted a hybrid harmony search algorithm and TRANSYT hill-climbing algorithm (HSHC-TRANS) for solving stochastic equilibrium network design (SEQND) in the context of optimal traffic signal setting problems [128]. The effectiveness of HSHC-TRANS was evaluated against HS and GA in terms of network performance index (PI). Results showed that the proposed hybrid model yielded about 11% in the network's PI compared to the GA-based model. In another study, Gao et al. addressed the urban traffic signal scheduling problem (TSSP) using a discrete harmony search (DHS) with an ensemble of local search [115]. The primary objective was to minimize the network-wide total delay under a pre-defined finite horizon. Extensive simulation experiments were carried out using traffic data from a partial transport network in Singapore. Comparative analysis showed that the HS algorithm as a meta-heuristic achieved better performance compared to fixed-cycle traffic signal control (FCSC). Dellorco et al. also investigated the applicability of HS for signal control optimization on the two-junction network with the fixed flow on the links [116]. A comparative analysis of HS with GA and HC algorithms showed that HS resulted in a better network's PI compared to its counterparts. Afterward, the validity of the proposed HS algorithm was assessed by applying it to a test network.

6.2 Jaya algorithm

The Jaya algorithm is a recently proposed metaheuristic initially introduced by R.V. Rao [129]. The word Jaya comes from Sanskrit, which means "victory." In the Jaya algorithm, the search strategy always attempts to be victorious by reaching the optimal and best solution, and thus it is named "Jaya." It is arguably one of the simplest and easy-to-implement metaheuristics. The main benefit of Jaya for optimization problems lies in the fact that this algorithm requires only common controlling parameters such as population size and the number of iterations and does not require any additional algorithm-specific constraints/parameters. While this algorithm has been successfully used for several scheduling and optimization problems in recent years, its applications in the domain of traffic scheduling and management are relatively scarce.

A recent study conducted by Gao et al. compared the performance of Jaya algorithms with other metaheuristics (like water cycle algorithm (WCO), genetic algorithm (GA), artificial bee colony, and harmony search (HS), and hybrid ABC-LS) for solving traffic light scheduling problem [121]. Simulation results showed all the algorithms achieved competitive results; however, the hybrid algorithm attained better accuracy and convergence. The proposed models were also tested on real-time traffic and phase data from a network of intersections in the Jurong area of Singapore. In another study, the authors proposed an improved Jaya algorithm for solving traffic light optimization problems in the context of large-scale urban transport networks [122]. The chosen performance index was to minimize the network-wide total traffic delay within a given time horizon. To enhance the search performance in the local search space, a neighborhood search operator was proposed. Experiments were carried out using traffic data for a case study from the Singapore transport network. Study results demonstrated the robustness and better performance of proposed improved Jaya algorithms against standard Jaya algorithm and exiting traffic light control scheme. In another follow-up study, Gao et al. studied large-scale urban traffic lights scheduling problems using three different metaheuristics, namely Jaya, WCO, and HS [117]. The objective function was to optimize the delay time of all vehicles network-wise under a fixed time horizon. This study also proposed a feature search operator (FSO) to improve the search performance of proposed metaheuristics. To examine the efficacy of proposed methods, experiments were carried out using real-time traffic data. It was concluded that metaheuristic-based traffic control could significantly improve the network performance compared to existing traffic control strategies. Numerical simulation results showed that in comparison to feature-based search (FBS), operator for all algorithms improved the total vehicle delay time by more than 26% in their worst case scenarios.

Figure 7a depicts the relationships between total network delay time (sec) and sampling intervals for a typical urban traffic network with 100 junctions from the west Jurong area in Singapore [117]. Minimum (min.), average (avg.)

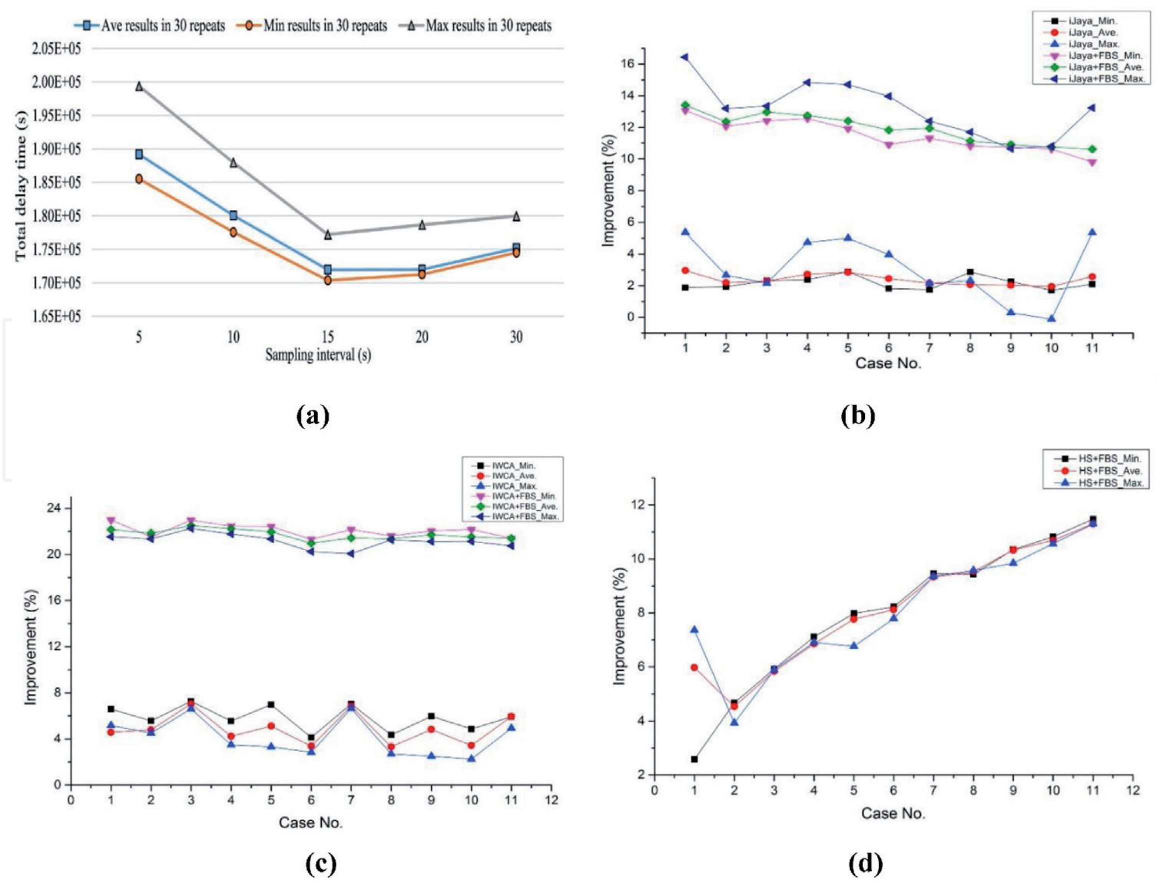

Figure 7.
(a) Results comparison with different sampling times for network of 100 junctions, (b) the % improvement of iJaya and iJaya+FBS with standard Jaya, (c) the % improvement IWCA and IWCA+FBS with standard Jaya, (d) the % improvement HS + FBS and standard HS. Ref. [117].

and maximum (max.) total delay values each for 30 repeats and five sampling intervals (5, 10, 15, 20, and 30 sec) are reported. It is evident from the results that a sampling period of 15 seconds yielded the best results, which were then adopted for subsequent experiments. **Figure 7b** shows the relative percentage improvement in network performance (reduction in network delay) for standard Jaya algorithm with improved Jaya (iJaya), and Jaya with FBS operator (iJaya+FBS) for a sample 11 cases of traffic network from the same study [117]. Compared to standard Jaya, the iJaya yielded the improvements in range for 0–6% for min., avg., and max. Results, while iJaya+FBS algorithm resulted in corresponding improvement values between 9 and 11%. **Figure 7c** depicts the percentage improvement of IWCA and IWCA+FBS algorithms relative to standard WCA optimizer. The IWCA improved the standard WCA in terms of min., avg., and max. Results for 11 test cases in the range of 2–8%, while the corresponding improvement for IWCA+FBS algorithm is approximately 20–24%. **Figure 7d** shows the network performance improvement of standard HS and HS + FBS algorithms for the same network of traffic junctions [117]. The improvement for HS + FBS algorithm compared to standard HS optimizer are between 2 and 12% for min., avg., and max. Results for the considered cases.

Figure 8 presents the graphical comparison among the three optimization algorithms (iJaya+FBS, IWCA+FBS, and HS + FBS) in terms of the average relative percentage deviation (ARPD) of the resulting network delay time values [117]. It is clear from the results that the IWCA+FBS algorithm with an average delay reduction of 28.54% outperformed the iJaya+FBS and HS + FBS having the corresponding values of 28.22% and 27.84%, respectively. Further, all the algorithms yielded an improvement of at least 26% in the worst-case scenarios.

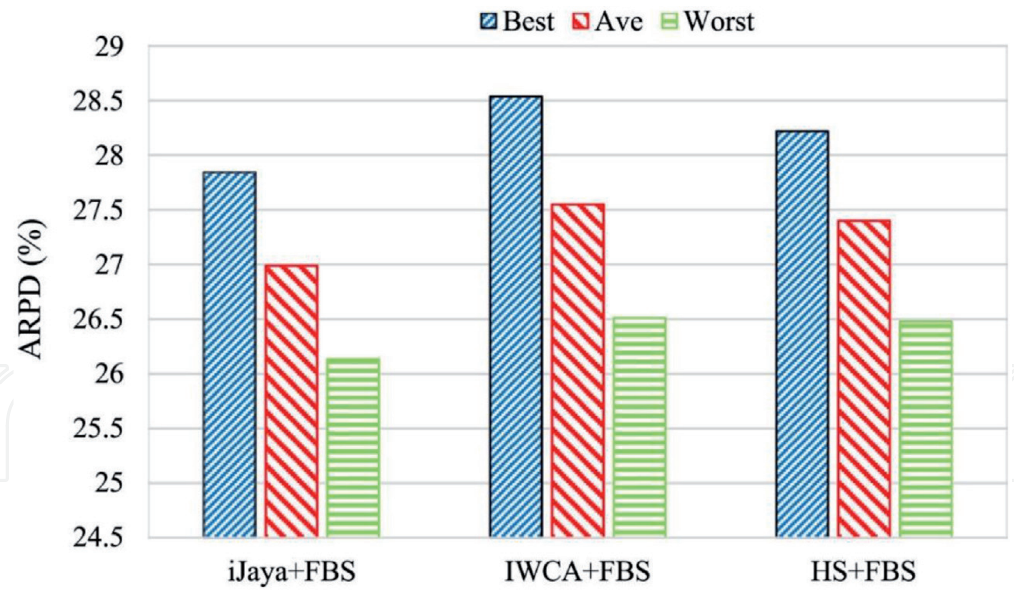

Figure 8.
ARPD improvements comparison for different optimizers. Reprinted with permission from Ref. [117] copyright (2021), Elsevier Ltd.

6.3 Water cycle algorithm (WCA)

The water cycle algorithm (WCA) is another recently proposed metaheuristic whose search mechanism is inspired by the natural water cycle process, where streams and rivers flow down the hill to reach the sea [130]. The surface run-off model is imitated in WCA for updating the current candidate solutions and the generation of new offspring. The effectiveness of WCA has been explored for various applications such as truss structures, constrained and unconstrained engineering design problems [130–133]. However, very few studies have used WCO for traffic control, management, and optimization.

A recent study by Gao et al. proposed the application WCO for traffic signal scheduling and optimization based on actual traffic data from a case study in Singapore [121]. WCO was compared with four other metaheuristics and a hybrid algorithm (ABC-LS), considering the network delay as the main optimization objective. Numerical simulation results proved the benefits of adopting metaheuristic-based traffic control strategies instead of existing fixed traffic light schemes. In another study, Gao et al. compared WCO with the Jaya algorithm and Harmony search using the field traffic data from the same transportation network. The performance metric minimized the network-wide total traffic delay within a given time horizon [117]. The study proposed a neighborhood search operator to enhance the search performance of all the algorithms in the local search space. Study results showed that WCA, with an average better improvement of in network-wide delay (28.54%), outperformed HS (28.22%) and Jaya algorithm (27.84%).

7. Conclusions, current challenges, and future research directions

Traffic control and management using metaheuristics have emerged as an effective solution to mitigate urban congestion. This study provided a comprehensive review of state-of-art research on traffic signal optimization using different metaheuristics approaches. The surveyed literature is categorized based on the nature of applied metaheuristics, i.e., swarm intelligence (SI) techniques, evolutionary algorithms, trajectory-based metaheuristics, and others. Although numerous metaheuristics have been employed for signal optimization, GA, PSO, ACO, and ABC algorithms have been widely explored. Various traffic signal parameters such as cycle length, green splits, offsets, and phasing sequence are considered decision variables to solve signal control optimization problems. Similarly, studies have considered several optimization objectives such as delay, number of stops, travel time, throughput, queue, fuel consumption, exhaust emissions to address the problem. Some studies have adopted single-objective optimization, while others have attempted to solve traffic signal control as a multi-objective optimization problem. However, little work has been done to understand the correlations between the conflicting objectives which is vital for traffic engineers and decision-makers to evaluate their relative importance. Based on the presented survey work, the following passages present key challenges, research gaps, and future research directions in this area.

- The review has shown that most of the previous works have adopted a single metaheuristic method for TSC optimization. However, very few studies have investigated the applicability of hybrid or ensemble metaheuristics for solving TSC optimization problems. In general, hybrid techniques are more useful than traditional metaheuristics. Hence, the application of hybrid metaheuristics for signal optimization could be a promising research direction.

- Traditional evolutionary algorithms and swarm intelligence optimizers could yield acceptable solutions. However, the performance of these optimization techniques may be compared with recent state-of-the-art optimization approaches such as Teaching Learning Based Optimization Algorithm (TLBOA), Gravitational Search Algorithms (GSA), Rock Hyraxes Swarm Optimization (RHSO), hyper-heuristics, which are not explored yet for traffic signal optimization problems.

- The literature review also noted that most previous studies were focused on single-objective optimization; however, traffic engineers often have to deal with multiple conflicting objectives to optimize the performance at the network level. Alternatively, for multiobjective optimization, the vast majority of existing works introduce weights for different objectives and consequently tackle signal optimization as a signal objective optimization problem. To optimize different performance indicators along optimal paretofront, multiple objectives have to be properly optimized. Developing an optimizer for multi-objective scenarios remains a challenging issue and is worth exploring in future studies.

- Objective functions based on energy consumption and exhaust emissions have become a topic of increasing interest in recent years. From the reviewed literature, it was concluded that various approximate fuel consumptions and emission models were used for signal control optimization. Application of such approximate models could lead to an un-realistic traffic light setting. Future studies should consider the calibration of fuel consumption and emission models for a given network.

- It was also evident from the presented literature that there is a shortage of research on statistical performance evaluation of proposed metaheuristics. Therefore, it would be interesting to explore the statistical analysis of such optimization strategies in terms of worst, average, and best results. Likewise, statistical significance tests may be conducted to compare the performance among various metaheuristics in solving signal optimization problems.

- Lack of appropriate validation protocol is another important issue. Some studies have employed mere traffic simulation platforms to assess the validity of applied metaheuristics, while others have used them for isolated intersection scenarios or small traffic networks. Network optimization has become popular in recent years. For achieving desired improvements at the network level, the methods should be tested for large-scale complex transportation networks.

- The surveyed literature also indicated that most previous studies considered only vehicular traffic and neglected the pedestrian traffic in solving the TSC problem using metaheuristics. It is important to consider all forms of traffic and driving systems to improve the overall efficiency of the transport system.

- The surveyed literature also revealed that many studies develop metaheuristic-based traffic control considering specific traffic demand conditions, neglecting the other potential scenarios. It is essential to consider all ranges of traffic flow conditions (undersaturated, saturated, and oversaturated flow conditions) and traffic disturbances in developing metaheuristic to address TSC optimization problems.

- The accuracy and reliability of the signal timing plan obtained using metaheuristics are highly dependent on the accuracy of traffic flow prediction models. In recent years, with rapid advances in computational power, big data technology has been successfully used for accurate traffic flow prediction. Therefore, the application of metaheuristics coupled with big data technology for traffic signal optimization appears to be another interesting research direction.

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Conflict of interest

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