# Application of Metaheuristics in Signal Optimisation of Transportation Networks: A Comprehensive Survey

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**Abstract**

With rapid population growth, there is an urgent need for intelligent traffic control techniques in urban transportation networks to improve the network performance. In an urban transportation network, traffic signals have a significant effect on reducing congestion, improving safety, and improving environmental pollution. In recent years, researchers have been applied metaheuristic techniques for signal timing optimisation as one of the practical solution to enhance the performance of the transportation networks. Current study presents a comprehensive survey of such techniques and tools used in signal optimisation of transportation networks, providing a categorisation of approaches, discussion, and suggestions for future research.

**Keywords**

Signal optimisation, Intelligent control, Transportation, Network, Metaheuristics.

## Contents

## Nomenclature

ABC Artificial bee colony

ACO Ant colony optimisation

AFSA Artificial fish swarm algorithm

AVSM Average vehicle speed maximisation

BA bat algorithm

BBO Biogeography-based optimisation

BFOA Bacterial foraging optimisation algorithm

CFP Cyclic flow profile

CM Conflicts minimisation

CS Cuckoo search

| | |
|---|---|
| CT | Cycle time |
| DE | Differential evolution |
| DIM | Delay imbalance minimisation |
| DoD | Degree of detachment |
| DTM | Delay time minimisation |
| DUM | Drivers’ unhappiness minimisation |
| EEM | Excess exposure minimisation |
| EM | Emissions minimisation |
| FCM | Fuel consumption minimisation |
| GA | Genetic algorithm |
| GOA | Grasshopper optimisation algorithm |
| GSA | Gravitational search algorithm |
| GT | Green time |
| GTO | Green times oscillations |
| GWO | Grey wolf optimiser |
| HC | Hill climbing |
| HS | Harmony search |
| ICA | Imperialist competitive algorithm |
| JA | Jaya algorithm |
| KH | Krill herd |
| ML | Machine learning |
| N/A | Not available |
| NBL | Number of bus lanes |
| NC | Number of cars |
| NP | Number of phases |
| NSGA-II | Non-dominated sorting genetic algorithm II |
| NSM | Number of stops minimisation |
| OD | Origin destination |

| | |
|---|---|
| OIO | Optics inspired optimisation |
| OT | Offset time |
| PDUEC | Predictive dynamic user equilibrium condition |
| PFD | Path flow distribution |
| PI | Performance index |
| PS | Phase sequence |
| PSO | Particle swarm optimisation |
| QM | Queue minimisation |
| RGRTM | Ratio of green to red times minimisation |
| RM | Recall Mode |
| RS | Random search |
| SA | Simulated annealing |
| SCM | Schedule adherence minimisation |
| SCPG | SUMO cycle programs generator |
| SFLA | Shuffled frog-leaping algorithm |
| SM | spillover minimisation |
| SS | Scatter Search |
| STM | Stop time minimisation |
| SUMO | Simulation of urban mobility |
| TLBO | Teaching-learning-based optimisation |
| TM | Throughput maximisation |
| TP | Timing plans |
| TS | Tabu search |
| TS | Traffic safety |
| TST | Turning signal type |
| TTM | Travel time minimisation |
| VT | Vehicle extension |
| VVSM | Variance of vehicle speeds minimisation |
| WCA | Water cycle algorithm |
| WOA | Whale optimisation algorithm |

## 1 Introduction

Recent decades have seen rapid population growth and the emergence of various transportation modes in cities creating an urgent need for performance optimization of transportation systems to enhance the capabilities of transportation networks. Although the capacity expansion by adding new infrastructure to the existing transportation networks is one solution to this problem, the growth rate of transportation demand often outstrips the capacity to construct new transportation infrastructure. Furthermore, building new streets and increasing traffic capacity is unlikely to be an optimal choice when environmental, economic and urban planning constraints are considered. An additional consideration is the potential for road networks to be affected by Braess's paradox (Brockfeld, Wagner, 2003) where additional capacity can, counterintuitively, lead to the slowing of traffic through the network. These considerations therefore increase the significance of performance optimisation of the current transportation infrastructure operation without the requirement to invest in additional capacity.

In most of the major cities of the world, traffic congestion is one of the most serious daily problems in urban transportation networks and increases fuel consumption and the emission of pollutants. In an urban transportation network, the intersections (junctions) and their traffic lights play an important role in the formation of traffic congestion. Traffic signals control the vehicles and pedestrian movements at intersections, and have a significant effect on reducing congestion, improving safety, minimising delays, prioritizing public transport, and improving environmental pollution. The optimisation of signal timings is one of the practical solutions that can be performed to enhance the performance of the network as well as avoiding traffic congestion. As a result, developing efficient signal optimisation techniques to enhance the performance of urban networks is a significant research topic of interest in the field of transportation engineering.

Recently, some interesting literature surveys have been performed by researchers to show the necessity of controlling traffic signals in urban transportation networks. Wang et al. (2018) reviewed the self-adaptive traffic signal control systems for heterogeneous traffic flow composed of connected vehicles and autonomous vehicles. Guo et al. (2019) presented a literature review on potential benefits of connected and automated vehicles for urban traffic control, in which it has been revealed that more efforts are required to verify the advantages of signal optimisation based where connected and automated vehicles are concerned. Shahgholian, Gharavian (2018) indicated that the advanced traffic management systems consist of traffic information, traffic assignment, traffic optimisation, and traffic prediction. Wei et al. (2019) surveyed conventional traffic signal control methods such as Webster, Greenwave, Maxband, Actuated, and Max-pressure, as well as reinforcement learning-based methods. Araghi et al. (2015) reviewed machine learning methods for traffic signal timing. Recent research revealed the capabilities of machine learning techniques for the management of traffic congestion through signal timing control (Sadollah et al., 2019).

Timing plans of traffic signals have a significant effect on the performance of transportation system. Since a transportation system is a large non-linear complex system (Zhao et al., 2011), achieving optimal signal timings for the entirety of the network is a difficult task. The timing optimisation of traffic signals can be performed in different ways, such as fixed, dynamic, and adaptive modes (Zhang et al., 2015; Bai et al., 2020). As its name suggests, the fixed signal control assumes that the signal timing plans are constant during different cycles. In dynamic signal optimisation, the signal timings are controlled using collected information from the previous cycles (Bai et al., 2020). In adaptive signal optimisation, the timing plans are generated based on the traffic demands in real time (Khattak et al., 2018).

From a computational perspective, the signal optimisation problem of urban transportation networks under various constraints is a non-convex and highly non-linear optimisation problem, which make the challenge of finding optimum signal timing hard. To address this, in some cases, researchers have focused on convexification or reducing the complexity of this problem (**??**). It has been shown that the signal optimisation problem belongs to the category of NP-complete problems (Wünsch, 2008). The complexity of the problem is dramatically increases for larger and real-world transportation networks with long study periods.

Classical optimisation methods have some features that are found to be not suitable for signal optimisation problems. For example, they require gradient computation of the objective function and constraints, and are very sensitive to the initial estimates of the solution vector. In addition, the discrete nature of the timing and phase sequence variables of traffic lights makes the application of conventional approaches even more difficult. Signal optimisation for the single junction case has been addressed by problem specific models such as SCOOT, MOVA (Wood et al., 2008) and Webster (Webster, 1958) that have been shown to be effective in practice. However, these methods focus on single junctions are not scalable for larger networks with multiple signals where the interdependence of signals can be explored. In addition, these methods do not consider the interdependence of signals and the dependencies and connectivity of signal are inherent features in larger highly interconnected networks such as those found in cities, so the need for alternative techniques for these networks is vital. Metaheuristic techniques are attractive alternatives to classical optimisation techniques, as they can be easily adapted to solve the signal optimisation problems of large-scale transportation networks with mixed types of discrete and continuous variables. In the literature there are a range of definitions of metaheuristics. According to (Voß, 2000), a *heuristic* is a approximate random method which can find acceptable solutions with relatively fewer amount of computational effort, whereas a *metaheuristic* is an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions. Metaheuristics do not require the gradient information of the objective and constraints functions with respect to the signal timing variables and the solution finding process is more straightforward.

Inspired from the nature or physical phenomena, metaheuristic optimisation methods, such as Genetic Algorithms (GAs) (Holland, 1992), Particle Swarm Optimisation (PSO) (Eberhart, Kennedy, 1995), Tabu Search (TS) (Glover, Laguna, 1998), Ant Colony Optimisation (ACO) (Dorigo, Birattari, 2010), Differential Evolution (DE) (Storn, Price, 1997) algorithm, Simulated Annealing (SA) (Van Laarhoven, Aarts, 1987), Cultural Algorithms (CAs) (Maheri et al., 2021), Biogeography-Based Optimisation (BBO) (Simon, 2008), Harmony Search (HS) (Geem et al., 2001) algorithm, Artificial Bee Colony (ABC) (Karaboga, Basturk, 2007), and Teaching-Learning-Based Optimisation (TLBO) (Rao et al., 2011), have attracted a lot of attention from researchers in various fields of engineering and science. By adopting a natural concept as a source of inspiration, metaheuristics use solution perturbation and stochasticity to solve optimisation problems. As described earlier, the applicability of these methods is not limited to the optimisation problems with continuous and differentiable objective functions and constraints, and they can be easily implemented to solve a wide variety of optimisation problems with continuous and discrete variables. However, the performance of the metaheuristics is sensitive to the type of the problem and the balance between the exploitation and exploration abilities during the search process. As a consequence, researchers have trialled a wide variety of algorithms and formulations to solve the signal optimisation problem.

The current study presents a comprehensive survey of metaheuristic optimisation techniques applied to the signal optimisation of transportation networks. This review covers the range of metaheuristic techniques applied to the problem of traffic signal optimisation, providing classifications of the techniques, objective functions, and decision variables. This is supplemented with a review of the most common simulation packages used in academic research and real-world systems for the simulation of traffic systems.

The remainder of the paper is organised as follows. Section 2 describes the computational simulation of transportation networks. Section 3 describes the signal optimisation problem in more details. Then, Section 4 reviews the various metaheuristic methods and approaches developed to provide solutions to the traffic signal optimisation problem. In Section 5, a publication analysis on the signal optimisation using metaheuristics is presented. Finally, Section 6 provides overall conclusion and future research directions.

## 2 Modelling and simulation of transport/signalling systems

The modelling and simulation of signalling systems are often categorised with respect to their level of detail, referring to Macro, Micro and Meso scale models. In the following section these categories will be explained along with the various other features and capabilities of modelling and simulation software. These modelling and simulation systems play an important role in the state of the art signal optimisation as they can be employed as the cooperating model within a signal optimisation framework. In the case of metaheuristic optimisation, the ”fitness/objective function” is represented by a particular transport/signalling simulator. A given transport simulation software outputs the objective value based on a set of performance matrices (waiting time, delay, carbon emissions etc.) for a given set of traffic signal variables. These different objectives and variables considered in the literature will be discussed in Section 3.

### 2.1 Macro simulation models

Macroscopic modelling is a mathematical modelling technique where relationships among traffic flow characteristics such as density, flow, mean speed of a traffic stream, etc. are considered ( Khan, Gulliver (2018)). The method of modelling traffic flow at the macroscopic level originated under an assumption that traffic streams as a whole are comparable to fluid streams.

Analytical study by Daganzo, Geroliminis (2008) provides insights into macroscopic models based on Macroscopic Fundamental Diagram approximating the relationship between the number of vehicles and the average flow. Similarly, model based control approaches such as Lin et al. (2009) and Zhou et al. (2013) and cell transmission models such as Daganzo (1995) and Lo (2001) provide insights into different ways of modeling of traffic networks. Some of the fundamental concepts have been extended to concrete simulation software products and in the following paragraphs some of widely known such software is presented. These simulators have been shown to be useful as the fitness/cost function for the meta heuristic signal optimisation approaches.

Saturn is one of the classical macroscopic traffic assignment models found in the literature (Hall et al., 1980). A major feature of Saturn is the cyclic flow profile (CFP) that describes the flow of traffic past a certain point as a function of time over a single cycle. The model is a collection of routines to modify the CFPs according to given conditions. Two distinct forms of input data are required by SATURN; an Origin Destination (O-D) trip matrix representing zone to zone trip demands for the period of interest, and a network description. Saturn assigns travel demands between discrete geographical areas to routes, and then simulates travel times on roads and through junctions. The complete model is based on an iterative loop between the assignment and simulation phases. Thus, the simulation determines flow-delay curves based on a given set of turning movements and feeds them to the assignment. The assignment in turn uses these curves to determine route choice and updated turning movements. These iterations continue until the turning movements reach reasonably stable values.

Visum is fairly recent macroscopic traffic simulation software similar to Saturn. As per the documentation of Visum it claims to have a comprehensive set of features such as trip distribution, line cost calculations, fare calculations and timetable-based assignment for public transport, and a traffic safety module that contains historical data of accidents etc (Software, 2016).

TRANSYT ( Penic, Upchurch (1992)) is another macroscopic software tool for traffic signal simulation and optimisation. It simulates a traffic network with signal lights and optimises signal settings through an objective function which is a linear combination of delay time and the number of stops experienced by vehicles in the network of signalised intersections. Similar to Saturn, TRANSYT is based on deterministic macroscopic modelling with CFPs. Features of the simulator include platoon dispersion, queue spill-back, and actuated control simulation. A genetic algorithm is employed as the optimiser module in TRANSYT. However, with TRANSYT its not possible detach the simulator module to use with new optimisation methods. Nevertheless, TRANSYT can be used as a state-of-art simulator and optimiser combination to benchmark new combined methods.

Similar to TRANSYT, Synchro (RAT (2014)) is a macroscopic analysis and optimisation software application. Synchro's traffic model is similar to the link-based model in TRANSYT. Unlike TRANSYT, Synchro's traffic model does not consider platoon dispersion. Synchro's signal optimisation routine allows the user to weight specific phases, thus providing users more options when developing signal timing plans. Similar to TRANSYT, Synchro also has the drawback of not being able to use the simulation framework to develop new optimisation methods.

### 2.2 Micro simulation models

Microscopic modelling explicitly represents individual vehicles, and attempts to replicate the behaviour of individual drivers and vehicles as agents within an agent-based simulation. This makes them particularly appropriate for examining certain complex traffic problems such as intelligent transport systems, complex junctions, shock waves and effects of incidents ( Samaras et al. (2017)).

Simulation of Urban MObility (SUMO) ( Krajzewicz et al. (2002)) is an agent based multi model traffic simulation software. SUMO claims to be scalable in network size and the number of simulated vehicles. An agent in SUMO is described by a departure time and the route taken and each route is composed of sub-routes that describe a single traffic modality. The traffic flow is simulated microscopically. In every one second time-step, these values are updated in dependence to the vehicle ahead and the street network the vehicle is moving on. The simulation of street vehicles is time-discrete and space-continuous. The car-driver model is continuous and basic traffic rules such as maximum velocity and right of way rules are adhered to when simulating traffic. Due to the simplicity of use and free and open source access SUMO has won great popularity in transport simulation. However, the simulation time increases with the city size and features in the simulation, making it rather time consuming for real time modelling or optimisation (i.e modelling accidents and other emergencies due to weather etc).

MATSim provides a set of tools to implement a very large agent-based simulation (Horni et al., 2016). It can simulate the traffic of a vast region throughout the day. MATSim pursues an activity-based approach to demand generation. Similar to SUMO, MATSim is agent-based. Unlike Saturn and other classical dynamic traffic assignment software, MATSim generates individual activity plans as input to the network loading rather than (time-dependent) origin-destination matrices.

Quadstone (Q) Paramics is a modular suite of microscopic simulation tools claiming to provide a powerful, integrated platform for modelling a complete range of real world traffic and transportation problems ( Essa, Sayed (2016)). A Paramics model is represented by a combination of nodes, links and other associated objects to replicate real life geometry constraints. Upon release from an origin zone, each vehicle attempts to complete its journey towards a destination zone whilst being bounded by physical and dynamic vehicle parameters. ( Panwai, Dia (2005)).

Corsim is a microscopic simulation model designed for the analysis of urban networks (Bloomberg, Dale, 2000). Corsim's capabilities include simulating different intersection controls in different surface geometries including number of lanes and turn pockets, and a range of traffic flow conditions. Corsim is based on a link-node network model. The links represent the roadway segments while the nodes mark a change in the roadway, an intersection, or entry points. The car-following model sets a desired amount of headway for individual drivers. The model generates travel times for each link which can be aggregated to determine travel time for a particular route.

Vissim ( Fellendorf, Vortisch (2011)) is another multi modal simulator that allows users to define a range of vehicle types including passenger cars, buses, trucks, and heavy and light rail vehicles as well as pedestrians and cyclists. The software features include the analyses a wide range of traffic activities and a dynamic routing system. The simulator claims to be flexible with abilities to add an object with the desired effect on road users and to choose the duration for the analysis. Drawbacks of Vissum includes the inability to model delays in specific time periods and inflexibility in adjusting lane change behavior for heavily congested conditions ( Jolovic et al. (2016)).

Transims is a multi modal transport simulator designed for regional transportation system based on a cellular automaton (Smith et al., 1995). Transims claims to be different from other travel demand forecasting methods in continuous representation of time, a detailed representation of persons and households and time-dependent routing.

Mainsim is an open source traffic simulation tool for fast what-if-analyses (Dallmeyer, Timm, 2012). Parameters such as the amount of traffic, the routing behavior and the composition of traffic can be set arbitrarily. Mainsim provides simulation models for cars, bicycles and pedestrians. Similar to the majority of the other models, Mainsim too is continuous in space and discrete in time with one simulation iteration lasting one second in real time. The models focus urban traffic and the interdependencies between different types of road users.

Dracula is another time-based multi model traffic micro-simulator (Liu, 1994) where vehicle states change at discrete intervals. Vehicle movements in a network are governed by a car-following model, a lane-changing model and traffic regulations on the road. Public transport is represented with reserved lanes, bus stops and bus laybys being modelled. The traffic signals used are fixed-plan or adaptive according to prevailing traffic condition or to priorities for public transport. The traffic condition is supplied by detectors on the roads.

MITSIMLab (Yang, Koutsopoulos, 1996), is a traffic simulator that assesses the impacts of potential designs of traffic management systems, information systems for travelers, public transport operations, and various transport systems' strategies at the operational level. It claims to evaluate systems such as advanced systems for traffic management and road guidance systems. Traffic and network elements are represented in detail in order to capture the sensitivity of traffic flows to the control and routing strategies. MITSIMLab is an open-source application.

### 2.3 Meso simulation models

Mesoscopic simulation is conceptually located between micro and macro levels. The individual vehicles are simulated but the activities and interactions are described in macroscopic relationships (Kessels, 2019). This approach is often used when evaluating traveller information systems.

Aimsun (Barcelí et al., 2005) is a simulation software that supports static and dynamic simulations. Aimsun integrates three types of transport models: static track assignment tools; a mesoscopic simulator; and a microsimulator (Casas et al., 2015). Aimsun has capabilities for modeling of various delay values coupled with the standard deviation per specified time period. This option was used to model and calibrate wait times at inspection booths. However, having one turning movement table for each time period, can be inconvenient when navigating between different time periods to change the numerical values. Another drawback is that background maps are not embedded in the software (Jolovic et al., 2016).

TransModeler is a mesoscopic modelling based simulation software that can balance traffic flows entering the model. TransModeler also has linkage on micro and macro levels under the same platform. The user has an option to choose which links are to be modeled on a micro scale and which ones on a macro scale. This option can be useful when simulating large scale networks and the user wants to shorten the simulation time. TransModeler has tools for lane closures and work zones modeling by desired time interval, which gives an advantage over other models such as Aimsun and Vissim. The limitations of the model includes turning movement table being available only for intersections. For all other inputs such as inputs for freeways or physically separated toll road facilities the user has to use O-D matrices.

### 2.4 Comparison on simulation software capabilities

The studies by Kotusevski, Hawick (2009), Saidallah et al. (2016), Brockfeld, Wagner (2003) and Jau (2010) consider certain comparative features of traffic simulation software. The following tables extend their study through the inclusion of more recent traffic simulation software (see Tables 1 and 2). Note that we consider simulation only software for a fair comparison. Table 3 provides some studies these simulation software have been used.

Table 1: Comparison of simulation software

| heightFeature/software | Aimsun | Corsim | Dracula | Mainsim | Matsim | Q-Paramics | Transims |
|---|---|---|---|---|---|---|---|
| Open Source and Free Use | No | No | No | Yes | Yes | No | Yes |
| Macro/Micro/Meso | Meso | Micro | Micro | Micro | Micro | Micro | Micro |
| OS Portability | No | No | No | Yes | Yes | No | No |
| Documentation and UI | Yes | Yes | Yes | Yes | Yes | Yes | Limited |
| Creating traffic networks | graphical editor | No | graphical | OD matrix | Manual-xml file | wizard | Manual |
| GUI | 3D | 2D | 2D | 2D | 2D | 3D | 2D |
| Simulation output | realtime tools | real statistical tools | files | files | files | tools | files |
| Very large networks | Yes | Yes | No | Yes | No | Yes | Yes |
| Pedestrians and vehicles | Yes | Yes | Yes | Yes | Yes | Yes | No |

Table 2: Comparison of simulation software

| heightFeature/software | MITSimLab | TransModeller | Saturn | Sumo | Vissim | Visum |
|---|---|---|---|---|---|---|
| Open Source and Free Use | Yes | No | No | Yes | Free for research | Free for research |
| Macro/Micro/Meso | Micro | Meso | Macro | Micro | Micro | Macro |
| OS Portability | Yes | No | Yes | Yes | No | No |
| Documentation and UI | Yes | Yes | Yes | Yes | Yes | Yes |
| Creating networks | Manual | limited flexibility | OD matrix | xml file | graphical editor | graphical editor |
| GUI Simulation | 2D | 3D and 2D | 2D | 2D | 3D | 3D |
| Simulation output | files | realtime tools | files | files | tools | tools |
| Very large networks | No | Yes | No | Yes | Yes | No |
| Pedestrians and vehicle types | No | Yes | No | Yes | Yes | No |

Table 3: The traffic simulation tools used by various references for signal optimisation.

| Simulation tool | Reference(s) |
|---|---|
| SATURN | Teklu et al. (2007), Guan et al. (2008) |
| Matlab | He, Hou (2012), Tong et al. (2006), Tan et al. (2016), Tan et al. (2017), Ma, Liu (2019) |
| Vissim | Chentoufi, Ellaia (2018), Stevanovic et al. (2007), Gökçe et al. (2015), Ghanim, Abu-Lebdeh (2015), Park, Lee (2009), Guangwei et al. (2007),Stevanovic et al. (2008), Cakici, Murat (2019), Dabiri, Abbas (2016), Nguyen (2019), Stevanovic et al. (2015), Stevanovic et al. (2013), Mulandi et al. (2010), Li et al. (2013), Stevanovic et al. (2011b), Zargari et al. (2018), Teng et al. (2019), Zhang et al. (2018) |
| TRANSYT | Dell'Orco et al. (2014), "Brian" Park et al. (2000), Ceylan (2006), Jamal et al. (2020), Mulandi et al. (2010), Cantarella et al. (2015) |
| Celullar automata | Sánchez et al. (2008) |
| TRANSIMS | Kwak et al. (2012) |
| CORSIM | "Brian" Park et al. (2000), Park, Kamarajugadda (2007), Sun et al. (2006), Hajbabaie, Benekohal (2013), Li, Gan (1999),Yun, Park (2012), Hirulkar et al. (2013), Mulandi et al. (2010) |
| Synchro | Park, Kamarajugadda (2007), Park et al. (2004), Mulandi et al. (2010) |
| Paramics | Zhou, Cai (2014), Lee et al. (2005), Araghi et al. (2017) |
| SUMO | Kai et al. (2014), Thaher et al. (2019),Singh et al. (2009), Nguyen et al. (2016), Davydov, Tolstykh (2019), Abushehab et al. (2014), Garcia-Nieto et al. (2013), García-Nieto et al. (2012), Teng et al. (2019), Olivera et al. (2015b) |
| Matsim | Armas et al. (2017) |
| Aimsun | Nigarnjanagool, DIA (2005), Vilarinho et al. (2014), Papatzikou, Stathopoulos (2018), Wijaya et al. (2015) |
| TransModeler | Colombaroni, Fusco (2009) |
| Visum | Baskan, Ozan (2015) |
| MitSimlab | Angulo et al. (2011) |
| Mainsim | Cervone et al. (2019) |
| Dracula | Maher et al. (2013) |

## 3 Signal optimisation problems

This review of the literature reveals that a wide variety of problem formulations, decision variables, and objective functions have been employed by researchers for the signal optimisation problem. Table 4 categorises the metaheuristics, decision variables, problem types, and objective functions investigated by each publication for signal optimisation. In the following subsections, various problem formulations, decision variables, and objective functions adopted by the literature will be reviewed.

### 3.1 Decision variables

Generally, the main objective of a signal optimisation problem is to improve the performance of the traffic network by optimising the values of signal timing parameters (e.g., phase plans, cycle length, green splits, offsets, and phase sequence) under some constraints. Each *phase* plan indicates a particular state of the red and green lights of the traffic lights in an intersection. The *cycle* refers to the time it takes for a traffic signal to get from the start of the green light through the yellow and red and until it again becomes green (Warberg et al., 2008). The *offset* determines the start time of green light for each phases, which is measured from a given reference point and is used to specify how the different signals are shifted to each other. The *phase sequence* parameter represents the order of phases appearing within a intersection. Figure 1 shows the control parameters of a traffic light consisting of two phases.

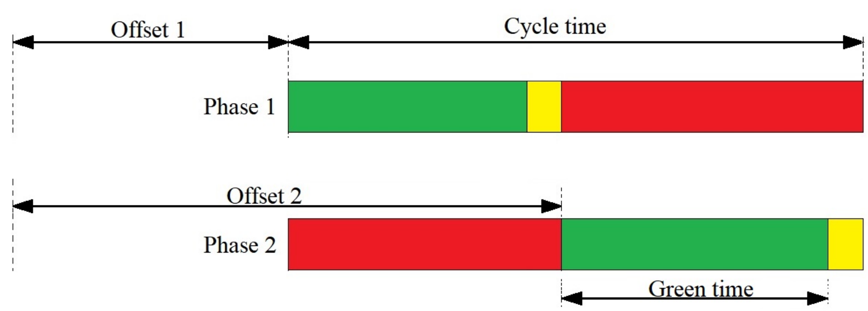


Figure 1: Signal variables of traffic light.

Tables 4 and 5 list the decision variables adopted by different researchers for this problem. From this table, it can be seen that the most of the research in the literature considered the cycle, green and offset times as well as phase sequence as decision variables within the optimisation procedure. However, some studies adopted other types of decision variables besides the signal parameters. For example, in addition to the mentioned variables, Yun, Park (2012) considered the actuated signal setting parameters, including vehicle extension and recall mode. He, Hou (2012) optimised the signal timing plans by considering the saturation flow of the intersection as another decision variable, which indicates the maximum number of vehicles passing by the intersection when the green light is in a signal cycle. In a different approach, Varia et al. (2013) solved the signal optimisation problem by assuming the appropriate path flow distribution of the dynamic user equilibrium (DUE) traffic assignment for the congested urban road network.

### 3.2 Objective function

As described previously, the aim of the signal optimisation problem is to enhance the performance of the traffic network. Researchers have investigated this problem by using various types of objective functions. From the perspective of the objective function, the signal optimisation problems can be categorised into four types as follows: i) single-objective optimisation, ii) bi-level optimisation, iii) multi-objective optimisation, and iv) performance-based optimisation. The type of optimisation problems and the objective functions adopted by different references for the signal optimisation are summarised in Tables 4 and 5. In the following subsections, the research related to the each category is discussed in more detail. It should be noted that, in this study, we will focus only on works related to the signal optimisation problems in which metaheuristic methods are used as the optimiser.

Table 4: The metaheuristics, decision variables, problem types, and objective functions adopted by various references for the signal optimisation problems.

| Reference | Method | Signal variables | Single-objective | Multi-objective | Bi-level | Objective functions |
|---|---|---|---|---|---|---|
| Memon, Bullen (1996) | GA | N/A | ✓ | | | DTM |
| Park et al. (1999) | GA | CT, GT, OT, PS | ✓ | | | DTM |
| "Brian" Park et al. (2000) | GA | CT, OT, GT, PS | ✓ | | | TM, DTM |
| Takahashi et al. (2002) | GA | OT | ✓ | | | TTM |
| Sun et al. (2003) | GA | GT | | ✓ | | DTM, NSM |
| Park et al. (2004) | GA | CT, GT | ✓ | | | DTM |
| Varia, Dhingra (2004) | GA | GT | ✓ | | | TTM |
| Lee et al. (2005) | GA | GT | ✓ | | | DTM |
| Sun et al. (2006) | GA | CT, GT, OT | | | ✓ | TTM |
| Abbas, Sharma (2006) | GA | TP | | ✓ | | DTM, NSM, DOD |
| Tong et al. (2006) | GA | CT | ✓ | | | DTM |
| Cantarella et al. (2006) | GA | CT, GT | ✓ | | | TTM |
| Teklu et al. (2007) | GA | CT, OT, GT | ✓ | | | TTM |
| Park, Kamarajugadda (2007) | GA | CT, GT | ✓ | | | DTM |
| Branke et al. (2007) | GA | GT | | ✓ | | NSM, TTM |
| Guangwei et al. (2007) | GA | CT, GT, PS | ✓ | | | DTM |
| Sánchez et al. (2008) | GA | GT | ✓ | | | TM |
| Guan et al. (2008) | GA | CT, GT, OT | ✓ | | | TTM |
| Stevanovic et al. (2008) | GA | CT, GT, OT, PS | ✓ | | | TM, DTM, TTM, NSM |

*Continued on next page*

Table 4 – *Continued from previous page*

| Reference | Method | Signal variables | Single-objective | Multi-objective | Bi-level | Objective function(s) |
|---|---|---|---|---|---|---|
| Park, Lee (2009) | SFLA | GT, OT | ✓ | | | TTM |
| Karoonsoontawong, Waller (2009) | TS | CT, GT, OT, PS | | | ✓ | TTM |
| Colombaroni, Fusco (2009) | GA | CT, OT, GT | ✓ | | | DTM |
| Kesur (2009) | GA | GT, CT | ✓ | | | DTM |
| Peng et al. (2009) | PSO | GT | ✓ | | | TTM |
| Renfrew, Yu (2009) | ACO | GT | ✓ | | | DTM |
| Stevanović et al. (2009) | GA | CT, OT, GT, PS | ✓ | | | FCM, EM |
| Kesur (2010) | GA | CT, OT, GT, PS, NP | | ✓ | | DTM, DIM |
| Putha, Quadrifoglio (2010) | ACO | GT | ✓ | | | QM |
| Tawara, Mukai (2010) | ACO | CT, GT, OT | ✓ | | | TTM |
| Stevanovic et al. (2011b) | GA | CT, OT, GT, PS | ✓ | | | DTM |
| Baskan, Haldenbilen (2011) | ACO | CT, GT | | | ✓ | TTM |
| Stevanovic et al. (2011a) | GA | CT, GT, OT, PS | | ✓ | | CM, TM |
| Chin et al. (2011) | GA | CT, GT, OT, PS | ✓ | | | DTM |
| Lertworawanich et al. (2011) | GA | CT,OT,GT | | ✓ | | DTM, SM, TM |
| Shen et al. (2011) | GA | CT, GT, OT | ✓ | | | TM |
| Jahangiri et al. (2011) | SA | CT | | | ✓ | TTM |
| Liu, Xu (2012) | BFOA, DE | GT | ✓ | | | DTM |
| Hu, Chen (2012) | TS | GT, OT | ✓ | | | DTM, TTM |
| Putha et al. (2012) | GA, ACO | GT | ✓ | | | TM |
| Kwak et al. (2012) | GA | CT, OT, GT, PS | ✓ | | | FCM |
| Yun, Park (2012) | GA | CT, GT, OT, PS, VE, RM | ✓ | | | DTM |
| Renfrew, Yu (2012) | ACO | GT | ✓ | | | DTM |
| Li et al. (2013) | GA | CT,GT | | ✓ | | TM, QM |
| Stevanovic et al. (2013) | GA | CT, OT, GT | ✓ | ✓ | | TM, CM |
| Varia et al. (2013) | GA | CT, GT, PS, PFD | ✓ | | | PDUEC |
| Kesur (2013) | GA | CT, GT, OT, PS | | ✓ | | DTM, NSM |
| Hirulkar et al. (2013) | PSO | CT, PS, OT | ✓ | | | DTM |
| Ren et al. (2013) | GA, PSO, SA | CT, GT, OT | | | ✓ | TTM, PI |
| Hu, Liu (2013) | GA | OT | ✓ | | | DTM |
| Garcia-Nieto et al. (2013) | PSO | CT | ✓ | | | TM |

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Table 4 – *Continued from previous page*

| Reference | Method | Signal variables | Single-objective | Multi-objective | Bi-level | Objective function(s) |
|---|---|---|---|---|---|---|
| Zhang et al. (2013) | GA | CT, GT, OT, PS | | ✓ | | DTM, EEM |
| Kai et al. (2014) | DE, PSO | GT | ✓ | | | DTM |
| Abushehab et al. (2014) | GA, PSO | GT | ✓ | | | TTM |
| Tung et al. (2014) | GA | GT | ✓ | | | TTM |
| Abu-Lebdeh et al. (2014) | GA | CT,OT, GT | ✓ | | | TM |
| Kesur (2014) | GA | CT, GT, OT | ✓ | | | DTM |
| Zhou, Cai (2014) | GA | GT | | ✓ | | DTM, EM, FCM |
| Cantarella et al. (2015) | GA, SA, HC | GT, OT | | ✓ | | TM, DTM |
| Olivera et al. (2015a) | PSO | CT,GT,OT | ✓ | | | FCM |
| Li, Schonfeld (2015) | GA, SA | CT, OT, GT | ✓ | | | DTM |
| Adacher et al. (2015) | PSO | N/A | ✓ | | | TTM |
| Gökçe et al. (2015) | PSO | GT | ✓ | | | TTM |
| Hajbabaie, Benekohal (2015) | GA | CT, GT, PS | ✓ | | | TM |
| Han et al. (2015) | SA, PSO | GT | | | ✓ | TTM |
| Stevanovic et al. (2015) | GA | CT, OT, GT, PS | | | ✓ | TTM, FCM, CM |
| Hale et al. (2015) | GA, SA, TS | GT | ✓ | | | DTM |
| Tan et al. (2016) | GA | GT | ✓ | | | DTM |
| Gao et al. (2016b) | HS | PS | ✓ | | | DTM |
| Dabiri, Abbas (2016) | PSO | CT, GT, OT | ✓ | | | DTM |
| Jiao et al. (2016) | PSO | CT, GT | | ✓ | | TM, NSM |
| Gao et al. (2016a) | JA | PS | ✓ | | | DTM |
| Wu, Wang (2016) | PSO | N/A | ✓ | | | DTM |
| Nguyen et al. (2016) | GA | GT | | ✓ | | DTM, TM |
| Chuo et al. (2017) | PSO | GT | ✓ | | | DTM |
| Gao et al. (2017c) | ABC | GT | | ✓ | | DTM |
| Srivastava, Sahana (2017) | GA, ACO | N/A | | | ✓ | DTM |
| Tan et al. (2017) | GA | GT | ✓ | | | DTM |
| Armas et al. (2017) | GA | CT, OT, GT | | ✓ | | EM, TTM, FCM |
| Gao et al. (2017a) | JA, HS, WCA | PS | ✓ | | | DTM |
| Jovanović et al. (2017) | ABC, SA | CT, OT, GT | ✓ | | | TTM |
| Araghi et al. (2017) | CS, GA, SA | GT | ✓ | | | DTM |
| Gao et al. (2017b) | ABC | PS | ✓ | | | DTM |

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Table 4 – *Continued from previous page*

| Reference | Method | Signal variables | Single-objective | Multi-objective | Bi-level | Objective function(s) |
|---|---|---|---|---|---|---|
| Zhao et al. (2018) | ABC | CT, GT | | ✓ | | DTM, NSM |
| Chentoufi, Ellaia (2018) | PSO, TS | CT, GT | ✓ | | | DTM |
| Kou et al. (2018) | GA | CT,GT,OT | | ✓ | | EM, TTM, NSM |
| Costa et al. (2018) | GA | GT | | ✓ | | AVSM, VVSM |
| Li, Sun (2018) | GA | TST, CT, OT, GT | | ✓ | | TM, DTM, TS, SM |
| Gao et al. (2018b) | JA, ABC, GA, HS, WCA | PS | ✓ | | | DTM |
| Ardiyanto et al. (2018) | ABC, HS | GT | ✓ | | | N/A |
| Gao et al. (2018a) | ABC, HS | PS | | ✓ | | DTM |
| Papatzikou, Stathopoulos (2018) | SS, HS | GT | ✓ | | | DTM |
| Thaher et al. (2019) | WOA, BA, GA | GT | ✓ | | | TTM |
| Cakici, Murat (2019) | DE | GT | ✓ | | | DTM |
| Jia et al. (2019) | PSO | CT, GT | | ✓ | | TM, DTM, EM |
| Li, Sun (2019) | GA | CT, GT | | ✓ | | DTM, TM, SM |
| Ma, Liu (2019) | GA | GT | ✓ | | | DTM |
| Zhang et al. (2019) | GA, HS | GT | | ✓ | | DTM, DUM |
| Gao et al. (2019) | ABC | PS | ✓ | | | DTM |
| García-Ródenas et al. (2019) | SA, GA | CT, GT | | | ✓ | DTM |
| Ma, He (2019) | GA, AFSA | CT, GT | ✓ | | | DTM |
| Sharma, Kumar (2019) | GA | GT, CT | ✓ | | | DTM |
| Nguyen (2019) | GA | GT | | ✓ | | TM, QM |
| Shi et al. (2020) | SA | GT, NC, NBL | | ✓ | | DTM |
| Jamal et al. (2020) | GA, DE | GT | ✓ | | | DTM |
| Liang et al. (2020) | GA | PS | ✓ | | | DTM |
| Nallaperuma et al. (2020) | GA | GT | ✓ | | | DTM, FCM, EM |

### 3.2.1 Single-objective optimisation

The objective functions employed by researchers in the single-objective framework of signal optimisation can be classified into four types as follows: i) delay time minimisation, ii) travel time minimisation, iii) throughput maximisation, iv) fuel consumption minimisation and emissions minimisation.

**i) Delay time minimisation** The *delay time minimisation* (DTM) is one of the popular objective functions within the single-objective optimisation framework of signal timing design, which can be expressed as the difference between the existing travel time of signalised network and the travel time in the free-flow conditions without traffic control devices. In other words, this objective function aims to minimise the waiting time of the vehicles due to network signalisation. Pioneering work on the single-objective optimisation of traffic signals was carried out by Webster (1958), in which an approximate delay formula is proposed for a single intersection. In the field of signal optimisation using metaheuristics, the delay time has been extensively employed by researchers as the objective function. For example, Chentoufi, Ellaia (2018) and Jamal et al. (2020) optimised the delay at an isolated intersection. Tan et al. (2017) minimised the average delay time during the morning peak hour. Whereas Park et al. (1999), Kai et al. (2014), Park, Kamarajugadda (2007), Guangwei et al. (2007), and Tan et al. (2016) used average delay of the entire system as the objective function. Wu, Wang (2016) minimised the overall delay of the network in each time interval. Li, Schonfeld (2015) and Lee et al. (2005) adopted the total delay of the system within the simulation period as the objective function.

To reduce the run time of the traffic simulation model related to the traditional delay measures, Kesur (2009) proposed an alternative measurement of delay, called extended network delay, which is applicable to both undersaturated and oversaturated conditions. "Brian" Park et al. (2000) proposed a modified delay minimisation approach based on the exponential-type penalty function. Gao et al. (2017a) assumed the total network-wise delay time within a set of sampling intervals as the objective function. Cakici, Murat (2019) used the average delay at a three-leg intersection as the objective function to optimise green times.

**ii) Travel time minimisation** *Travel time minimisation* (TTM) is another popular objective function in the field of signal optimisation, which aims to reduce the total travel time of all vehicles in the network. Teklu et al. (2007),Varia, Dhingra (2004), Cantarella et al. (2006), Guan et al. (2008), and Adacher et al. (2015) employed this measure as an illustrative fitness function. In contrast, Gökçe et al. (2015) considered the mean travel time through the roundabout to optimise signal variables.Thaher et al. (2019) formulated the signal scheduling problem as the minimisation of average travel time, in which the total trip time is divided by the total number of vehicles.

**iii) Throughput maximisation** The *throughput maximisation* (TM) aims to maximise the number of vehicles processing through the network by choosing appropriate values for signal timing parameters. Putha et al. (2012) formulated the total number of vehicles processed by the network throughout the oversaturation period as the objective function for optimum signal timing. Authors added a penalty term to their objective function to prevent the occurrence of queues at the end of the green time along coordinated arterials. Abu-Lebdeh et al. (2014) and "Brian" Park et al. (2000) optimised signal variables by maximising the network output. In other research, Sánchez et al. (2008) solved the signal optimisation problem by maximising the absolute number of vehicles that left the network. Shen et al. (2011) assumed the number of vehicles that leave the road network during the given period as the objective function for traffic signal timing optimisation.

**iv) Fuel consumption minimisation and emissions minimisation** The transportation sector is one of the main contributors to the fossil fuel consumption and the global greenhouse gas emissions. In the congested urban networks, the high stop-and-go rate and speed variations of the vehicles increase the fuel consumption and emissions. As a practical approach, traffic signal optimisation can reduce fuel consumption as well as emission of pollutants associated with vehicles, such as carbon monoxide ($CO$), carbon dioxide ($CO_2$), volatile organic compounds ($VOCs$) or hydrocarbons ($HCs$), nitrogen oxides ($NO_x$), and particulate matter ($PM$)s. However, signal optimisation problems with the objective to minimise emissions or fuel consumption are challenging problems. Some traffic signal optimisation tools, such as VISSIM, TRANSYT-7F, and SYNCHRO, uses a weighted combination of the total travel time, total delay, and number of stops to estimate the emissions and fuel consumption in the network. However, this approach is affected by the number of stops and cannot be used as reliable model to estimate the amount of the emissions and fuel consumption in the network. Hence, researchers have employed various emission models to measure vehicle emission and fuel consumption within the urban traffic network, such as CMEM (Scora, Barth, 2006) and VT-Micro (Ahn et al., 2002).

*Fuel consumption minimisation* (FCM) and *emissions minimisation* (EM) have attracted considerable attention in the literature as objective functions. Stevanović et al. (2009) suggested to optimise the signal timing plans by assuming fuel consumption and $CO_2$ emissions as the objective functions. Authors used a CMEM model to estimate the fuel consumption and $CO_2$ emission of each signal timing plan. CMEM is a power-demand model developed based on a parameterised analytical representation of fuel consumption and emissions production (Scora, Barth, 2006). This model estimates the tailpipe emissions and fuel consumption by using speed, acceleration, road grade,and some model calibrated parameters (Scora, Barth, 2006). In comparison to the amount of fuel consumption obtained from the delay or performance index optimisations, the results demonstrate that considering the fuel consumption as an objective function can reduce fuel consumption still further. (Stevanović et al., 2009).

In another study, Kwak et al. (2012) investigated the impacts of traffic signal timing optimisation on vehicular fuel consumption and emissions in an urban corridor, in which a VT-Micro model is employed to estimate the vehicle emissions and fuel consumption. VT-Micro model, which is developed based on the Oak Ridge National Laboratory (ORNL) and the US Environmental Protection Agency (Ahn et al., 2002), estimates the vehicle emissions and fuel consumption by using the instantaneous vehicle speed and acceleration levels as input variables. Kwak et al. (2012) optimised the traffic signal timing plan by assuming the network-wide fuel consumption derived from the VT-Micro model as the objective function. In comparison to the classical optimum fuel consumption approaches, the optimisation results demonstrated that the approach can improve fuel consumption, emissions, and travel time in the network.

Olivera et al. (2015a) optimised signal timing programs to reduce the gas emissions

($CO$ and $NO_x$) and fuel consumption based on the Handbook of Emission Factors for Road Transport (HBEFA). HBEFA suggests the emission factor for all categories of vehicles based on the size, type, cylinder capacity, fuel mode of the vehicle (gasoline or diesel), type of exhaust technology (with/without catalytic converter), driving style (acceleration and speed), road gradient, and maintenance (Colberg et al., 2005).

Since the vehicle emissions and fuel consumption models applied by the literature are approximate, the nature of the signal optimisation problem can be affected by these approximate models, and the obtained optimum signal timing plans should be investigated in more detail.

### 3.2.2 Bi-level optimisation

A bi-level optimisation problem consists of two optimisation problems, including upper-level and lower-level optimisation problems. In this type of the optimisation problems, the lower-level optimisation problem is a constraint for the upper-level optimisation problem and both have their own objective functions, decision variables, and constraints. The feasible solutions for this problem not only should satisfy the constraints of the upper-level problem, but also should be a near-optimal solution of the lower-level problem.

In some cases, researchers have formulated the signal timing problem within a bi-level optimisation framework. For example, Sun et al. (2006) formulated a bi-level optimisation problem for dynamic traffic signal optimisation in networks under time dependent demand and stochastic route choice, in which the traffic signal optimisation is the upper-level problem and the user travel behavior is the lower-level problem. Authors used the travel time as the objective function for the upper-layer problem. In another study, Srivastava, Sahana (2017) investigated another bi-level optimisation problem, in which optimal signal timing problem represents the upper-level problem and stochastic user equilibrium indicates the lower-level problem. Authors used the total waiting time as the objective function for the upper-level problem, while the objective function of the lower-level problem is the travel cost.

Ren et al. (2013) formulated a bi-objective optimisation approach for evacuation routing and traffic signal optimisation with background demand uncertainty. The authors considered the multi-objective signal optimisation as the upper-level problem with the objective functions of travel time and a performance index, in which the performance index is composed of delay time and background traffic impact degree (i.e., an extent measure of the spill-back) occurrence in the network due to the influence of background traffic. While the lower-level problem is the maximisation of background traffic impact degree under a logit-based stochastic assignment constraint and background demands constraint. García-Ródenas et al. (2019) formulated a bi-objective problem, in which the upper-level problem is the determining of the time-of-day breakpoints and the lower-level problem is the signal control optimisation problem for minimum total delay times. Han et al. (2015) investigated a bi-objective model of dynamic traffic signal control with continuum approximation, in which the upper-level problem is the signal optimisation of green times and the lower-level problem is a dynamic user equilibrium with embedded dynamic network loading. Karoonsoontawong, Waller (2009) solved the signal optimisation problem as the upper level problem in a bi-objective problem, in which the dynamic user equilibrium is the lower-level problem.

#### 3.2.3 Multi-objective optimisation

As its name suggests, the multi-objective signal optimisation involves more than one objective function to be optimised simultaneously. Branke et al. (2007) solved a multi-objective signal optimisation problem by assuming the travel time and the number of stops as the objective functions. Kesur (2010) formulated a multi-objective optimum signal design problem by considering the overall delay and delay imbalance minimisations. In another study, Kesur (2013) suggested to minimise the delay and number of stops in traffic signal networks.

Li, Sun (2018) developed a multi-objective signal optimum design problem based on maximising system throughputs, minimising traveling delays, enhancing traffic safety, and avoiding spillovers. In another study, Taale et al. (1998) assumed the delay per vehicle and the number of stops per vehicle as objective functions for signal timing optimisation. Zhang et al. (2013) optimised the signal parameters with respect to the minimisation of traffic delay and the risk associated with human exposure to traffic emissions. Sun et al. (2003) adopted the average delay and the number of stops as two separate objective functions for optimising signal parameters.

Zhou, Cai (2014) investigated the signal timing optimisation of a single intersection in Guangzhou as a multi-objective optimisation problem, in which the vehicle emissions, fuel consumption, and vehicle delay are considered as objective functions. Stevanovic et al. (2011a) optimised the traffic signal variables by minimising conflicts and maximising throughput within the network. The study by Kou et al. (2018) presented the trade offs between the emissions and travel efficiency. Nguyen et al. (2016) assumed delay time minimisation and throughput maximisation as the objective functions. Gao et al. (2018b) and Gao et al. (2018a) considered the delay time of the vehicles and pedestrians as the objective function. Li, Sun (2019) assumed the throughput, delay time, and spillbacks as the objective function for multi-objective signal timing optimisation. Zhang et al. (2019) investigated the signal optimisation problem by considering the driver's unhappiness as well as delay minimisation as the objective functions.

Stevanovic et al. (2015) performed a multi-objective signal timing plans optimisation by considering minimising the fuel consumption and number of vehicular conflicts. Stevanovic et al. (2013) assumed the number of conflicts and delay time as the objective functions. Li et al. (2013) adopted the throughput maximisation and queue ratio minimisation as the objective functions. Abbas, Sharma (2006) defined a new performance measure, called degree of detachment (DoD), representing the degree by which a traffic state is detached from adjacent states. Authors optimised the signal timing plans for simultaneous DoD, delay time, and number of stops minimisations.

The key to multi-objective optimisation is that the objectives should usually be conflicting and for many aspects of the signal optimisation problem, the objectives are likely to be correlated. This therefore required careful selection of the objectives for use in these studies.

### 3.2.4 Performance-based optimisation

In the fourth category of signal optimisation problems, a performance index (PI) is formulated by combining two or more above-mentioned objective functions and other measures. Table 5 lists the researches in which a given performance measure criteria is developed. For example, Yang et al. (2013) formulated an PI by considering the Webster delay, Webster stop rate, and traffic throughput based on the weight coefficient method. To achieve better traffic efficiency, Stevanovic et al. (2011a) suggested a linear combination of stops and delays for optimising signal variables. The authors also measured the performance of the traffic network by using a conflicts/throughput ratio as the objective function.

In another study, Ghanim, Abu-Lebdeh (2015) developed an PI for signal timing optimisation by considering weighted combinations of network general traffic performance, transit travel time, and transit schedule adherence. Chen, Xu (2006) combined the average delay and average number of stops to form a PI, which is a function of signal setting variables. By introducing weighting coefficients, He, Hou (2012) proposed a objective function consisting of time delay, number of stops, and traffic capacity. Dell'Orco et al. (2014) presented a weighted combination of the delay and stop times as PI for signal timing optimisation. Ceylan (2006) employed a weighting method to formulate a PI based on the delay time and number of the stops, in which the cost of the vehicle stops is considered. Ezzat et al. (2014) formulated a objective function based on the two performance metrics, including queue length and vehicular waiting time. Stevanovic et al. (2007) used a PI by hybridising the total delay and number of stops.

Lertworawanich et al. (2011) investigated the multi-objective signal optimisation of over-saturated networks for the delay and spillover minimisations as well as throughput maximisation, in which the mentioned objective functions are converted to a single objective function by using weighting coefficients. Spillover is a type of traffic congestion, in which the vehicles on the link of the downstream intersection overflow backward to the subject intersection. Singh et al. (2009) optimised the green times by considering PI consisting of number of the vehicles in different roads. Garcia-Nieto et al. (2014) assumed the average of total $CO_2$ and $NO_x$ emissions and fuel consumption as the fitness function. Stevanovic et al. (2013) and Duerr (2000) formulated a PI based on the linear combination of delay time and stops. Ma et al. (2014) defined a PI consisting of the delay time, fuel consumption, and emissions. García-Nieto et al. (2012) formulated a fitness function based on the travel time and the number of vehicles that reach their destinations to measure the performance of the timing plans. Hu et al. (2016) formulated a new performance measure based on the ratio of waiting time to the travel time and the ratio of green times to the red times. Olivera et al. (2015b) formulated an PI based on the emissions, fuel, and travel time minimisations. Zhang et al. (2018) expressed the PI as a weighted combination of the vehicle and pedestrians' delay times.

The development of these performance-based methods allows for multiple, potentially correlated, performance criteria to be combined into a single objective function to be optimised. A key factor in this is the weighting or normalisation of criteria to ensure that one criterion does not dominate, or to ensure that the weightings are appropriate for the purpose of the optimisation and the stakeholders involved.

Table 5: The metaheuristics, decision variables, and objective functions considered by various references for the performance-based signal optimisation problems.

| Reference | Method | Signal variables | Performance Index (PI) |
|---|---|---|---|
| Duerr (2000) | GA | GT | DTM, NSM |
| Ceylan (2006) | GA | CT, OT, GT | DTM, NSM |
| Chen, Xu (2006) | PSO | CT, GT, OT | DTM, NSM |
| Stevanovic et al. (2007) | GA | CT, OT, GT, PS | DTM, NSM |
| Stevanovic et al. (2008) | GA | CT, GT, OT, PS | DTM, NSM |
| Singh et al. (2009) | GA | GT | TM |
| Zhang et al. (2010) | GA | GT | EM, FCM |
| Mulandi et al. (2010) | GA | CT, OT, GT, PS | DTM, NSM |
| Dong et al. (2010) | PSO, SA | GT | DTM, NSM |
| Stevanovic et al. (2011a) | GA | CT, GT, OT, PS | DTM, NSM, CM, TM |
| Lertworawanich et al. (2011) | GA | CT,OT,GT | DTM, SM, TM |
| He, Hou (2012) | ACO | CT, intersection saturation | DTM, NSM, TM |
| García-Nieto et al. (2012) | PSO | GT | TTM, TM |
| Yang et al. (2013) | GA | GT | DTM, NSM, TM |
| Ezzat et al. (2014) | GA | GT, CT | QM, DTM |
| Dell'Orco et al. (2014) | ABC | GT, OT,CT | DTM, NSM |
| Garcia-Nieto et al. (2014) | PSO | CT | EM, FCM |
| Ma et al. (2014) | GA | GT | DTM, FCM |
| Wijaya et al. (2015) | PSO | OT, CT, GT | TTM, DTM |
| Olivera et al. (2015b) | PSO | GT | TM, EM, FCM, TTM |
| Ghanim, Abu-Lebdeh (2015) | GA | CT, GT, OT | TTM, SCM, DTM, NSM |
| Hu et al. (2016) | PSO | PS | TTM, DTM, RGRTM |
| Hamami, Akbar (2018) | PSO | GT | TM, RGRTM |
| Zargari et al. (2018) | SA, ICA | GT | TM, QM, GTO |
| Zhang et al. (2018) | HS | PS | DTM |
| Teng et al. (2019) | GWA, GOA | GT | TM, DTM, RGRTM |
| Segredo et al. (2019) | GA, PSO | GT, OT | TM, TTM, DTM, NSM, RGRTM |
| Davydov, Tolstykh (2019) | PSO | GT, CT, OT | TTM, DTM, TM |
| Nallaperuma et al. (2020) | GA | GT | DTM, FCM, EM |

## 4 Metaheuristics

This section reviews the literature regarding the most popular metaheuristic methods applied to the field of signal optimisation. As previously described, these methods usually simulate some natural phenomena to inspire the numerical optimisation, such as evolutionary theory, physical processes and swarm behaviours of birds and insects. Tables 4 and 5 present various metaheuristic techniques employed by researchers for optimising signal timings. In this section, the popular metaheuristic algorithms in the field of the signal optimisation, such as Genetic Algorithms (GAs), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO), Simulated annealing (SA), Tabu Search (TS), and Artificial Bee Colony (ABC), are briefly introduced and their applications to the signal optimisation will be discussed.

## 4.1 Genetic Algorithms (GAs)

GAs are tpopulation-based algorithmic models inspired by genetic evolution theory (Holland, 1992), in which the characteristics of each individual are represented by using genotypes. The solution candidates are encoded into chromosome, and chromosomes are iteratively used as parent solutions to create offspring solutions based on the cross-over and mutation operators. GAs have been widely used by researchers to solve single and multi-objective and performance-based signal optimisation problems and are described below.

### 4.1.1 Single objective optimisation

Teklu et al. (2007) employed GA for optimising green and cycle timings. By considering rerouting of traffic, authors used the total travel time over an urban network as the objective function. The results showed that considering rerouting can enhance the performance of signal timing for more congested networks. Yang et al. (2013) proposed a traffic signal controller with a golden ratio-based genetic algorithm (TSCGRGA) to optimise the signalised intersections. In comparison to other heuristic approaches, the numerical results reported from a single intersection experiment demonstrated that TSCGRGA is capable of reducing delay and stop time.

Kesur (2009) developed an improved version of a GA for the fixed time optimisation of traffic signals by applying the cross-generational elitist selection, heterogeneous recombination, and cataclysmic mutation search algorithm with real crossover and mutation operators. The results revealed that the enhanced algorithm is capable of reducing the delay time better than the standard GA. Tong et al. (2006) applied a GA for real-time traffic signal optimisation based on the maximum traffic flow capacity and minimum delayed vehicles of an intersection. The optimisation results demonstrated that a GA is able to produce effective and feasible signal timings. Tan et al. (2016) applied a GA for the traffic signal optimisation of an urban intersection under oversaturated conditions by minimising average delay time. Authors investigated an isolated urban intersection and reported that the GA is able to reduce the delay time efficiently. Chin et al. (2011) proposed a traffic signal timing management approach based on a GA (GATSTM) for optimising signal timing variables of multiple intersections, such as offset, cycle time, green split and phase sequence. The simulation results obtained from a simple network with two intersections indicated that the GATSTM has a good performance in the traffic flow control of networks with multiple intersections.

Varia, Dhingra (2004) applied a GA to solve the dynamic system optimal traffic assignment problem by optimising the signal timings. In comparison to the traditional methods, authors stated that GAs require significantly fewer assumptions to solve this problem. Park et al. (1999) proposed a GA-based signal optimisation, which is able to handle oversaturated intersections. The obtained results are compared to those produced by the TRANSYT-7F Penic, Upchurch (1992), a traffic and signal timing optimisation program, which uses hill-climbing for optimisation of signal parameters. For the low and high demand scenarios, numerical results indicate that the GA-based signal optimisation provide better signal timing plans than the TRANSYT-7F.

By considering day-to-day variability in traffic demand, Park, Kamarajugadda (2007) proposed a GA-based signal optimisation approach. In this approach, the variation in the network delay time arising from the varying traffic demand is considered based on a integration technique. The authors evaluated the performance of their approach on an isolated intersection under moderate and heavy traffic conditions. The obtained results were compared with those provided by Synchro (RAT, 2014), a deterministic signal optimisation software (see Section 2). The results showed that the GA can generally yield better signal timing plans than Synchro.

By using a GA, Kwak et al. (2012) investigated the impact of the signal optimisation on the vehicular fuel consumption and emissions in an urban corridor. Authors performed a microscopic traffic simulation by using TRANSIMS ( Smith et al. (1995)) with VT-Micro model used to estimate emissions and fuel consumption and the GA is applied to optimise the traffic signal timing plans. The numerical results obtained from a case study were compared to those yielded by the Synchro. Results demonstrated that integrating the GA with the microscopic TRANSIMS simulation tool and VT-Micro model can provide much better network performance than Synchro in terms of the air quality, energy, and mobility measures.

A study by Stevanović et al. (2009) applied GA to minimise the fuel consumption and carbon emissions. The approach combined the VISSIM (Fellendorf, Vortisch, 2011) microscopic simulator with the CMEM emission model and VISGAOST optimisation program. VISGAOST is an stochastic signal timing optimiser based on the GA and VISSIM microscopic simulator. Authors considered seven objective functions to find the lowest $CO_2$ emissions and fuel consumption. The results obtained from a network with 14 intersections in Park City revealed that the formula commonly used to estimate fuel consumption in traffic simulation tools cannot be used as a reliable objective function. The results also indicated that the integrated VISSIM-CMEM-VISGAOST with the objective function of fuel consumption obtained from the CMEM model can provide 1.5% reduction of fuel consumption.

A study by Kou et al. (2018) employed a GA to optimise carbon emissions and travel efficiency as a single objective where the carbon emissions, travel times and the number of stops are considered within an aggregated fitness function. This approach is simple to implement and the experimental results suggest that it has improved carbon emissions, travel times and vehicle stops for the considered cases. However, this work does not provide any recommendations of experimental or theoretical basis pon how to determine the weights for the different objectives that are aggregated into a single objective.

Tan et al. (2017) applied a decentralised genetic algorithm (DGA) to optimise the traffic network signal during the morning peak. The results obtained from the signal optimisation of a case study showed that the DGA can reduce the average delay of the network. In another study, "Brian" Park et al. (2000) suggested an enhanced GA-based program for signal optimisation under oversaturated traffic conditions. Authors considered three different strategies during the optimisation procedure, including throughput maximisation, average delay minimisation, and modified average delay minimisation with a penalty function. The performance of the enhanced GA-based signal optimisation procedure was evaluated by optimising a set of intersections with different spacing. The results revealed that the GA-based signal optimisation with average delay minimisation produced a better signal plan than other GA-based strategies and TRANSYT-7F program in terms of queue time.

In order to improve the performance of the GA, Abu-Lebdeh et al. (2014) discussed different techniques and proposed a parallel GA (PGA) for transportation systems. In PGA, the population of GA is divided to several sub-populations working separately. It is expected that using PGA requires fewer number of function evaluations and reduced running time (Abu-Lebdeh et al., 2014). By using the parallelisation technique, the results showed that PGA can significantly reduce the computational time for the complex problems.

Varia et al. (2013) proposed a joint optimisation of signal parameters and dynamic user equilibrium (DUE) traffic assignment for the congested urban road network. The authors applied the GA for optimising signal setting parameters. The results obtained from a real case study verify the efficiency of the GA in solving the joint optimisation problem for the real network. In another study, Sharma, Kumar (2019) applied the GA to minimise the delay at an intersection by finding red and green cycle intervals. The performance of the GA is investigated by optimising three t-intersections in the city of Hardwar, India. The results revealed that GA is able to enhance traffic control performance of the network.

Yun, Park (2012) employed GA to optimise the coordinated actuated traffic signal systems, in which a given path in Charlottesville, Virginia, USA was investigated as the case study. Stevanovic et al. (2008) developed a new signal optimisation tool, known as the VISSIM-based Genetic Algorithm Optimisation of Signal Timings (VISGAOST), in which GA is used as the optimiser within the simulation tool. Tung et al. (2014) compared the performance of GA against Expectation-Maximisation (EM) method with local information for signal timing optimisation and demonstrated that GA is capable of generating better delay times than EM method.

Shen et al. (2011) investigated the throughput maximisation of a road network with 4 intersections through optimising signal timing plans. Park et al. (2004) employed a GA to optimise the time-of-day breakpoints for better traffic signal control, in which a two-loop optimisation was performed. Authors optimised the outer loop for time-of-day breakpoints and performed inner loop optimisation for timing plans of corresponding intervals. They investigated the signal optimisation of three coordinated actuated signalised intersections on Reston Parkway in Fairfax, Virginia, USA. Ma, Liu (2019) proposed an improved GA with an improved fitness calibration method and an adaptive cross-mutation function for optimum signal timing of a intersection by considering the travel safety of the elderly, in which a given intersection in Lintao County of Gansu Province, China is investigated as a case study. Authors reported that the improved version of GA was able to provide better results than standard GA and Webster methods.

Liang et al. (2020) investigated the performance of different versions of GA in signal optimisation, including the standard GA, sequential GA, and voting GA. From a computational prospective, authors reported that the sequential GA is more efficient and the required time for each signal control action grows less rapidly with the number of vehicles considered during the simulation process. Hu, Liu (2013) employed a GA to optimise the delay time of a grid network consisting of six intersections, in which the performance of intersections in different directions are considered. Duerr (2000) proposed a new concept for a corridor control system and applied GA to optimise a signalised arterial in Würzburg, Germany. Takahashi et al. (2002) applied GA to optimise the traffic lights of a 13-mile corridor in Detroit, USA.

Overall, the single-objective GA approach has been found to be very successful in optimising the signal timings for transportation networks across a variety of scales. However, with multiple potential criteria for optimisation within a transportation network, it can be difficult to determine the objective weightings, which makes the multi-objective optimisation approach an attractive alternative.

#### 4.1.2 Multi-objective optimisation

Branke et al. (2007) applied a non-dominated sorting genetic algorithm II (NSGA-II) for traffic-actuated signal control by considering different combinations of objective functions, including the travel time and the number of stops. NSGA-II is a multi-objective evolutionary algorithm originally developed by Deb et al. (2002). Authors employed VISSIM as a microscopic simulation tool to evaluate the signal timing plans generated by NSGA-II. The optimisation results obtained from a single intersection revealed that the signal timing plans yielded by NSGA-II are better than those obtained by a traffic engineer.

In another work, Stevanovic et al. (2007) employed a GA to optimise signal plans by using the VISSIM software as an evaluation environment. The results reported from a real-world traffic network illustrated that the signal timing plans optimised by GA are better than those yielded by Synchro. Zhang et al. (2013) employed GA for the signal timing plans of a bi-objective model to minimise the traffic delay and the mean excess exposure simultaneously. Sun et al. (2003) applied a Non-dominated Sorting GA (NSGA-II) to solve the multi-objective signal timing optimisation problem by considering the delay and number of stops as the objective functions. The numerical results reported by Sun et al. (2003) demonstrated that NSGA-II can efficiently solve multi-objective signal optimisation problems under uniform and stochastic traffic arrival patterns.

Kesur (2013) employed NSGA-II for minimising delay and the number of stops in large traffic networks under fixed-time signal control. Authors used a MSTRANS stochastic microscopic traffic simulation model to evaluate each signal timing plan. The performance of the multi-objective approach against the single-objective delay-minimisation strategy is evaluated by optimising two test networks under over-saturated and under-saturated conditions. For under-saturated condition, both of the single-objective and multi-objective approaches provided a relatively similar results, while the benefits of the multi-objective approach were more obvious under over-saturated condition.

Sun et al. (2006) defined a bi-level programming formulation and proposed an heuristic solution approach for signal control optimisation problem under stochastic route choice and time-variant demand. Authors formulated the signal timing optimisation as a upper level problem with the objective function of travel time, while the users' route choice behaviour is modeled as the lower level problem. Sun et al. (2006) solved the upper level signal timing optimisation problem by using Elitist GA and Micro GA methods. Elitist GA method is the simple GA with replication mechanism of the best individual of the current generation and Micro GA is a class of GA with low population sizes, in which the population is restarted for a sufficient number of times. For fewer amounts of fitness evaluations, the results obtained from a simple network with 10 signalised intersections demonstrated that both of the Micro GA and Elitist GA methods provide identical results. While the Micro GA method is capable of generating better results than Elitist GA method for higher amounts of fitness evaluations.

Nguyen (2019) solved the multi-objective signal optimisation problem for throughput maximisation and queue minimisation of a oversaturated Intersection by NSGA-II algorithm. Costa et al. (2018) applied a Memory-Based Variable-Length Non-dominated Sorting Genetic Algorithm 2 (MBVL-NSGA2) for solving a multi-objective optimisation signal problem with two objective functions, including maximisation of the average vehicle speeds and minimisation of the variance of the vehicle speeds. The performance of the MBVL-NSGA2 was validated by using a multi-intersection network with real data and the obtained results were compared with those yielded by the traditional NSGA-II method. The simulation results revealed that the MBVL-NSGA2 is able to produce better traffic signal plans than those provided by the NSGA-II method and the usual solutions adopted by the traffic engineers.

Armas et al. (2017) developed a GA optimiser to optimise the travel times, carbon emission, and fuel consumption. The modelling used the Matsim (Horni et al., 2016) microscopic traffic simulator and hierarchical clustering was performed on the best solutions found in several runs of the algorithm. An analysis of signal clusters and their geolocation, estimation of fuel consumption, spatial analysis of emissions, and an analysis of signal coordination provide an overall picture of the systemic effects of the optimisation process. However, within their study, the multi-modality of transport network is not considered.

Nguyen et al. (2016) developed an improved version of NSGA-II algorithm based on a local search technique, called NSGA-II-LS, for multi-objective signal optimisation of delay minimisation and throughput maximisation. Authors applied NSGA-II-LS to optimise the signal timings of the area around a football stadium in Bologna city in Italy for big events such as football matches or concerts. Li, Sun (2019) employed GA to solve the multi-objective optimisation of signal timing plans for simultaneous delay minimisation, throughput maximisation, and spill-back minimisation, in which a grid network consisting of 9 intersections was investigated. Ren et al. (2013) solved a bi-objective problem using the NSGA-II algorithm, in which the upper-level problem is the multi-objective signal optimisation for travel time minimisation and a performance index composed of delay time and spill-back.

Stevanovic et al. (2013) investigated the signal optimisation of a 12-intersection corridor on Glades Road in Boca Raton using a VISSIM-based GA and the Surrogate Safety Assessment Model (SSAM) to reduce surrogate measures of safety and reduce the risks of potential real-world crashes. Stevanovic et al. (2015) integrated VISSIM-based GA, SSAM, and Comprehensive Modal Emission Model (CMEM) for the multi-objective signal optimisation of a network of 5 intersections in West Valley City, Utah, USA. The authors plotted a 3-dimensional Pareto front surface for the objective functions of throughput, fuel consumption, and the number of conflicts. Li et al. (2013) tested the performance of NSGA-II against Synchro and Webster methods for signal optimisation of a single intersection, in which NSGA-II performed significantly better than other methods. Abbas, Sharma (2006) applied NSGA-II algorithm to find a set of optimal timing plans for each traffic light by considering the traffic condition at different times of the day, in which the delay time, degree of detachment, and number of delays were considered as the objective functions.

#### 4.1.3 Performance-based optimisation

GAs have been also previously been used to solve performance-based signal optimisation problems. For example, Ezzat et al. (2014) proposed a mathematical model representing the stochastic environment of the traffic control and used a GA to provide practical solutions and effective signalisation plans. The results demonstrated that the signal timings generated by the GA can improve the performance of the network in terms of the queuing lengths and vehicular waiting times. Stevanovic et al. (2011a) optimised the signal timing parameters using a GA to reduce the risks of potential real-world crashes while maintaining efficiency of traffic signals. Ghanim, Abu-Lebdeh (2015) developed a real-time traffic signal control by integrating signal timing optimisation and transit signal priority. The authors proposed an algorithm in which artificial neural networks (ANNs) are used to keep track of transit vehicle trajectories along the traffic control, and then a GA is applied to optimise the signal timing parameters. Lertworawanich et al. (2011) transformed the multi-objective signal optimisation of spillover and delay minimisations as well as throughput maximisation into a single-objective optimisation problem based on some equivalent weight coefficients and solved it by standard GA. Authors used a grid consisting of nine intersections as a case study and showed the potential of the model to resolve spillovers in oversaturated networks.

### 4.2 Particle Swarm Optimisation (PSO)

PSO developed by Eberhart, Kennedy (1995) is a multi-agent metaheuristic method, which simulates the flocking behaviour of birds and their social interactions in nature. In PSO, the solution candidates for the optimisation problem are represented by a swarm of particles looking for the best positions within a search landscape. It is assumed that each particle has its own position and velocity in the search space and the initial positions and velocities are randomly generated within the search space. During the optimisation process, the position and velocity of each particle are updated based on its own previous best experience (i.e., *pbest*) and the best experience obtained by the whole swarm (i.e., *gbest*).

Chen, Xu (2006) applied PSO to optimise the traffic signal timings. In their traffic model, a local fuzzy-logic controller installed at each junction is used to generate initial solutions for PSO algorithm, in which the coordination parameters from adjacent junctions are also considered. The results indicated that PSO is able to enhance the performance of the network in terms of delay per vehicle. In another study, Wu, Wang (2016) modelled the online traffic network with Cell Transmission Model (CTM) and applied PSO for signal optimisation of the network. Gökçe et al. (2015) proposed a new microscopic traffic model and applied PSO for the signal optimisation. The numerical results obtained by the proposed approach demonstrated that PSO is able to significantly reduce average delay time per vehicle passing through the roundabout.

The study by Olivera et al. (2015a) applied PSO as a swarm intelligence technique for optimising signal timing programs in metropolitan areas. Authors employed SUMO microscopic simulation tool (Krajzewicz et al., 2002) to simulate the traffic within the city. The performance of PSO is evaluated by using two areas extracted from Malaga and Seville cities, in Spain, and the obtained results are compared to those obtained by Differential Evolution (DE) and Random Search (RS) methods as well as SUMO cycle programs generator (SCPG). Authors performed a statistical comparison between the mentioned algorithms in terms of the best, mean, worst, and standard deviation of the results yielded from 30 independent trial runs of each algorithm. The comparative results indicated that not only the signal timing plans obtained by PSO outperform to those obtained by the DE, RANDOM, and SCPG methods, but also they reduce the $CO$ and $NO_x$ emissions with regards to human experts.

Dabiri, Abbas (2016) integrated PSO and VISSIM simulation software and optimised the signal timing parameters of an arterial with three intersections located in Blacksburg, Virginia, USA. Jiao et al. (2016) applied a Pareto front–based PSO algorithm for signal timing control of a intersection in Beijing, China. In another study, Jia et al. (2019) developed an improved PSO (IPSO) algorithm for multi-objective signal optimisation. In IPSO, a hybrid difference operator is used to update the position of particles, which combines the differential operator and an inertia weight. Davydov, Tolstykh (2019) applied PSO to optimise signal timings of a roundabout in Novosibirsk, Russia. Garcia-Nieto et al. (2013) applied PSO to find the optimal cycle programs of metropolitan areas located in Bahıa Blanca and Malaga in Spain. Peng et al. (2009) proposed a PSO algorithm with niche isolation technique to solve the urban traffic light scheduling problem, in which the population of particles are divided into several subgroups. Olivera et al. (2015b) employed PSO for green times optimisation of a given parts of urban networks of Malaga and Seville cities in Spain.

Premature convergence and trapping into local optimum points in the search space are the main disadvantages of the PSO method. Hence, the studies on the convergence analysis of PSO should be carefully considered in application of this algorithm for signal optimisation (Ozcan, Mohan, 1999; Clerc, Kennedy, 2002). It appears that little research has been carried out on the performance comparison of PSO against the GA approach and it would be interesting to perform a statistical comparative study of the convergence properties of these algorithms in the signal optimisation problem. In recent years, multi-objective versions of the PSO method have attracted much attention from the researchers in different areas (Beiranvand et al., 2014; Sha, Lin, 2010). A comparison of a multi-objective version of the PSO method with a multi-objective GA approach, like NSGA-II, is another aspect that worth investigating. Moreover, PSO has three internal parameters controlling the search process, namely inertia weight ($\omega$) and the acceleration coefficients ($c_1$ and $c_2$). The effects of these parameters on the algorithm's performance in solving signal optimisation problem also are important research topics to be investigated.

### 4.3 Ant Colony Optimisation (ACO)

ACO, introduced by (Dorigo, Birattari, 2010), models the foraging behavior of natural ants while identifying the shortest path between their nest and food source. In ACO, the optimisation process starts by randomly distributing the ants on the nodes of a graph that map to the problem being solved (e.g. cities in the Travelling Salesman Problem). In each iteration, the ants try to find the shortest path by using a communication protocol, called *pheromone*. Pheromone is a chemical substance deposited by ants on their way back to the nest, which evaporates over time. By using these pheromone trails, the ants share information between each other to guide the colony towards the food source. During the optimisation process, the pheromone intensities are iteratively updated by the ants in proportion to the optimality of their total route. Paths with greater amounts of pheromone attract more ants and an autocatalytic process ensues.

He, Hou (2012) suggested an efficient algorithm based on the ACO to solve the single-objective signal optimisation problem. The authors reported that ACO is able to perform remarkably better than the Webster and GA methods, and provide smaller delay time, fewer number of stops, and larger traffic capacity. Putha et al. (2012) applied ACO to solve the over-saturated network traffic signal coordination problem by maximising the number of vehicles processed by the network throughout the oversaturation period. The authors compared the results obtained from ACO to those provided by a GA. Comparison results showed that ACO performs better than GA for their problem. However, the study considered only green times as the decision variables. Renfrew, Yu (2012) employed rank-based ACO with local search to optimise the delay time in a single intersection. Karoonsoontawong, Waller (2009) applied ACO with reduced search space mechanism to solve bi-level signal optimisation problem, in which each ant only searches the reduced search space around the best ants. Tawara, Mukai (2010) applied ACO to solve the signal optimisation problem with a traffic congestion prediction model.

Although the comparison results reported from the above studies indicate that ACO performs better than a GA, superiority of ACO against GA should be investigated by performing statistical analyses and sensitivity analyses of internal parameters. Moreover, the application studies of ACO in signal optimisation are focused on the single-objective category. Recently, a multi-objective version of ACO has been proposed by researchers (Lopez-Ibanez, Stutzle, 2012). Hence, it seems that the performance of the multi-objective version of ACO algorithm should be investigated in solving multi-objective signal optimisation problem as well.

### 4.4 Differential Evolution (DE)

DE algorithm developed by Price et al. (2006) is one of the popular population-based metaheuristic algorithms, in which the solution finding process is based on the information obtained from the weighted difference of the individuals in the population. Cakici, Murat (2019) applied DE for the signal phasing optimisation of three-leg signalised intersections. Jamal et al. (2020) compared the performance of DE and GA on the signal optimisation of two signalised intersections in the city of Dhahran, Eastern Province, KSA. They reported that the convergence speed of DE is faster than a GA. However, their results showed that a GA can provide more reductions in delay times.

Broadly speaking, the potential capabilities of DE algorithm for the signal optimisation has not been fully addressed yet. A review of the literature reveals that a wide variety of mutation operators have been proposed by different researchers for the DE algorithm (Qin et al., 2008; Mezura-Montes et al., 2006; Price et al., 2006). Future researches can be focused on the performance evaluation of different variants of DE algorithm in signal optimisation..

### 4.5 Other metaheuristics

In recent years, a wide variety of novel meta-heuristics inspired by the physical, ecological and social phenomena have been developed to solve engineering optimisation problems(Rashedi et al., 2009; Gandomi, Alavi, 2012; Jalili et al., 2017; Yang, Gandomi, 2012; Jalili, Husseinzadeh Kashan, 2019). In some cases, researcher have employed other types of metaheuristic methods to solve signal optimisation problem, including Artificial Bee Colony (ABC) algorithm, Shuffled Frog-Leaping Algorithm (SFLA), Tabu search (TS) algorithm, Simulated Annealing (SA) algorithm, Jaya Algorithm (JA), Harmony Search (HS) algorithm, Water Cycle Algorithm (WCA), Whale Optimisation Algorithm (WOA), Cuckoo Search (CS), Imperialist Competitive Algorithm (ICA), Bat-inspired Algorithm (BA), Grey Wolf Optimiser (GWO), and Grasshopper Optimisation Algorithm (GOA).

Artificial Bee Colony (ABC) was developed by Karaboga, Basturk (2007) and is inspired by the collective foraging behavior of a honey bee colony in seeking nectar sources. ABC consists of population of artificial bees, in which each bee represents a solution candidate for the problem. In ABC, the artificial bees are categorised into three types as follows: employed bees, onlooker bees, and scout bees. These three types of bees cooperate with each other to find food sources in the search space. The algorithm uses employed bees to find some food sources and shares the information about these sources with onlooker bees. Then, the onlooker bees select some of the food sources provided by the employed bees and try to find new food sources around them. The food sources with more nectar amounts (i.e., better fitness functions) have more chance to be selected by the onlooker bees. If a food source investigated by a onlooker bee is not improved through a given number of trials, the associated employed bee will become a scout bee. The scout bee is a randomly generated solution within the search space. Dell'Orco et al. (2014) developed a model consisting of ABC algorithm with TRANSYT-7F (ABCTRANS) for signal timings optimisation in coordinated signalised networks. The numerical results revealed that the performance of ABCTRANS is better than TRANSYT-7F and it can improve the PI of the networks. Gao et al. (2017c) implemented ABC algorithm to multi-objective optimisation of urban traffic lights for minimum delays of vehicles and pedestrians. Authors used a non-domination strategy based metric to compare and rank the solutions for the two objectives. They studied the traffic network of Jurong area in Singapore and reported that the ABC algorithm can outperform the multi-objective version of the GA (NSGA-II) method. In another study, Gao et al. (2019) proposed an improved ABC (IABC) for signal optimisation of a grid network consisting of 9 intersections, in which the performance of the standard ABC is improved through generating new food sources in employed bee and onlooker bee phases. Jovanović et al. (2017) employed ABC algorithm to urban traffic signal control of a grid network with 9 intersections. Authors compared the results obtained by the ABC algorithm to those yielded by SA method, and reported that ABC is able to provide higher quality solutions for the problem. Zhao et al. (2018) proposed a non-dominated sorting ABC (NSABC) algorithm to solve the multi-objective signal optimisation problem of a given intersection in Lanzhou city, China.

Shuffled Frog-Leaping Algorithm (SFLA) is a population-based metaheuristic technique developed by Eusuff, Lansey (2003) inspired by the behavior of a group of frogs when they are seeking for food. SFLA imitates two main behaviors of frogs as follows: leaping and shuffling. SFLA starts with initialising a random population of frogs within the search space of the problem. Based on the fitness values of the frogs, the population is divided into several small colonies called memeplexes. The frogs in each memeplex perform local search to find higher quality solutions. Then, each memeplex shares information with other memeplexes through the shuffling process. Park, Lee (2009) developed a stochastic optimisation method (SOM) based on SFLA (SFLASOM) for optimisation of coordinated-actuated traffic signal system. Authors investigated an arterial network consisting of 16 signalised intersections and reported that SFLASOM is able to improve the total network travel time.

Tabu search (TS), devloped by Glover, Laguna (1998), is a local or neighborhood metaheuristic search method. From a given random initial solution, TS tries to find a better solution in its neighborhood until the termination criterion is satisfied. TS has a short-term memory, called the *tabu list*. In TS, new solutions are generated by using a local search and the short-term memory where a list of the *tabu* solutions is stored. Hu, Chen (2012) applied a greedy randomised TS (GRTS) algorithm to solve the network-level signal optimisation problems. The authors investigated the performance of GRTS on two networks and the obtained results compared to those provided by a GA. The results showed that GRTS can perform better than a GA.

Simulated Annealing (SA) is another metaheuristic algorithm which mimics the physical process of heating a material when the temperature is gradually reduced to minimise the defects and system energy (Van Laarhoven, Aarts, 1987). Shi et al. (2020) employed SA to solve the mix-integer-nonlinear-programming signal optimisation problem, in which the the discrete variable of the number of lanes and the continuous variable of green lights duration were considered simultaneously. Han et al. (2015) compared the performance of SA against PSO in solving a bi-objective problem, in which the upper level is the green time optimisation. The results obtained from the six-node network showed that SA is able to produce comparable results to those yielded by PSO. Hale et al. (2015) compared the performance of SA against GA and TS on signal optimisation of the isolated intersections in terms of the optimality and required computational effort. The authors reported that SA is able to provide competitive results. Jahangiri et al. (2011) employed SA to find optimum cycle times for urban network consisting of 9 signalised intersections in Hashtgerd city, Iran.

Harmony Search (HS) is another population-based metaheuristic algorithm developed by Geem et al. (2001), which imitates the searching process of a musician in finding a perfect state of harmony to model a searching strategy for global optima in optimisation problems. Gao et al. (2018a) applied HS and ABC algorithms to solve the multi-objective traffic lights scheduling for minimum delay times of vehicles and pedestrians in Jurong area of Singapore. The authors compared the results between these approaches and NSGA-II showed that ABC and HS perform better than NSGA-II algorithm. Zhang et al. (2019) developed a non-dominated sorting HS (NSHS) algorithm for simultaneous delay and the drivers' unhappiness minimisation. In another study, Gao et al. (2016b) proposed a discrete HS (DHS) algorithm for optimising urban traffic light scheduling problem, in which a new solution finding strategy is defined based on the a small harmony memory to improve the performance of standard HS. In addition, authors used a set of three local search techniques within the DHS algorithm to enhance the exploitation ability. Authors investigated the performance of DHS by using the available traffic data from a partial traffic network in Singapore and reported the superiority of DHS over the standard HS algorithm. Zhang et al. (2018) investigated the signal optimisation problem for the pedestrian-vehicle mixed-flow network, in which the problem is converted to a mixed-integer linear programming problem and then, the DHS algorithm is used to optimise the signal settings.

Jaya Algorithm (JA) and Water Cycle Algorithm (WCA) are relatively new metaheuristic approaches developed by and Rao (2016) and Eskandar et al. (2012). Jaya is a

Sanskrit word meaning victory and the JA is a population-based metaheuristic which strives to become victorious by reaching the best solution. WCA is a population-based algorithm inspired by the natural water cycle process, in which the flowing of rivers and streams towards the sea are simulated to perform the search process. Gao et al. (2016a) applied JA to solve the urban traffic signal control of a network with 100 intersections based on real-life traffic data in Singapore. The authors used a neighborhood search technique to improve the exploitation ability of JA. Gao et al. (2017a) applied HS, WCA, and JA methods to solve a large-scale urban traffic light scheduling problem. Authors improved the performance of the modified JA and WCA methods by adding a feature based search (FBS) strategy. Comparison between the results obtained from mentioned metaheuristics and the existing traffic control systems revealed that the the metaheuristics were able to significantly reduce delay times. Numerical results were also demonstrated that the performance of the methods depends on the sizes of case studies. For large-scale networks, WCA performs better than HS and JA in terms of the statistical results and required computational effort. However, for the smaller sizes of networks, HS and JA are slightly better than WCA. In another study, Gao et al. (2018b) compared the performance of five different metaheuristic algorithms, including JA, HS, ABC, GA, and WCA, for traffic signal scheduling of the Jurong area in Singapore. The authors proposed three local search operators to improve the performance of the metaheuristic algorithms. The results showed that the ABC algorithm with local search technique performs than other algorithms.

Thaher et al. (2019) applied novel metaheuristic algorithms, including Whale Optimisation Algorithm (WOA) (Mirjalili, Lewis, 2016) and Bat-inspired Algorithm (BA) (Yang, 2010), to solve traffic scheduling problem of a real signalised segment at the centre of Nablus city, Palestine. WOA imitates the social behavior of humpback whales and BA mimics the echolocation system of micro-bats in nature. The results obtained from three case studies revealed the efficiency of WOA over BA and GA methods.

Scatter Search (SS) algorithm is a population-based metaheuristic algorithm, which belongs to the category of the evolutionary algorithms. The main difference between SS algorithm and other evolutionary algorithms is that the solution finding process in SS algorithm is based on the deterministic combination of previous solutions Glover (1998). Papatzikou, Stathopoulos (2018) applied SS algorithm and GA to find best combination of signal phases for a single intersection. Authors reported that SS algorithm can provide better signal timing plans in terms of the total delay time and the required run time.

Cuckoo Search (CS) is another metaheuristic population-based algorithm developed by Yang, Deb (2009) inspired by the lifestyle of the cuckoo. Araghi et al. (2017) applied CS to optimise the performance of adaptive interval type2-fuzzy traffic signal controllers, in which the results revealed the superiority of CS algorithm in comparison to GA and SA algorithms.

Imperialist Competitive Algorithm (ICA) developed by Atashpaz-Gargari, Lucas (2007) belongs to the category of socially inspired metaheuristic algorithms, which mimics the imperialistic competition process. Zargari et al. (2018) employed ICA for signal optimisation of a given area in Tehran, Iran. The authors compared the performance of ICA and SA algorithms and reported that ICA is able to provide comparable results.

### 4.6 Hybrid metaheuristics

Nowadays, hybrid metaheuristic search techniques have gained much attention and been well developed for solving a wide variety of optimisation problems in different areas of science and engineering (Blum et al., 2011; Pellerin et al., 2019). These approaches combine the components of various standard metaheuristic methods in such a way that the newly generated algorithm is expected to perform better than the standard algorithms. In some cases, researchers proposed hybrid metaheuristic methods to solve the signal optimisation problem. For example, Srivastava, Sahana (2017) formulated a bi-level model, in which the upper layer is the traffic signal optimisation and the lower layer is the stochastic user equilibrium. Authors suggested a hybrid ACO and GA algorithm to optimise the traffic signals and minimise the total waiting time. Numerical results demonstrated that the hybrid model performs remarkably better than the standard ACO and GA methods.

Ceylan (2006) developed a hybrid GA with TRANSYT hill-climbing optimisation routine (GATHIC) for signal control by considering the coordination effects. In GATHIC, a decreased search space algorithm (ADESS) is used to reduce CPU time required by GA. Authors reported that GATHIC is more efficient than TRANSYT in providing optimal signal timings with better PI. Li, Schonfeld (2015) developed a hybrid SA and GA (SA-GA) method for arterial signal timing optimisation under oversaturated traffic conditions. The experimental results showed that the hybrid SA-GA method is more efficient than the standard SA and GA methods in terms of the solution quality. García-Ródenas et al. (2019) investigated the performance of hybridised versions of GA and SA with Nelder–Mead (NM) simplex algorithm on the bi-objective signal optimisation problem of Nguyen–Dupuis network with 13 nodes and 23 links.

Kai et al. (2014) applied a Collaborative Evolutionary-Swarm Optimisation (CESO) algorithm for real-time signal control, which combines Crowding DE (CDE) algorithm and PSO. Experimental results revealed that CESO performs better than PSO algorithm in terms of the average delay time of all vehicles in various scenarios. Chentoufi, Ellaia (2018) suggested a hybrid PSO and TS (PSO-TS) method for adaptive signal timing optimisation. PSO-TS updates the position and velocity of particles by using the information of best neighbor and based on the best historical position and a tabu list.

Bacterial foraging optimisation algorithm (BFOA) is a recently developed metaheuristic algorithm inspired by the social foraging behaviors of bacteria Das et al. (2009). Liu, Xu (2012) developed a hybrid BFOA and DE algorithm (DEBFA) for signal timing optimisation of some intersections in Guangzhou, China. In DEBFA, authors used DE operators to improve the performance of the BFOA method.

Artificial fish swarm algorithm (AFSA) is another swarm intelligence-based metaheuristic algorithm, which is inspired from the cooperative behavior of fish swarm in finding food sources. Ma, He (2019) hybridised AFSA and GA to optimise signal timings of Jianning Road with 5 intersections in Lanzhou, China. In genetic-AFSA algorithm, the mutation and crossover operators were used to enhance the performance of AFSA.

Grey Wolf Optimiser (GWO) and Grasshopper Optimisation Algorithm (GOA) are the recently population-based metaheuristic algorithms, which are inspired by the social behavior of wolves during the hunting process and the behaviour of grasshopper swarms in nature, respectively (Mirjalili et al., 2014; Saremi et al., 2017). Teng et al. (2019) developed grey wolf grasshopper hybrid algorithm (GWGHA) to optimise the cycle times for urban networks of different cities in Taiwan, Spain, and Argentina. In GWGHA, GWO is used to enhance the exploration ability of GOA method.

According to the reviewed articles in this area, it can be observed that researchers employed very simple networks with limited number of intersections to evaluate the performance of the hybrid algorithms. However, large-scale transportation networks can be optimised efficiently by taking the advantages of hybrid metaheuristic algorithms.

## 5 Publication analysis

In this section, a brief analysis on publications related to the signal optimisation using metaheuristics are presented. In this survey, around 170 related references are investigated in which the metaheuristics were used to solve the optimal signal control problem. Figure 2 shows the chronological distribution of the papers in which metaheuristics are applied to solve the signal optimisation problems. Figure 3 shows clearly the fast growing interest in the application of metaheuristics in this field. In addition, Figure 3 shows the distribution of these publications based on the type of the applied metaheuristic. From Figure 3, it can be seen that most of the published papers in the literature applied GA and PSO as the optimiser to solve the signal optimisation problem.

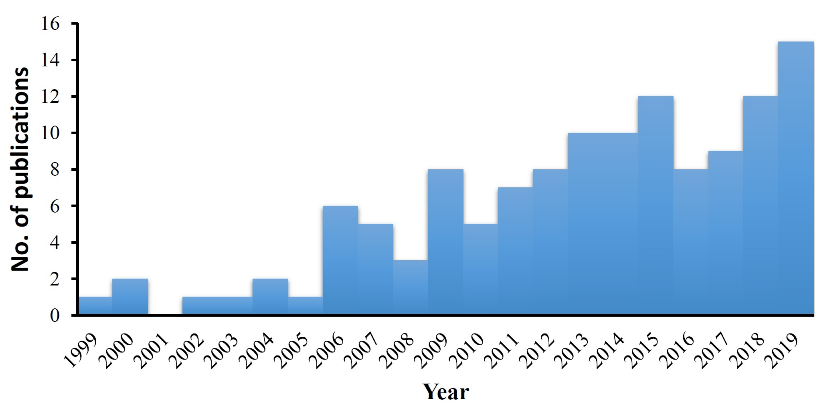


Figure 2: The chronological distribution of related publications to the signal optimisation using metaheuristics

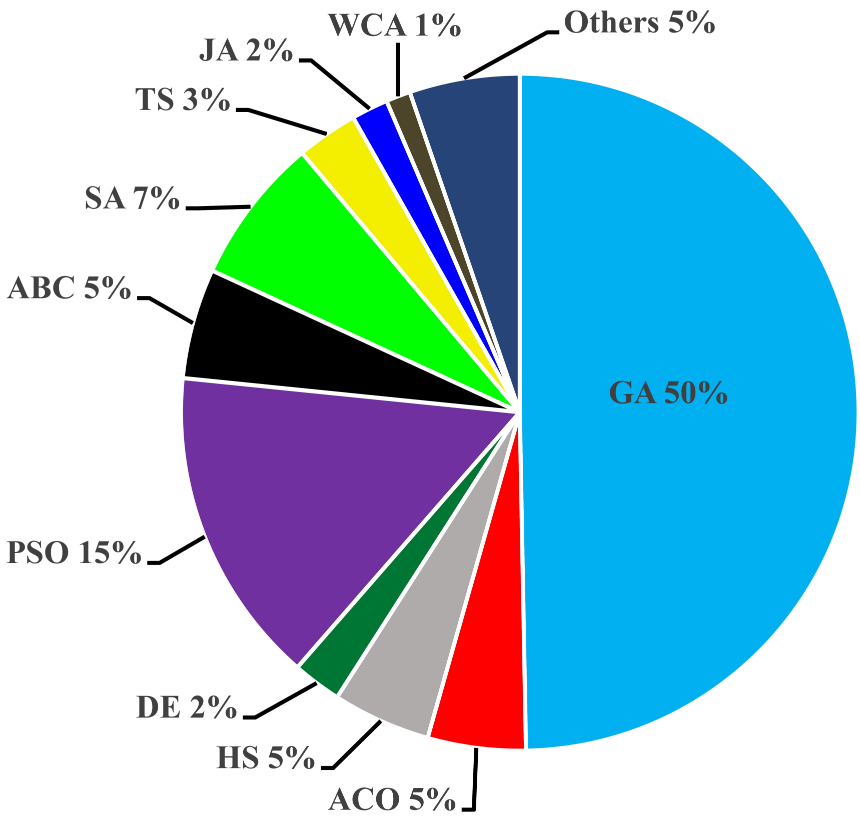


Figure 3: The distribution of the publications based on the type of the metaheuristics

## 6 Conclusions and future research directions

In this survey paper, a comprehensive review over the application of metaheuristic approaches to the traffic signal optimisation problems is presented. Regarding the problem formulation, different types of network performance criteria and decision variables were used to define the objective functions. Some studies have considered multiple objectives either aggregated to a single-objective or optimised in parallel using multi-objective optimisation techniques. Based on this survey, available signal optimisation problems can be categorised into single-objective, multi-objective, performance-based, and bi-level optimisations. However, less work has been done in understanding the correlations between different objectives. This understanding is essential for practitioners to decide the relative importance of conflicting objectives. Moreover, it is indicated that most of the studies adopted the cycle length, green splits, offsets, and phase sequence as the decision variables for the signal timing optimisation problem.

According to the presented literature review, there are some new research directions in this field which would benefit from further investigation:

- The review has shown that most of the previous work have been focused on the application of GA and its variants to solve the signal optimisation problems. Therefore, it may be of interest to investigate the performance of recently developed metaheuristics, such as BBO (Simon, 2008), TLBO (Rao et al., 2011), KH (Gandomi, Alavi, 2012), OIO (Jalili, Husseinzadeh Kashan, 2018), and GSA (Rashedi et al., 2009), in solving traffic signal optimisation problems.

- The review has shown that little work has been carried out on the statistical performance of the metaheuristics in solving signal optimisation problems, it would be interesting to perform a statistical analysis of various metaheuristics in terms of the best, mean, and worst results. In addition, a set of statistical tests can be carried out to provide a statistically fair performance comparison between the algorithms (Chiarandini et al., 2007).

- Most of the signal optimisation approaches presented in the literature are based on a single metaheuristic method. However, the hybrid metaheuristic methods can be more promising than the standard methods. The research on optimum signal timing using hybrid metaheuristics is still in its early days. This should encourage researchers to further develop efficient and effective hybrid metaheuristics to solve signal optimisation problem of large-scale transportation networks.

- Application of metaheuristic algorithms to the real-time signal optimisation of large-scale transportation networks can be computationally expensive. As it was recommended in a recent review of bio-inspired computation (Del Ser et al., 2019), the efficiency of the metaheuristics can be enhanced through replacing the original expensive objective functions by the prediction models built based on Machine Learning (ML) techniques, known as surrogates. Thus, future research will definitely be required to integrate metaheuristics and ML techniques to deal with signal timing of large-scale networks.

- According to the No Free Lunch theorem (Wolpert et al., 1997), there is no general metaheuristic approach able to solve different type of problems in an equally efficient manner. The performance of the metaheuristics depends on the type of the problem and the properties of the search space. As an alternative approach, *Hyper-heuristics*, which form an emerging search technology, provide a new approach to overcome the problem of such dependencies in metaheuristics. The learning element of hyper-heuristics are assumed to be problem independent, but domain-specific heuristics can be used to augment the performance on specific problems. The term has been defined to broadly describe the process of using metaheuristics to choose the most appropriate heuristics to solve the problem at hand.

- From the literature review, it is demonstrated that different approximate emissions and fuel consumption models have been employed for traffic signal optimisation with the objective functions of the vehicle emissions and fuel consumption. However, the approximate models within the signal optimisation problems can lead to unrealistic signal timing plans. Hence, it seems that the future works should be focused on the calibration of various emissions and fuel consumption models to a given network.

- A description of the various modelling and simulation software for transport networks is presented. The majority of the simulation software are only available commercially. Most classical simulation models are macroscopic whereas most modern models are microscopic. As per the future research directions for transport simulation software, the ability to simulate the large networks with real time data is vital.

- The quality of the timing plans obtained from the signal optimisation depends on the accuracy of the traffic flow models. Recently, big data technology has been successfully applied for the traffic flow predictions in large transportation networks. Therefore, the application of metaheuristics on the big data based signal optimisation would also appear to be an attractive research direction.

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