Whale Optimization Algorithm for Traffic Signal Scheduling Problem

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Abstract. Traffic congestion is one of the most important problems with respect to people daily lives. As a consequence, a lot of environmental and economical problems were emerged. Several works were proposed to participate in problem solving. Traffic signal management introduced a promising solution by minimizing vehicles average travel times and hence decreasing traffic congestion. Studying vehicles' activities on roads is non-deterministic by nature and contains several continuously changing parameters which makes it hard to find an optimal solution for the mentioned problem. Therefore, optimization techniques were intensively exploited with respect to Traffic Signal Scheduling (TSS) systems. In this work, we propose TSS control methodology based on Whale Optimization Algorithm (WOA) in order to minimize Average Travel Time (ATT). Experimental results show the superiority of WOA over other related algorithms specially with the case of large-scale benchmarks.

Keywords: Whale Optimization Algorithm · WOA · Metaheuristics · Traffic Signal Scheduling · Simulation

1 Introduction

With the rapid increase in population and the lack of infrastructure availability for transportation systems in the urban areas, traffic congestion has became a major challenge for both urban planners and researchers [2]. Heavy traffic congestion usually causes various serious problems that impact different aspects of people personal lives, such as high pollution levels, increased fuel consumption, safety problems, time wasting, frustration, disaster management, and consequent economic loss [3]. Therefore, planners seek to utilize the existing infrastructure in an optimal way [4]. In this manner, efficient traffic signals scheduling approaches became highly required to contribute in solutions for traffic congestion problem [2].

Traffic Signal Scheduling (TSS) is defined as the mechanism of finding the optimal time schedule of traffic lights to enhance the overall traffic conditions (e.g. minimizing travel times for vehicles). However, TSS is considered a difficult optimization problem because traffic system consists of various interconnected subsystems with dynamic and stochastic behavior that leads to non-deterministic outcomes which results in huge solutions space that makes exhaustive search infeasible for such a problem. [8].

Exact optimization methods are impractical to handle complex problems with multi-dimensional search spaces. Therefore, heuristic methods are employed in tackling TSS problem instead. The framework of TSS optimization consists of two main stages: (1) the search process that considers the different time schedules, and (2) the evaluation approach to asses these schedules. In this stage, microscopic models for traffic simulation are exploited [3].

Heuristic methods have become popular for TSS optimization problems such as Genetic Algorithms (GAs), Swarm intelligence, and others [6]. However, TSS optimization requires exploiting recent optimization algorithms to handle large-scale cases. In this paper, a simulation-based approach is proposed to solve TSS optimization problem based on a recent swarm optimization algorithm, namely, Whale Optimization Algorithm (WOA). Our contributions are summarized as follows:

(i) A WOA-based Traffic Signal Scheduling (TSS) optimization methodology is proposed to find the best duration for different phases for TSS systems in an input network topology.
(ii) Extensive experiments are performed to investigate the sensitivity of WOA to common and specific controlling parameters.
(iii) The proposed algorithm has been evaluated in terms of Average Travel Time (ATT) on small, medium, and large scale benchmarks.
(iv) The proposed algorithm has been compared with other state-of-art algorithms and have outperformed them with significant improvement in large-scale benchmarks.

Traffic signal optimization process includes evaluation phase which is conducted by simulation in order to evaluate the objective function in which it is a time consuming process. Therefore optimization techniques that give better solutions within a reasonable time frame are preferred. Our experiments show that WOA gives better schedules within the given time period compared with other well known techniques.

In the rest of the paper, and after considering related work in Section 2, Section 3 shows TSS problem formulation while Section 4 clarifies the proposed optimization methodology involved in this work, Section 5 contains the set of experimental tests conducted in the work as well as the discussion and analysis of the results, then finally Section 6 concludes the work as a whole.

2 Related Works

Several techniques and algorithms have been proposed to tackle the Traffic Signal Scheduling (TSS) problem including mathematical optimization models and simulation-based approaches. However, due to the complexity and dynamism of the transport network, most researchers turned to propose simulation-based approaches.

, Meta-heuristic (MH) algorithms have been widely employed in the field of traffic signal timing like evolution-based (eg. GA), swarm-based (eg. PSO and ACO), physics-based (eg. SA) and human-based (eg. HS) algorithms. The work of Kachroudi [5] is related to PSO area. Two versions of multi-objective PSO algorithm were applied on a virtual urban network to optimize the cycle programs for private and public vehicles. A complex model was built to determine the optimal green splits and the offsets of the traffic lights.

Signal timing optimization methodology of phase combination was proposed in [14]. The objective function of the work is to minimize the number of stops at intersection by combining the least different flow ratio of two streams into one stream using PSO where the number of stops is decreased by 19.04%.

A robust heuristic was proposed in [1] to use the history information in predicting the future traffic load on each street leading to an intersection controlled by a traffic light. Simulation results show that the proposed algorithm optimized the traffic flow up to 18% more than standard traffic systems.

Recent efficient swarm optimization algorithms have not been exploited in TSS problem. Moreover, most methods are investigated on a special traffic network with limited elements, and thus the scalability of such algorithms have not been tested. However, based on the No-Free-Lunch theorem which states that there is no universal algorithm which outperforms the other methods for all problems [12], the door is still open to investigate new algorithms in the field of traffic optimization.

Mirjalili and Lewis have recently developed an innovative meta-heuristic algorithm which is called the Whale Optimization Algorithm (WOA) [9]. The idea of this algorithm is inspired by the natural behavior of humpback whales which employ a distinctive hunting technique known as bubble net feeding method. WOA is classified as a swarm intelligence based algorithm where a group of whales (each represents a candidate solution) team up to follow the location of prey (represents the fittest solution). This method is simulated using two main phases: the exploitation phase which mimics the process of encircling prey and attacking it, while exploration phase mimics the process of searching randomly for prey.

Our work is related to applying WOA on a set of predefined parameters to introduce a solution for the traffic congestion problem. Promising results were achieved that add a value to the set of proposed solutions to the mentioned problem.

3 Traffic Signal Scheduling (TSS) Problem Formulation

The design of a Traffic Signal Scheduling System (TSS) should ensure minimizing the stop delay for different vehicles without violating the core requirement of avoiding conflicts between opposing through traffic [2].

3.1 TSS Basic Terminology

Universally, each conjunction is controlled by a set of traffic lights to control the flow of vehicles in which a round robin technique is used to give traffic light a slice of time to allow the flow of its related vehicles. A state (or phase) for a given conjunction is defined by the set of current lights for all of the light signals installed for the conjunction. Each light state (Red, Yellow and Green) has a predefined interval of time [3].

The key component in the design of a TSS system for an intersection is to separate the conflicting movements of the traffic into different phases. Typically, a phase includes the state of allowed movements, followed by the yellow and red states for the opposing movement. For example, consider the four-legged intersection shown in Fig.1, the traffic movement in this intersection can be controlled by a 4-phase signal system as shown in Fig.2 left side.

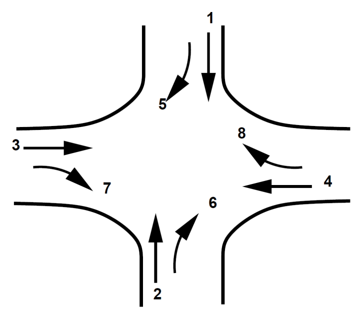


Fig. 1: An intersection with 8 different traffic approaches.

3.2 TSS as an Optimization Problem

The functionality of a TSS for an intersection can be described as a sequence of phases represented as a state diagram. Right part of Fig. 2 shows the state diagram for the 4-phase TSS shown in left part of the figure.

Optimization of the timing of traffic signals aims to find the best interval for each phase in the sequence of functionalities in the TSS, such that the overall flow of the vehicles in the intersection is enhanced. Thus, our key objective is to find the best interval allocated for each phase in each intersection in a network topology such that the average travel arrival time for all vehicles in the topology is minimized.

Solution Representation: Given a network topology that consists of n intersections. Each intersection is controlled by a number of phases. Let P_i represent the number of phases for intersection i. Each solution for TSS optimization problem is represented as a one-dimensional vector of integers X such that each element in X represents the duration of a phase in an intersection, as illustrated in Fig.3.

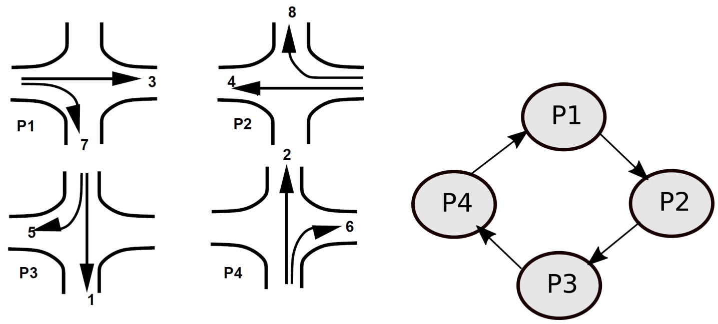


Fig. 2: The right figure represents the transitions between phases for the TSS shown in the left figure that has the 4-phase signaling system for an intersection with 8 different traffic approaches.

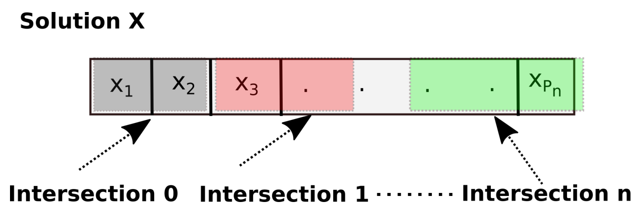


Fig. 3: Solution Representation.

Fitness Function: A candidate solution is evaluated in terms of Average Travel Time (ATT) for all vehicles in the network. ATT is defined as the total trip time for all vehicles divided by the total number of vehicles in the system. Thus, TSS optimization problem aims to find the duration for all phases in all intersections in a network such that the ATT is minimized. This optimization problem is formulated in eq.1 where $f(X) = ATT(X)$. Notice that the ATT should be bounded by predefined lower bound L and upper bound U.

$$\begin{aligned} \underset{X}{\text{minimize}} \quad & f(X) \\ \text{subject to} \quad & L \leq f(X) \leq U \end{aligned} \tag{1}$$

4 Proposed TSS Optimization Methodology

Fig.4 illustrates our proposed optimization methodology. The input for our algorithm is a network topology that consists of number of intersections. An initial random population including vector of durations for different phases is generated. The WOA algorithm is applied following fitness function evaluation for each candidate solution by simulation. The Average Travel Time (ATT) guides the next iteration in the WOA recipe until a satisfactory solution in terms of the durations for different phases in the TSS systems is outputted.

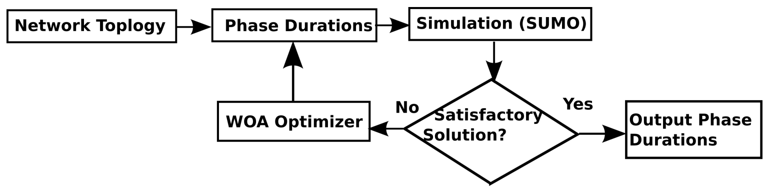


Fig. 4: Optimization Methodology.

5 Results and Discussion

In this work, our focus is to study the efficiency of WOA in tackling TSS problem. For this purpose, we compare WOA with other modern meta-heuristic algorithms from the literature. Thereafter, the performance of WOA is validated and compared with other traditional optimization models. In the following subsections detailed description of the experiments is explained.

5.1 Experimental Setup

Three test cases (sites) were developed. These sites range in their scale and topology. The first test site is relatively small-sized which simulates the real signalized segment at the center of Nablus city, Palestine, while the other two are software created. Second and third sites can be classified as medium and large size networks, respectively. The number of parameters that need to be optimized in the created sites are 13, 34, and 141 respectively.

The experimental work involves two main phases; sensitivity analysis of WOA, and comparison phase. In the first phase, the real network was used while investigating the sensitivity of WOA to common parameters. In the second phase, four well-known algorithms were implemented to confirm the performance of WOA. Finally, we validated the proposed WOA-based model with common optimization models (e.g. Highway Capacity Manual-HCM, Webster and Synchro)[10].

The networks were modeled using SUMO v1.1.0 [7], and all optimizing algorithms were implemented using python 3.7.3. We tested the experiments on the RMACC Summit supercomputer [3]. To have a fair comparison, all optimizing algorithms were evaluated using the same common parameters; 100 iterations, and population size of 30. Table 1 presents the setting of specific parameters of optimizing algorithms. These parameters were selected based on the settings recommended in previous researches (PSO [11], BAT [13]). Due to the stochastic behaviour of MH algorithms, we presented the average results of 20 independent runs for each conducted experiment. Please note that the best obtained results in the reported tables were highlighted using a boldface format.

[3] The RMACC Summit supercomputer, which is supported by the National Science Foundation (awards ACI-1532235 and ACI-1532236), the University of Colorado Boulder, and Colorado State University. The Summit supercomputer is a joint effort of the University of Colorado Boulder and Colorado State University.

Table 1: The used settings of algorithms.

Algorithm	parameter	value
WOA	Exploration/Exploitation switch 8 factor a	from 2 to 0
GA	crossover prob. mutation prob. selection method elite	0.9 0.01 roulette wheel 2
PSO	inertia wight acceleration coefficients	from 0.9 to 0.4 2
BAT	Qmin, Qmax A loudness r pulse rate	0, 2 0.5 0.5

5.2 Sensitivity Analysis of WOA

In this section, the real test site is considered to evaluate the sensitivity of WOA. We tuned both (1) the common parameters (i.e. population size and the number of iterations), and (2) the internal parameter a (in Table 1) in which is the main control parameter of WOA.This is useful for getting the best performance of WOA in handling the problem.

Convergence behavior To examine the convergence behavior of WOA, different number of iterations (from 20 to 200) with a fixed search agents (population size of 30) are used. The reported results in Table 2 show that increasing the iterations from 20 to 100 significantly improves the average travel time from 58.5 to 55.91. However, the further increase in the number of iterations (more than 100) does not significantly improve the results. Therefore, 100 iterations (i.e. 3000 evaluations) are enough to get a good solution within an acceptable time. We need to mention that the evaluation of the objective function includes running a simulation which means it is computationally heavy problem. Therefore, the number of iterations is an important factor to be considered.

Table 2: The average travel time results of WOA for case 1 using population size of 30 and different numbers of iterations.

#terations	20	50	70	100	150	200
#evaluations	600	1500	2100	3000	4500	6000
AVG	58.50	56.72	56.38	55.91	55.71	55.65
STD	3.63	2.41	2.24	2.31	2.35	2.37

Impact of population size After determining the suitable number of evaluations in the previous section, now we need to asses the impact of changing the population size on the performance of WOA. For this purpose, the number of evaluations are fixed to 3000 while the population size is used with 6 different values (5,15,30,50, and 150). Table 3 presents the obtained results for the considered population sizes. It is noticed that WOA with the population size of 30 is able to give the best average result.

Table 3: The average travel time results of WOA for case 1 with fixed 3000 evaluations and various population sizes.

Mesure	Population size					
	5	15	30	50	100	150
AVG	58.61	58.32	55.91	57.18	56.32	56.90
STD	3.862	3.751	2.313	2.537	1.970	2.106

Using a small number of different solutions will result in the loss of diversity. Therefore, during the limited evaluations, a trade-off between the population size and the number of iterations is highly demanded. Consequently, the next experiments and comparative studies are conducted using 100 iterations and population size of 30 (i.e 300 evaluations).

Impact of main controlling parameter of WOA The WOA algorithm has the ability to change the searching pattern from exploration to exploitation based on the parameter (a). This parameter is decreased linearly inside the interval [a_0 0] where the initial value a_0 was set to 2 in the original paper [9]. In this experiment, WOA is tested with five different values of a_0 including 0.5, 1, 2, 3, and 4 to investigate how the behavior of WOA can be influenced. The obtained results are visualized in Fig. 5.

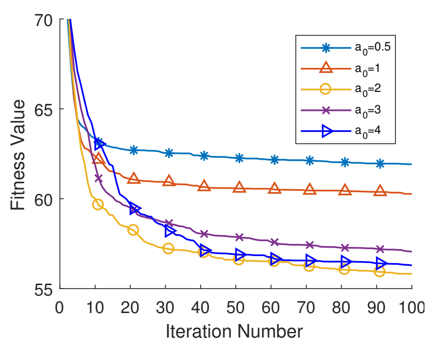


Fig. 5: Convergence behavior of WOA with different initial values of parameter (a).

According to the convergence patterns in Fig. 5, we can see that when $a_0 < 2$ the algorithm is stuck early into local optima because all iterations are utilized for exploitation. While, when $a_0 > 2$ the algorithm shows better performance to avoid local optima since most iterations are used for exploration. However, WOA with a_0 equals to 2 can make a balanced shifting between the exploratory and exploitative potentials.

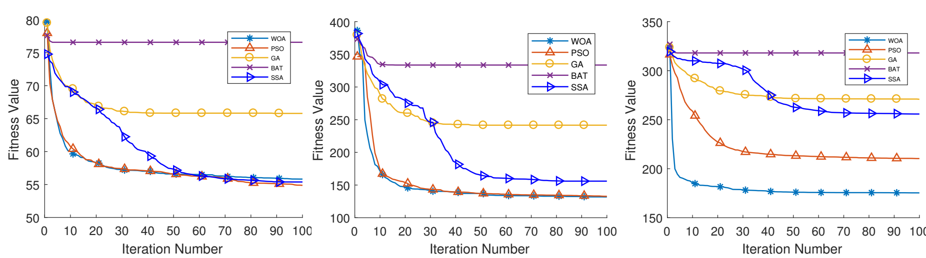
5.3 Performance of WOA versus other Optimization Algorithms

To validate the performance of WOA we conducted a comparison study with four well-known algorithms from literature. These algorithms are Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Bat algorithm (BAT), and Slap Swarm Algorithm (SSA). The obtained numerical results in terms of average and standard deviation of fitness value are presented in Table 4.

Table 4: Comparison between the travel time results obtained by WOA versus other algorithms in terms of average and standard deviation.

Cases	WOA		PSO		GA		BAT		SSA	
	AVG	STD	AVG	STD	AVG	STD	AVG	STD	AVG	STD
Case 1	55.91	2.31	54.88	2.73	65.79	4.16	76.58	5.98	55.38	1.96
Case 2	131.80	11.609	132.81	20.352	241.59	47.195	333.61	55.636	155.98	37.884
Case 3	175.36	6.21	210.33	11.74	270.80	11.13	318.08	12.35	255.79	17.70
Mean rank (F-test)	1.67		1.67		4.00		5.00		2.67	
Overall rank	1		1		3		4		2	

The cases above are sorted according to the number of variables that need to be optimized, or search space size. Table 4 shows that PSO and SSA outperform and are very close to WOA in the first case while GA and BAT do not perform well. From Fig. 6a BAT does not converge at all. It is stuck and does not reach good values. It seems that BAT stays around local minima. GA starts to converge at the beginning but it stops in better minima compared with BAT but still is not as good as other algorithms. PSO and WOA show very similar convergence pattern. SSA is interesting, it shows unusual conversions pattern. It starts slow almost like GA but it continues to converge to reach PSO and WOA at the end.



(a) Case 1 (b) Case 2 (c) Case 3

Fig. 6: Convergence curves of all algorithms in dealing with all cases.

In test case 2, BAT and GA show the same poor behaviour . By observing the convergence trends in Fig 6b, we see that SSA has the same interesting behaviour as in case 1. The curve of SSA seems to have two phases; the first phase is slow convergence that may be exploration phase, while in the second phase it accelerates its convergence most probably towards some minima. The difference between PSO and WOA from one side and SSA from another side starts to be clear in this case. PSO and WOA outperform SSA slightly.

Regarding test case 3, which is the most complex one we experimented in this work, the reported travel time values of compared algorithms in Table 4 show that WOA achieves the best result, followed by PSO, SSA, and BAT respectively . As per convergence curves in Fig 6c, BAT starts and ends in the same neighborhood. It does not seems to make any improvement. GA suffers from slow convergence. SSA despite its interesting behaviour but still can not perform as PSO and WOA. It starts slower than GA but it switches its behaviour and outperforms GA slightly. From figure 6c it is obvious that WOA has superior performance if compared with other algorithms in this case.

As per F-test results, it is clear that both WOA and PSO are ranked first, followed by SSA, GA, and BAT respectively. This comparative study proves that WOA can perform better and very competitive results compared to other algorithms in dealing with TSS problem. Both the implementation of PSO used in this work and WOA use an adaptive control parameter that starts the iterations with high amount of exploration then it reduces exploration to give more emphasis on exploitation. WOA differs from PSO that it uses 50% of times a spiral movement. This movement searches for more places around the believed optimal solution so far found. This may overcome the deceptive behaviour of some objective functions.

Finally we compared our work with traditional TSS methods: HCM, Webster and Synchro as shown in Table 5. It is clear that WOA has outperformed the other traditional methods due to its effective exploration and exploitation in the entire solution space if compared with traditional isolated section-based optimization algorithms.

Table 5: Average travel time results of WOA-based method versus other traditional methods for the real study case.

Traditional methods			Heuristic
HCM	Webster	Synchro	WOA
149	202	92	55.91

6 Conclusion

In this work, a WOA-based simulation methodology was investigated to tackle traffic congestion problem. We compared WOA with widely used algorithms in this domain namely GA, PSO, SSA and BAT as well as traditional methods. Three test cases were developed: small, medium and big. This work emphasizes that WOA, PSO and SSA performed almost the same in small and medium size cases, while WOA shows preponderance with bigger size problems. This research realizes that WOA works fine with big traffic light scheduling problems and can be relied on with big cities. Our future work will be related to studying the effect of spiral motion on WOA. In addition to the reformulation of objective function in the case of emergencies.

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