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Review of Bio-inspired computations on optimisation of traffic signals

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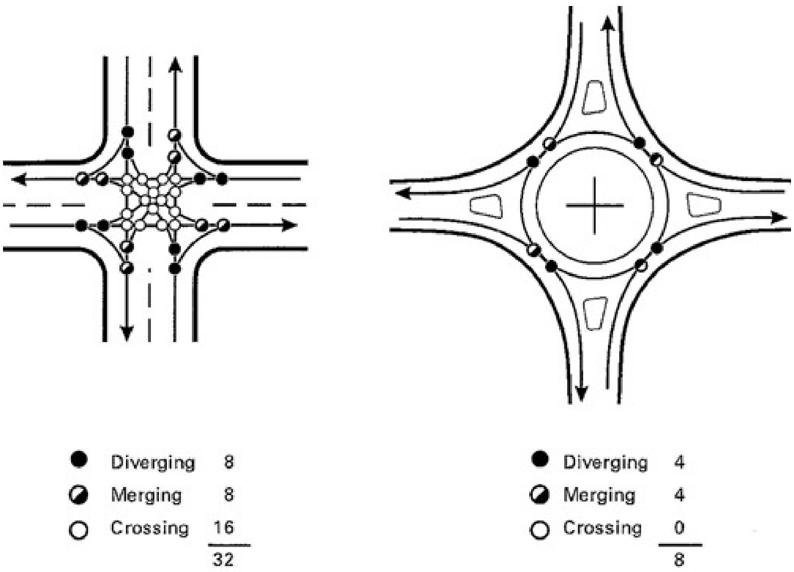
Abstract

Many novel studies have explored the context of vehicular traffic to make it less congested, safer, more economical and emit less pollution to the environment. Because of the explosion of data and improving performance of computational powers, bio-inspired algorithms have lately gained great traction in the scientific community. On the other hand, this popularity has not been extended to the domain of traffic control as such. Moreover, signalized intersections, where traffic controllers are mostly installed, have received even a lesser number of publications pertaining to bio-inspired algorithms. This paper addresses this gap through reviewing the published journals pertaining to bio-inspired algorithms applied in optimizing signalized intersections. This paper reviews the journal papers that study and propose new algorithms and methods in optimizing traffic signals using bio-inspired algorithms. Each algorithm is introduced: (i) the similarity between the natural behaviour of biological organisms and its computational one; (ii) the contributions of the paper; (iii) the strong and weak points of each paper in a chronological order. We then give a summary of all the existing bio-inspired algorithms and in which domain they have been implemented. This gives the scientific community the opportunity to determine the gaps and why not all bio-inspired algorithms have been explored in optimizing traffic signals.

1. Introduction

Recent studies reveal that congestions are the major cause of stress to drivers, car accidents and emitting large amounts of carbon footprint into the environment (Li, et al., 2016). Interestingly, economic challenges are another dimension of the adverse impact of vehicular traffic through which there is the need for extending road networks and, insurance pay-outs etc. Statistics from the New Zealand Ministry of Transport report show that in 2015 there were 291 fatal road crashes, 9,446 injury crashes, 319 deaths and 12,270 people were injured. Among all other setups of road geometry, intersections are the most hazardous as their architecture introduces several conflicting nodes (Figure 1) (Sarah, 2013). According to the New Zealand Transport Agency (NZTA), between 2008 and 2012, 30% of all deaths and serious injuries on NZ roads were at intersections, 17% of all fatalities on rural roads were at intersections and 46% of all fatalities were due to conflicting points of intersections (NZTA, 2013).

Figure 1: There are only 8 conflicting points in a roundabout compared to 32 in four-way stop condition



The seriousness of intersection safety has encouraged many researchers writing in the transport engineering field to focus their attention on searching for intelligent approaches that result in better optimization of traffic flow. Therefore, over the past several decades, research and practices have been dedicated to reducing traffic incidents and congestion. The outcome has been various optimization techniques, each assessing the problem from different angles (Silva, et al., 2006). However, the nonlinearity of traffic flow posed complex challenges to the efforts of achieving true optimized road networks. Consequently, conventional statistical methods such as autoregressive integrated moving average (ARIMA) methods, statistical regression and k-nearest-neighbour approaches (K. Chan, et al., 2012), have proven to be less effective in addressing the nonlinear nature of traffic flow (Huang, et al., 2013). That led to the emergence of intelligent transportation systems (ITS) in the 1990s to help with the advancement of the operations of road networks based on information available from the infrastructure and vehicles (Chen & Chang, 2014).

In addition to many other areas of science and technology, ITS implementations greatly benefited from studies developed in the domains of artificial intelligent (AI). Therefore, ITS has established capabilities to develop traffic optimization models that can outperform statistical methods. One of those methods that has recently started to gradually gain prominence in the traffic optimization space is the notion of bio-inspired computation. It essentially attempts to learn and adapt behaviour of various biological organisms in nature (Kar, 2016). The primary motivation for trying out bio-inspired algorithms is the ability of biological systems to adapt to changing conditions rapidly and efficiently (Kar, 2016). Neural networks, bacteria foraging, artificial immune systems and artificial neural networks are among some of the algorithms inspired by nature. Swarm behaviour in the colonies of social insects (bees, wasps, termites and ants) is another example of such theories that is characterised by autonomy, role distribution, self-organizing etc. (Gordon & Esponda, 2015). Hence, swarm behaviour has been used in many artificial intelligence applications that study the actions of individuals in decentralized communities (Prothmann, et al., 2011).

Bio-inspired computing, short for biologically inspired computing, studies computational intelligence and collective intelligence. Using principles of biology, computer science and mathematics (Jiang, et al., 2005), bio-inspired computing helps to improve the efficiency of computational programmes. Therefore, it is often closely related to the field of artificial intelligence and machine learning (Jiang, et al., 2005). Briefly put, it is the use of computers to model living phenomena, and simultaneously the study of life to improve the usage of computers. Biologically inspired computing is a major subset of natural computation.

In this context, bio-inspired algorithms are receiving attention by the scientific communities to address the:

- Increasing numbers of complex problems being studied,
- Dynamic nature of transport problems, and
- Nonlinearity of the problems and their influencing factors in which statistical and probabilistic methods cannot model realistically.

The vast and fast developments in the traffic optimisation domain are getting increasingly difficult to track due to different algorithms. However, to the best of our knowledge there has been no attempt to review the bio-inspired algorithms used in traffic controls. We address this gap through reviewing all the existing bio-inspired algorithms in that domain published in the scientific literature (Kar, 2016).

The reviews conducted so far on bio-inspired algorithms (Socha, et al., 2014) do not focus on a specific domain. They are rather a detailed explanation of the major bio-inspired algorithms applied in various applications and domains. This is the gap this paper is trying to address. The revision focuses on the more recent publications (last five to six years) surrounding bio-inspired algorithms applied in the domain of traffic signal optimizations. Towards the end, we highlight potential bio-inspired algorithms to be explored for traffic optimizations.

2. Traffic Signal Optimization

Traffic signal optimization entails a set of tools, techniques and practices aimed to primarily reduce time stopped in road traffic as well as vehicle congestion problems (Li, et al., 2016). Nevertheless, most of the techniques and algorithms intended to reduce delay use software packages designed for pre-timed coordinated systems. They do not explicitly optimize advanced controller settings such as minimum green time, extension time, detector recall mode, etc (Huang, et al., 2013) (Jiang, et al., 2005). For that, traffic engineers in many cases resort to selecting default parameters or go for trial-and-error options when more advanced settings are required (Lawe & Wang, 2016). Often, the same setting time is applied for several hours or even days. Therefore, it is a challenging task to dynamically set the phases of traffic signals and associated lights (green, red, and yellow) in order to address the issue of varying degrees of traffic congestion (Papatzikou & Stathopoulos, 2015) (Prothmann, et al., 2011). Additionally, the existing tools seldom account for individual vehicular driving behaviours (Chen & Chang, 2014).

Nevertheless, the question of dynamic configuration assignment in the traffic optimization domain is not new. The first attempt was in the early 1970s by Samuel Yagar which gave birth to the concept of the Dynamic Traffic Assignment (DTA) model (Samuel, 1971). Later, the concept was expanded to include three main classification models that are identified in literature as macroscopic, mesoscopic and microscopic (Papatzikou & Stathopoulos, 2015).

Traditional optimization methods are based on DTA, fixed traffic flows and fixed traffic control. This combination produces some degree of inconsistency for which there is a direct correlation between traffic control and traffic flows (Papatzikou & Stathopoulos, 2015). However, once operational, they no longer do evaluation of control decisions (Prothmann, et al., 2011). On the other hand, modern traffic control systems are designed to be adaptive and provide the capability to allow for optimising their control decisions on-line. Some of the well-known examples of those systems are Split Cycle and Offsets Optimization Technique (SCOOT), Sydney Coordinated Adaptive Traffic System (SCATS), Optimised Policies for Adaptive Control (OPAC), Balancing Adaptive Network Control Method (BALANCE), Method for the Optimisation of Traffic Signals in Online-Controlled Networks (MOTION) etc. (Shirvani & Maleki, 2016) (Prothmann, et al., 2011).

These systems could be quite costly to install and operate as they require the deployment of a complex set of hardware equipment such as sensors and traffic monitoring modules used for making decisions based on the gathered information (Cosariu, et al., 2015). Furthermore, the complex nature of traffic flow redistribution through intersections requires topological analysis. However, analysing traffic in large road networks for the purpose of centralized optimization is almost impossible (Cosariu, et al., 2015). One of the major challenges is the large amount of time taken to generate practical solutions for real world networks based on captured information from all roads (Cosariu, et al., 2015). To fill this gap, promising approaches have been proposed that can offer self-adapting mechanisms that cater for changing loads, traffic conditions, traffic disruptions, planned events etc. in the network to achieve a more continuous traffic flow (Papatzikou & Stathopoulos, 2015).

In this context, bio-inspired theories take a large space in the literature where they propose algorithms and mathematical models aimed to optimize traffic flow (Kumar & Rawat, 2015).

The following sections review some of the major bio-inspired techniques used in optimizing traffic control systems.

2.1 Artificial Neural Networks and Deep Learning Neural Networks

Artificial neural networks are a type of learning model inspired by the way biological neural networks function (Goves, et al., 2016). They are based on a large collection of processing units called neurons that form multiple layers of networks capable of modelling the way a biological brain solves problems. These systems are characterized by being self-adapting and self-organizing rather than explicitly programmed (Srinivasan, et al., 2006). The ecosystem learns through combining the values of all its inputs through a summation unit and a threshold function in a way that the weighted input signals from one or more neurons are summed until they are large enough to trigger message transmission (Goves, et al., 2016) (Li, et al., 2016). This process is called activation (Li, et al., 2016).

There are many implementations to artificial neural networks ranging from medicine, chemistry, biology etc. Recent literature has received a surge of studies surrounding using artificial neural networks in the transportation field which included traffic flow prediction, traffic signal timing, delay prediction, parking space prediction etc. (Goves, et al., 2016). Artificial neural networks have been used to predict traffic conditions in (Li, et al., 2016) (Smith & Demetsky, 1994) (Kirby, et al., 1977) (Zheng, et al., 2006) (Khodakaram & Ansari, 2013) (Wenhao, et al., 2014) (Royani, et al., 2013).

In the context of traffic signal optimizations, several early attempts have been noted in (Chin & Spall, 1997) (Bingham, 2001) (Wei & Zhang, 2002). However, most of these works are agent based, such that each one of them is tasked with updating the traffic signals of a single intersection upon traffic flow data received from all the approaches of the intersection in question (Srinivasan, et al., 2006). Bingham (Bingham, 2001) utilized the elements of intersection fuzzy control using neural networks, and an enhanced version of previous studies of fuzzy control (Royani, et al., 2013). Furthermore, the work in (Bingham, 2001) focuses on reinforcement theory in order to model the dynamics of complex systems by learning the control actions. Consequently, it analysed the impact reinforcement on traffic flow. The reinforcement approach in (Bingham, 2001) involved updating weights of the neural networks model using simultaneous perturbation stochastic approximation (SPSA) which promises to converge to local optima relatively quickly under certain conditions (Srinivasan, et al., 2006) even though no formal proof of convergence is presented. The model has implemented and tested the controller on an isolated single intersection. Therefore, it is not proven how the model will behave and perform when applied to a large-scale arterial traffic network with many signalized intersections.

Srinivasan et al. in (Srinivasan, et al., 2006) presented an enhanced version of the multiagent system approach based on SPSA-NN. The system is a combination of neural networks with fuzzy logic that is intended to control traffic signal timing. Here, the logic is programmed to update the relations using evolutionary algorithms in order to allow agents to dynamically adapt the varying conditions of the influencing factors. The model is developed using distributed unsupervised traffic responsive signal control. The authors' approach is to make each agent in the system a local traffic signal controller for one intersection in the arterial network. The paper proposes two multiagents in the model. The first one makes use of an online learning process to update information and adapt to the new decision-making mechanism. The online learning mechanism is comprised of reinforcement learning, learning rate and weight adjustment. Srinivasan and her team evaluated the performance of their model by trying it on a large traffic network with 25 intersections based on the Singapore Central Business District (Srinivasan, et al., 2006). The tests conducted showed reduction in the total mean delay by 40% and the total vehicle stoppage time by 50% compared with the Green Link Determining benchmark.

The results presented in (Srinivasan, et al., 2006) are a promising endeavour for online traffic signals; however, there seems to be three major concerns around the viability of the model. First, the speed at which the system dynamically tracks the changes and updates the network might degrade the performance of building an optimized knowledge base. Therefore, instead of flooding the network with all the changes and causing congestion in an environment that requires rapid reaction, it might be useful to tweak the algorithm so that it incrementally trains the model. Second, the identification of traffic patterns and assignment of time periods of each pattern is heuristics that mandates a manual process. Third, each time period seems to have a neural network whereby their weights are updated only during the allocated time period. In other words, the weight update is performed daily and whenever the same traffic pattern and time period is experienced. This would require the traffic controllers to quickly respond to changes in the traffic network within the same time period (Araghi, et al., 2015).

Royani et. al. in (Royani, et al., 2013) applied fuzzy neural network for real time traffic signal control at an isolated intersection. The authors integrated artificial neural networks (ANN) and expert systems approaches. The expert systems, also known as knowledge-based systems, rely on a knowledge base developed by human reasoning for decision making. The authors suggest integrating the two approaches for better performance than using a single approach. Furthermore, the paper uses genetic algorithms in order to fulfil parameters of FNN. This paper aims to assist with improving the vehicular throughput and minimize delays in real life.

Li et. al. (Li, et al., 2016) proposed an algorithm for traffic signal timing via deep reinforcement learning, which is a variation of deep learning neural networks. The authors investigated the feasibility and effectiveness of applying the deep reinforcement learning method. They concluded that the combination of deep knowledge representation, deep reinforcement learning method and parallel intelligent transportation systems may have a positive impact on the development of Intelligent Transport Systems (ITS) innovations. This conclusion is driven from comparing their results against the ones found in (LA & Bhatnagar, 2011). Since deep reinforcement is constructed on deep learning as an improvement to the conventional reinforcement learning, the authors' choice of comparison could have been expanded a little further. The paper does not include comparisons against other reinforcement papers nor does it check other variations of deep learning in the field of traffic signal optimization.

Moreover, the simulation design does not exemplify real world scenarios. In terms of intersection geometry, the authors not only selected one isolated intersection in the setup, but also had a limited number of movements with no right, left or U turns. Further, the neural network design includes four-layer SAE layers with two being hidden (Li, et al., 2016) with no real explanation as to why not more or less.

2.2 Genetic algorithm

Genetic algorithm (GA) was introduced to mimic the way nature uses computational techniques to obtain suitable working solutions while creating future generations in biological organisms (Kar, 2016). It is an evolutionary search heuristic (sometimes referred to as metaheuristic) that attempts to copy the process of natural selection and observes nature to identify good solutions for complex problems (Prothmann, et al., 2011). Kar et al in (Kar, 2016) define four basic mechanisms: inheritance, cross-over, reproduction and mutation.

One of the early papers about applying GA in traffic signal optimization seems to have been published by Foy et al. aimed to determine signal timing parameters (Foy, et al., 1992). Their experiment was focused on minimizing total delay on an octothorpe-shaped traffic network, a traffic network of four intersections, through optimizing the phase sequence and green time splits assuming the traffic flow remained fixed. The objective function used for minimizing delay is the reciprocal of the total waiting time. The optimization experiments included a simple microchip simulation model by taking minimized delay as the basis for evaluating alternative solutions. The results showed that the GA can lead to improving the performance of the system and provide optimal signal-timing (Foy, et al., 1992). However, those results were not compared against the performance of the commercial tools available at the time of the experiments (Ceylan & Bellb, 2004).

Ceylan and Bell (Ceylan & Bellb, 2004) presented a combined GA and hill-climbing algorithm that optimizes time parameters of traffic signals, taking into account drivers' routing decisions. The hill-climbing operation is based on numeric gradient, and the application of the approach is meant for area traffic controls that are built on the Transyt model (Ceylan & Bellb, 2004).

Their application of GA is used to solve traffic signal control and traffic assignment with stochastic user equilibrium link flows. The paper utilizes the Path Flow Estimator (PFE) to solve the lower level problem by combining it with GA and Transyt to determine what optimized solutions would look like. The resulting technique is called GATRANSPFE (GA, TRANSYT and the PFE) which is intended to solve the equilibrium network design problem. The authors' contribution promises a 34% increase in performance improvement over similar solutions applied in the area. The approach presents a simplified version of the GA chromosome such that they used a unified network cycle time for all signalized intersections, that may not be applicable in real world scenarios. Furthermore, the solution does not seem to have been tested on large-scale networks. Lastly, the model embraces time-dependent demand and time-variant control strategies (Sáez, et al., 2008).

Stevanovic et al. presented VISGAOST in (Stevanovic, et al., 2008), a VISSIM-based Genetic Algorithm to optimize signal timings. The optimization method used in their algorithm has four basic signal timing parameters: cycle time, phase sequence, phase durations and offsets for a network of coordinated traffic-actuated NEMA controllers. VISGAOST has two main features whereby it attempts to enhance and reduce computational time through optimization resumption and parallel computing techniques. VISGAOST has been tested in a simulation study for an arterial road network that was controlled by coordinated traffic-actuated NEMA controllers. SYNCHRO2 was selected as a reference traffic optimization tool, and it was found that VISGAOST could outperform the reference solution by at least 8%. The computing time taken to evaluate 7600 alternative traffic signals policies for an arterial network of 12 signalized intersections was 90 hours of distributed computing of 10 machines (Stevanovic, et al., 2008). By today's standards, this is quite a time-consuming process, considering the number of times larger networks have to be simulated until an optimized solution is achieved (Prothmann, et al., 2011).

Sanchez-Medina et al. (Sanchez-Medina, et al., 2010) proposed an optimization approach based on planned timing for traffic signals phase periods of a section of Saragossa city in Spain. The section has seven intersections, 16 input nodes, 18 output nodes and 17 traffic signals. The approach is achieved by combining three key components: (1) genetic algorithms (GAs) for optimization tasks; (2) cellular-automata-based micro-simulators for evaluating every possible solution for traffic signal programming times; and (3) a cluster of multiple computers. The resulting algorithm is a model that has a fitness function made of four different parameters: (1) number of vehicles, (2) mean travel time, (3) occupancy (TOC) and state of occupancy (SOC) and (4) global mean speed. Individual parameters are represented as an array containing light phase periods of all traffic signals. The algorithm was tested with different traffic conditions. The results show good performance in a more congested scenario; however, it does not bring any significant improvement to regular traffic conditions (Li, et al., 2016).

Tung et. al. (Tung, et al., 2014) propose a strategy for optimizing traffic signal timing based on a genetic algorithm (GA) and a well-known statistical method called Expectation Maximization (EM). The authors believe it is hard to obtain global information such as starting time and destination points of individual cars. Additionally, the computational cost in GA labs is relatively high. Therefore, they decided to apply learning algorithms to the solution obtained by EM based on the solution derived by GA. Through their analysis, the authors aimed to find the optimal traffic signal timing that leads to minimum average traffic time. They demonstrated that their application of the genetic algorithm outperforms the local car flow optimization methods used previously. The proposed algorithm defines the chromosome and fitness as traffic parameters. Chromosome, in their context, is suggested to represent a vector consisting of the traffic information of all intersections, while fitness represents the average traffic time for all vehicles to arrive at their destination. The paper's proposal to apply the strategy is to adjust the traffic signal timing according to the average traffic signal timing, the flow of cars passing through each intersection and the information of its adjacent intersections. To achieve optimized traffic signals the study suggests timing should be lowered to reduce the waiting time at each intersection.

2.3 Ant colony optimization algorithm (ACO)

The Ant colony optimization algorithm (ACO) is inspired by ants' behaviour in finding food resources. The theory copies the way ants leave footprints of pheromones for the other ants to follow when they are on the lookout for food resources (Jabbarpour, et al., 2014). In doing so, the ants manage to find the shortest (or optimal) path when going back and forth between the colony and food source (Prothmann, et al., 2011). Analogous to that, ACO suggests that agents (i.e ants) are in direct communication whilst foraging for information using artificial trails (the pheromones). The trails are constructed based on probabilistic search experience that can rapidly distribute the results among other agents through feedback processes (Kar, 2016).

The algorithm was first proposed by Dorigo et al. in (Maniezzo & Trubian, 1994), and later expanded to accommodate implementations in various other fields (Kar, 2016) such as the traveling salesman problem (Uğur & Aydin, 2009), vehicle routing (Kar, 2016), computer networks routing (Jabbarpour, et al., 2014), graph colouring (Claes & Holvoet, 2012) etc. In applications pertaining to transport systems; the ant colony algorithm aims to find the shortest or optimized path between a source and a destination. Despite a high number of studies in the transportation fields, ACO has been rarely used for optimizing traffic signal timing applications (He & Hou, 2012).

To the best of our knowledge, He and Hou (He & Hou, 2012) were the first to publish a journal paper exploring ACO capability in optimizing traffic signals. The authors focus on three parameters in benchmarking the performance of their optimization model: the smallest time delay, the fewest number of stops and the largest traffic capacity. The parameters are formulated to run as functions of cycle time and the saturation of an intersection. Therefore, the aim is to maximize traffic capacity and minimize time delay and number of stops. In order to achieve that, the paper suggests minimizing the signal timing objective function which includes two design variables, capacity c and intersection x. In addition to the two variables, the function has three weighting coefficients for optimization purposes.

The results are compared with values obtained from using an enhanced version of the Webster delay function and the genetic algorithm (GA). According to the paper, numerical computations show that ACO has greater performance advantage in comparison to the Webster equation and GA in relation to smaller time delay, fewer stops and larger traffic capacity (He & Hou, 2012). While the paper seems to be the first published journal literature and the results are promising, the defects are two-fold. Firstly, the authors compared their results only against GA and Webster – a formula very effective in high saturated traffic conditions (Prothmann, et al., 2011) even though there are many other algorithms that are used in optimizing traffic signals. Secondly, the ACO results are compared against GA and Webster experiments conducted by the authors themselves rather than other literature in the same field.

Yuan et al. (Yuan, et al., 2014) employed ACO using effective green time as decision variables in determining optimal coordinated signal timing plans for a regional traffic network. The paper presents a discrete-time model that helps analysing factors causing bottlenecks in which it is formed as a combination of the signal timing at intersections with static properties of left-turn and straight-through lanes (Yuan, et al., 2014). The authors also present another model, called bottleneck indicator, to measure the degree of bottleneck of individual roads in regional networks in order to identify traffic bottlenecks, bottleneck-free roads and bottleneck-prone roads. Therefore, the experiments conducted in that context focused on the measurement of two optimization approaches: a traffic bottleneck road and a regional network. The first approach adjusts the values of signal timing parameters to make sure that the degree of bottleneck < 0 which leads to elimination of traffic bottlenecks. On the other hand, if the degree of bottleneck > 0, this approach would improve the bottleneck capacities. For regional network optimization, the authors developed an algorithm for adjusting signal timing at an intersection such that it considers actions for all the adjacent roads and neighbouring intersections in the network. As such the authors believe the bottleneck indicators play an important role in identifying and optimizing traffic bottlenecks. While the work is a novel contribution in terms of identifying road traffic bottlenecks and proposing an approach that reduces impacts of traffic congestion, the study remains theoretical as the case study indicates. Other than mathematical computations based on the Baidu prediction model, no simulation work or implementation on real-world scenarios have been conducted.

2.4 Particle swarm optimization (PSO) algorithm

Particle swarm optimization (Kar, 2016) is inspired by the collective group behaviour of decentralized, self-organized organisms (systems or agents). These organisms interact with each other towards achieving a common objective (often optimal) decided based on feedback from individual members of the group. Organism groups like ant colonies, bird flocking, animal herding, bacterial growth and fish schooling all have swarm behaviour. In mimicking that, the algorithm was first introduced as a population based stochastic optimization technique by Eberhart and Kennedy in 1995 (Anon., 1995). Later Gerardo Beni and Jing Wang in 1989 developed Swarm Intelligence in the context of cellular robotic systems (Beni & Wang, 1993). The algorithm follows an iterative sequence of steps. The individual members in the swarm are on the lookout for a potential solution at any point in a multidimensional space of the parameter (real-valued optimization). The interaction is not only influenced by its own memory (its best solution found so far) but it is also driven by the best position sensed through the strength of the signal which is communicated by the other agents, and thus the suitability of the candidate solution based on a fitness function. When necessary, the agents try to determine better solutions by identifying new movements in the multidimensional space which guide the agents towards more optimal solutions.

García-Nieto et al. (García-Nieto, et al., 2012) developed an optimization approach based on a particle swarm algorithm that determines an optimal cycle programme for all the traffic lights located in Sevilla and Málaga cities (Spain). The approach aims to find optimized cycle programmes (OCP) for all the traffic lights in a network. Additionally, these programmes have to coordinate between traffic lights in neighbouring intersections for the purpose of improving traffic flow. Essentially, whenever the algorithm generates a new solution for the cycle programme, the simulation package starts a new procedure with streets, directions, obstacles, traffic lights, vehicles, speed, routes etc., under a new defined schedule of cycle programme. Following that, the simulation package provides necessary information for computing the fitness function. For that, the intended algorithm does not set the cycle programmes dynamically during isolated simulations, but sets them statically for each simulation procedure. This is because the objective is to obtain optimized cycle programmes for each scenario and schedule. The proposed algorithm was evaluated using microscopic traffic simulators to schedule a set of traffic light programmes. The number of intersections picked for the study was 70 in total (368 traffic lights in Sevilla and 312 in Málaga), with an average of 500 vehicles passing through each intersection at a maximum speed of 50 km/h. Hence, they set the simulation time to 500 s (iterations of microsimulation) for each city. When the authors compared the cycle times with predefined cycle programmes configured by the experts, they found out that the solutions had shown great improvement over the real ones in terms of individual vehicle trip times and global trip times. The major drawback of the paper is the process of manual intervention for the initial sequence of valid phases that need to be decided in the beginning of optimization (Hu, et al., 2016). Moreover, the proposed method does not provide adequate search capability for optimal scheduling in response to changing scenarios (Hu, et al., 2016).

Hu et al. (Hu, et al., 2016) proposed a swarm optimization method (PSO) fortified by combining it with an inner and outer cellular automaton (IOCA) mechanism, abbreviated as IOCA-PSO. The method includes an inner cellular model (ICM), an outer cellular model (OCM) and a fitness function. The ultimate objective of IOCA-PSA is to achieve a dynamic and real-time optimization scheduling of urban traffic signals. Their contribution can be divided into three parts: (1) transition rules to help phase cycle planning for different traffic problems; (2) a strong search capability to determine the optimal timing control; (3) the fitness function is used to dynamically adjust traffic signal timing. To demonstrate the performance of the approach, a set of comprehensive simulation tests has been performed using VISSIM with actual traffic data. The experiment was conducted in the Wuhan district in China where they subdivided traffic times into three periods: the congestion period (8:00 to 8:30), the half free flow period (10:00 to 10:30) and the free flow period (21:00 to 21:30) in ten minute intervals of each cycle duration. In order to find the best solution in the congestion period, the simulation generated 120,000 solution evaluations per cycle duration. The half free flow period and the free flow period in turn required the same optimization approach. To validate the superiority of the approach against other bio-inspired algorithms, the authors compared the IOCA-PSO against the traditional PSO method, the GA method and the RANDOM method. They found that the IOCA-PSO method outperformed the other limited iterations. In three different time periods, the fluctuation range was the largest for the IOCA-PSO method and reached the smallest fitness value which can help in better scheduling of intended networks of traffic signals. In terms of the lowest number of vehicles that lead to local and global traffic jams, the author found that the IOCA-PSO method was advantageous in achieving lower fitness values than three comparison methods.

3. Conclusion

While the bio-inspired algorithms have witnessed a lot of attention from the scientific community lately, their implementation within the domain of transport engineering is still quite limited. The focus has been on decision making across domains like agriculture, urban planning, military, healthcare, education, governance and other application industries. This paper reviewed all bio-inspired algorithms to determine the scale of their applications in optimization of traffic signals. It was found that they are far from being mature. Except for a few algorithms, namely Artificial Neural Networks, Genetic Algorithm, ant colony optimization algorithm (ACO) and particle swarm optimization algorithm (PSO), the literature presents a lot of challenges as well as opportunities on the usability of these algorithms.

Though there have been some reviews of the algorithms in general, they do not focus on a specific area. They merely go through the definition of those theories and where they have been applied. Therefore, subject specific reviews may be useful in order to equip scholars with sufficient knowledge of where the gap might be for them to explore further and develop theories and applications. The review conducted in this paper points the scientific community towards such review papers. Another benefit of reviewing these algorithms is that they provide practitioners good insights as to what the pros and cons of each algorithm are during their assessment of newer options available in the market.

The algorithms developed by the scientific community in the context of bio-inspired can easily be adopted since most of the algorithms and source codes of their applications have been made readily available and standardised. This gives a great opportunity and lower time to deploy the methods across different problem domains.

The aim of this paper has not been to provide solutions for traffic signal problems, but to highlight what the scientific community have published in this context and uncover opportunities for the researchers to explore. Reviews of artificial neural networks show broader spectrums than all other algorithms. One potential factor could be due to the number of recent papers and algorithms published by the scientific community on neural networks and deep learning. The other factor is the large amount of data available to be processed by much more powerful computers than there used to be. Among the algorithms used in traffic signals, optimized ACO has been explored the least.

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