*Available online www.jsaer.com*

***Journal of Scientific and Engineering Research*, 2021, 8(7):42-50**

**Research Article**

**ISSN: 2394-2630**
**CODEN(USA): JSERBR**

# Optimization of Green Wave Traffic Control Systems: A Literature Review and Research Directions

**Nanchen Nimyel Caleb*[1], Selfa Johnson Zwalnan[2], Bulus Azi Atang[3]**

*[1]Computer Engineering Dept., Plateau State Polytechnic, B/Ladi-Nigeria
[2]Metallurgical Engineering Dept. Plateau State Polytechnic, B/Ladi-Nigeria
[3]Electrical and Electronic Engineering Dept, Plateau State Polytechnic, B/Ladi-Nigeria

**Abstract** The huge economic losses caused by traffic congestions call for better approaches like Green Wave Traffic Control System (GWTCS) to reduce congestion especially at signalized intersections. The survey shows that good researches on optimizing GWTCS have been carried out but there are still traceable research gaps in the aspects of standardization of performance metrics, and also on combination of more promising Machine Learning types to obtain new optimums.

**Keywords** Green Wave, Machine Learning, Reinforcement Learning, Traffic Optimization, Offset

## 1. Introduction

Automobile Traffic congestion, which occurs mostly at intersections, causes delay that leads to economic losses in the form of travel time, vehicle operation costs, and environmental pollution from vehicular emissions. Vehicles moving through several signalized traffic intersections mostly experience very high travel times as they have to stop at almost every intersection on the path to destinations [1]. Several traffic lights can be synchronized to allow continuous traffic flow over many intersections, which is called Green Wave. Any vehicle moving at the progression speed in the green wave network will not have to stop at intersections but experience a progressive cascade of green lights [2].

The optimization of green wave traffic control system is multiobjective in nature. In essence, multiobjective optimization problems (MOPs) have several conflicting objectives. Almost all optimization approaches of green wave traffic control system are done in layers, and at each layer, the objective function and the subjected constraints or variables vary [3]. The first layer is always the optimization of traffic controls of individual intersections, which by nature is multiobjective. The final layer is the optimization of entire road network that yields green wave, which is also multi-objective. In-between the first layer optimization and final layer optimization could be some sub-layers in the form of sub-networks.

With advances in technology, especially in the area of Artificial Intelligence (AI) and powerful multiprocessing technologies, many complex problems with complicated tasks that require human-like intelligence and intuition could easily be solved within a short period of time [4]. Researchers now have different approaches that combine the AI technologies, especially Machine learning, with the Internet of Things (IoT) to seemingly handle the problems created by big data obtained from urban traffic networks and Global Positioning System (GPS) [5].

In search for understanding and keeping track of the efforts put in optimizing green wave traffic control systems, we focus on reviewing the use of evolutionary algorithms in the optimization of green wave in the light of prevailing technologies.

### 1.1. Multiobjective Optimization Approach

In real life, most problems have multiobjective solutions [6]. In multiobjective optimization, the aim is to solve problems of the type: -

$$\text{Minimize } f(x) = [\, f_1(x), f_2(x), \ldots, f_k(x)] \quad (1)$$

$$\text{subject to} \quad g_i(x) \le 0\,; \; i = 1, 2, \ldots, m, \quad (2)$$

$$h_i(x) = 0; \; i = 1, 2, \ldots, p, \quad (3)$$

where $x = [\, x_1, x_2, \ldots, x_n\,]^T$ is the vector of decision variables,

$f_i : R_n \rightarrow R$, $i = 1, \ldots, k$ are the objective functions and $g_i$, $h_j : Rn \rightarrow R$, $i = 1, \ldots, m$, $j = 1, \ldots, p$ are the constraint functions of the problem. A few additional definitions required to introduce the notion of optimality used in multiobjective optimization are: -

Definition 1

Given two vectors x, y $\in R_k$, we say that $x \le y$ if $x_i \le y_i$ for i = 1,. ., k, and that x dominates y (denoted by $x \prec y$ ) if $x \le y$ and $x = y$.

Definition 2

We say that a vector of decision variables $x \in X \subset Rn$ is non-dominated with respect to X, if there does not exist another $x' \in X$ such that $f(x') \prec f(x)$.

The classical approaches to solving such multiobjective problems were primarily focused on scalarizing the multiple objective functions into a single objective function, whereas in more recent researches the evolutionary approaches have been used to solve multi-objective optimization problems to obtain a vector of optimal solutions called Pareto Optimal Solutions [7]. In the optimization of multiobjective problems, it is not possible to typically have feasible solution that minimizes all the objective functions simultaneously, and so we settle for solutions that can no longer be optimized further without degrading at least one of the other objectives.

### 1.2. Multiobjective Optimization of Evolutionary Algorithms

Problems are becoming very complex, and at the same time our world is making us to reflectively look into the nature and solve these natural problems [8]. These nature-inspired algorithms, known as evolutionary algorithms, hinge on these features: Self organization, self-learning, self-healing and self-processing. Evolutionary Algorithms (EAs) can be broadly subdivided into Genetic Algorithms, Genetic Programming, Evolutionary Strategies, and the family of hybrids. In the light of this survey, Genetic Algorithms and associated Hybrids are considered further in the optimization of green wave traffic control systems.

### Genetic Algorithms

Genetic Algorithms (GAs) are stochastic search techniques based on the process of natural selection and natural genetics. By using genetic operators and increasing information, genetic algorithms prune the search space and generate a set of plausible solutions. These genetic algorithm operations include reproduction, crossover, and mutation. The selection of a participant in the operation of reproduction, crossover, and mutation on the basis of their fitness is an essential aspect of genetic algorithm. When a participant is selected into the next generation of the population, the new generation contains the characteristics it personifies [9].These evolutionary algorithmic operations, coupled with powerful computing environment, give genetic algorithms the potential capability to handle multiobjective optimization problems like green wave traffic control systems.

## 2. Materials and Methods

The ultimate goal of traffic control systems is to optimize space and time on our roads. At a cross intersection, for instance, there are about 32 possibilities of traffic conflicts of time and space between vehicles and pedestrians in a cross intersection [10] as indicated in fig. 1. It is worthwhile to mention here that the Right-Hand Traffic is exactly the mirror image of the Left-Hand Traffic when it comes to the design and implementation of traffic controls.

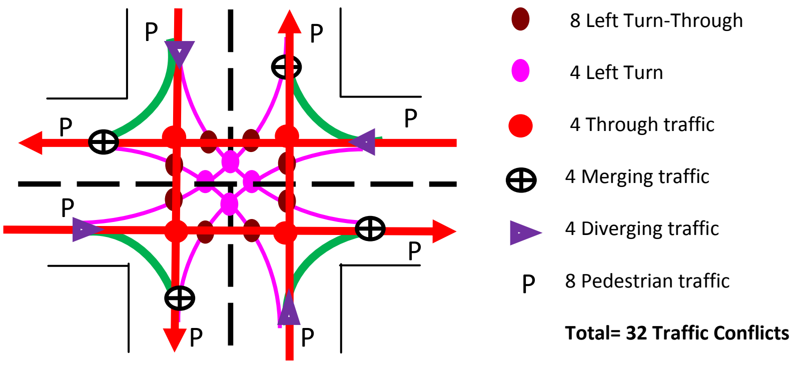


*Figure 1: Vehicle-Pedestrian Intersection Conflicts in RHT [10]*

### 2.1. Definitions of Traffic Control Terminologies

- *Cycle Length* is defined as the time needed for a complete sequence of indications.
- *Green Split Distribution* specifies the time allocation to the phases in one cycle.
- *Phase* specifies the green interval, the change interval, and clearance interval in a cycle assigned to definite movement(s) of traffic.
- *Release Matrix* is a vector which specifies the current traffic situation in any instance: the status of the current phase (i), the direction of movement (j), and the road-lane (k).
- *Offset* is the green time lag between two adjacent traffic intersections.

### 2.2. Traffic Control of Network of Intersections

A network of intersections can be coordinated to enhance traffic flow in the network. This can be implemented statically by the use of timers, or dynamically by the use of sensors. A network of intersections can be represented as a directed graph G (V, E) where V denotes the intersections and E denotes the roads (edges) between the intersections [11]. Fig 2 depicts a road network of four intersections (JW, JX, JY, JZ).

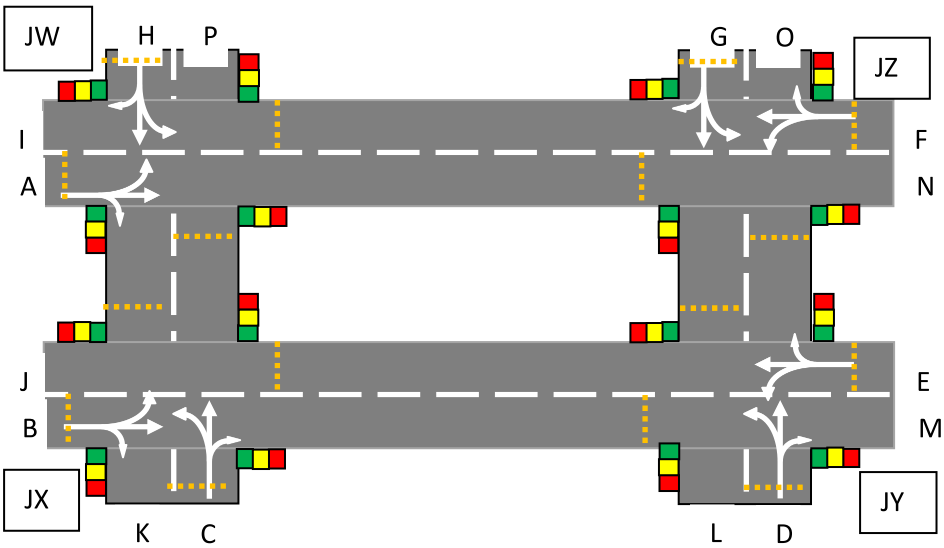


*Figure 2:* Road Network of 4 Intersections

According to Lee [11], relationships between nodes (intersections in terms of road networks) can be modeled by Relationship Matrix. If i = {1,2, . . ., n} is used to represent nodes, then the Relationship Matrix can be formulated as: -

$$R = \begin{bmatrix} 0 & r_{12} & \cdots & r_{1n} \\ r_{21} & 0 & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & 0 \end{bmatrix}.$$

Where the element $r_{ij}$ represents the relationship between node I and node j as given by

$$Rij = \frac{N(i \cap j)}{N(i \cup j)}$$

$N(i\cap j)$ considers common grounds, and $N(i \cup j)$ considers uncommon grounds. Matrix partitions are then considered as subnetworks in traffic controls. It is pointed out that graph partitioning is an NP-hard problem with multiple conflicting objectives, and hence it is in the class of Multiobjective Optimization Problems (MOPs) [12].

### 2.3. Components and Layout

Traffic components vary in composition and layout depending on the road architectures and the technologies used in the implementation of the traffic controls. In a generic view, traffic control layout is composed of traffic lights on all inlets to intersections, controller, sensors if adaptive, communication hardware/channels when remotely controlled, Satellite communication devices when Global Positioning System (GPS) in involved. This is shown in fig. 3.

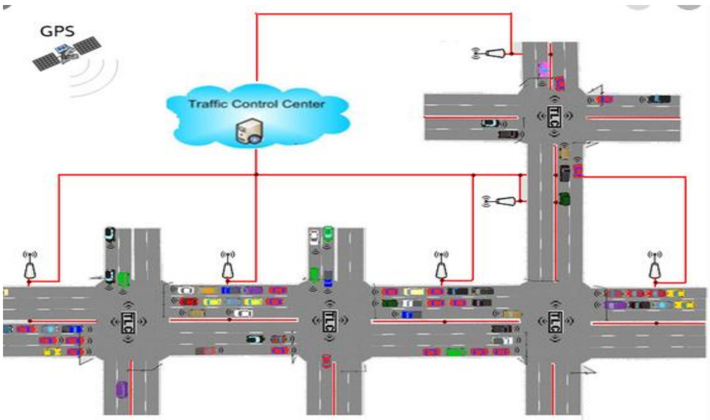


*Figure 3: A typical RHT control system layout*

### 2.4. Optimization of GWTCS

The optimization of Green Wave Traffic Control System (GWTCS) involves both the optimization of traffic signals at intersections, and the optimization of the entire traffic interconnections. For many years, the optimization of intersection traffic signals has been revolving around the optimization of the Split, Cycle, Offset and phase sequence of the traffic. The basic optimizing techniques are SCOOT- Split Cycle Offset Optimization Technique, and SCATS- Sydney Coordinated Adaptive Traffic System. Although very complex, expensive and high rate of failure, SCATS is more efficient than SCOOT. According to Alsrehin, [13] and Oblakova[14], the complexity of road traffic signal optimization is exponential to the number of intersections. Hence, the need for intelligent heuristic techniques that can handle large and heterogeneous road networks.

The most well-known and typical traffic signal cycle length models are the Transport and Road Research Laboratory (TRRL) model and the Australian Road Research Board (ARRB) model. The TRRL model is given

$$c_0 = \frac{1.5L + 5}{1 - Y},$$

as

where $C_o$ represents the optimal cycle length (sec); $L$ represents the total lost time (sec); and $Y$ represents the sum of the critical flow ratio of all phases. The ARRB model is given as: -

$$c_0 = \frac{(1.4 + k) + 6}{1 - Y},$$

where $C_o$ represents the optimal cycle length (sec); $K$ represents the parking compensation coefficient; and $Y$ represents sum of the critical flow ratio of all phases.

At the network level of the intersections, there are coordination approaches that optimize the traffic flow in the entire road network which include the coordination of the network of intersection controllers, incorporation of sensors (adaptive) at intersections, and load balancing of vehicles at intersections using Global Positioning System (GPS) datasets. The starkest design consideration for implementing GWTCS is the specification of cycle lengths of the intersections to be the same or multiples so that there would not be phase-off. Another consideration is the progression speed, which is the determinant of the intersection offsets, should be carefully computed [15-16].

**2.5. Implementation of GWTCS Optimization**

Heuristic techniques are simple and practical techniques that search for optimal solutions within costs but do not always guarantee optimality. These heuristic optimization algorithms include Mixed Integer Linear Programming (MILP), Hill Climbing Algorithm (HCA), Simultaneous Perturbation Stochastic Approximation & Neural Network (SPSA-NN), Simulated Annealing Algorithm (SAA), Genetic Algorithm (GA), Non-Linear Programming (NLP), Fuzzy Logic (FL), Ant Colony Algorithm (ACA), Particle Swarm Optimization (PSO), Cross Entropy Method (CEM), Maximum aposteriori Policy Optimization (MPO), Monte Carlo Problems (MCP), and Geometric Deep Learning (GDL).

As indicated earlier, graphs can be computationally expressed as Non-Euclidean data with 3D or higher dimensions. According to Monti [12], it is a fact that Artificial Neural Networks (ANNs) are actually just graphs, and so most computational operations on graphs can be extended to ANN. Artificial Neural Networks and its extended families like Recurrent Neural Networks (RNNs), Convolution Neural Networks (CNNs) and Graph Neural Networks (GNNs) are types of Deep Learning Algorithms. Deep Learning is a type of Machine Learning Algorithm, which in turn is a subset of Artificial Intelligence. Geometric Deep Learning is an extension of Deep Learning with special applications to Graph Neural Networks. Geometric Deep Learning (GDL) builds neural networks that can learn from ubiquitous Non-Euclidean data structures like graphs and manifolds (Cao et al., 2020). In other words, GDL is a new field of machine learning that can learn from complex data like graphs and multi-dimensional points. It seeks to apply traditional Convolutional Neural Networks (CNNs) to 3D objects or even multidimensional data structures like graphs and manifolds [17].

Wang Q. [18] used Mixed Integer Linear Programming on a framework of Model Predictive Control to dynamically optimize the coordination of traffic control networks. Kentaro[19] considered both MILP and Crossed Entropy Method (CEM) to optimize a coordinated traffic signal. Kinematic Wave (KW) model was also used for traffic dynamics as it has many intersections. Cell Transmission Model (CTM) was also incorporated for control problems based on Variation Technique (VT) of the KW model. The traffic scenarios of the research were under both deterministic and stochastic traffic demands. The main performance metric is the delay minimization control.

Zhao [20] implemented Hill Climbing Algorithm (HCA) on a grid road network with route-choices model and was seen to remarkably improve green wave traffic. Based on the kinematic wave traffic flow model, solution algorithm hinged on SPSA scheme is developed to solve multiobjective optimization problem [21]. Experiments indicate that SPSA algorithm is better balanced between efficiency and solution quality compared to other heuristics like genetic algorithm (GA) and hill-climbing algorithm. Wang Y. [22] proposed an SPSA algorithm that dynamically optimizes multiple-ramp metering control by maximizing the total throughput in a grid road network.

Chen D. [23] blended Genetic Algorithm with Sorting Algorithm to optimize the multiobjective problem of traffic controls. Traffic Delay and the number of stops at intersections were used to measure the efficiency, which prove to improve. Static and Adaptive traffic environments were set up to enable comparison of their optimizations.

Sabbani [5] integrated Ant Colony Algorithm, Internet of Things, and Genetic Algorithm to develop hybrid algorithm called Artificial Bee Colony (ABC). Experimentation with ABC indicated that it minimizes travel times. It follows the modeling of traffic road network as graph G (V, E). The result was validated in comparison with the tests made with Dijkstra’s Shortest Path Algorithm.

Dong [24] separately applied Chaos Genetic Algorithm (C-GA), Chaos Particle Swarm Optimization Algorithm (C-PSO), Simulated Annealing-Particle Swarm Optimization Algorithm (Sa-PSO) and Catastrophe-particle swarm optimization (Ca-PSO) to traffic control network, and all of these intelligent algorithms improved the traffic conditions but that they have different scopes strengths.

Cano [25] and Oblakova [14] focused on using Genetic Algorithm to optimize traffic at intersections and incorporating MAXBAND algorithm to coordinate the traffic network by optimizing the offset. A performance metric was introduced which measures the efficiency of green wave traffic control by the number of intersections passed without stopping.

Karagiannis [26] investigated the networking of vehicles enables diverse applications that are linked to traffic efficiency, traffic safety, and infotainment. In traffic efficiency and management applications, applications requirements which include systems capability requirements, and economic requirements are considered first. Standards and architectures are made to foster interoperability. Vehicular networking is the empowering technology that will support applications ranging from Global Internet Services to active road safety applications.

Peres [27] developed a combination of multi-objective evolutionary methods and simulation to simultaneously and dynamically optimize traffic flow and vehicular emissions. The integration of Non-dominated Sorting Genetic Algorithm version II from the family of MOEAs, and Generalized Differential Evolution, version 3 (GDE3) which extends Differential Evolution to solve multiobjective optimization problems. The selection operator is based on Pareto-dominance.

Zhou [28] applied the extended Particle *swarm* optimization (PSO) to multi-objective optimization of the traffic controls. Multiobjective algorithmic frameworks like decomposition-based MOEAs, memetic-based MOEAs, and Convolution-based MOEAs were implemented on the Multiobjective Optimization Problems (MOP). Unary quality indicators are used to specify the performance of the MOEAs. Farhangi, [29] used a class of MOPs called Multiobjective Combinatorial Optimization problems (MOCO) with a focus on multi-objective pure- and mixed-integer linear programming problems and their applications in System of Systems (SoS) architecting and Track Inspection Scheduling, and hence improving traffic coordination.

Bronstein [30] discussed on geometric deep learning also indicated that Cross-Entropy Method (CEM) is used to find the global optimum solution in a MOP. CEM tolerates both deterministic and Monte Carlo problems. Unlike Hill Climbing methods, CEM handles combinatorial problems which have local optima. It is discovered that CEM fits in a Monte Carlo traffic assignment model to estimate route choices [31-32].

### 2.6. Design Considerations and Measurement of Efficiency

In the design of efficient green wave traffic control systems, deliberate efforts should be made to consider the feasibility of the costs, scalability of the system, privacy & security, efficiency metrics, and communications latencies & effects.

#### 2.6.1. Cost Analysis

The economic feasibility of the deployment is first computed. The design should capture the short-term and long-term benefits and constraints. These costs (capital expenditure of the system and recurrent expenditure) against the benefits (reduced delays, minimal vehicle operation costs and less environmental pollution) should be considered before embarking on the implementation phase.

#### 2.6.2. System Scalability

The potential elasticity of the system scalability be checked by adding more resources and intersections to the network. This test of the elasticity of the green wave traffic control system will show its limits.

#### 2.6.3. Communications Latencies and Effects

Communications latencies between devices, and the prevailing error space of GPS accuracy (10 to 100m) is captured into the design. Communications between the intersection controllers and the central controller, between sensors and controllers, and between GPS devices and the central controller need to be considered.

#### 2.6.4. Efficiency Metrics

The measurement of efficiency of the system could be in the delay at intersections, travel times between sources and destinations, number of intersections passed without stopping, and number of stops on the queue at intersections.

#### 2.6.5. Privacy and Security

There are ethical issues pertaining to the privacy and security of unsuspecting road users that should be considered. Information generated by users on GPS and sensor devices should be protected and classified.

## 3. Results & Discussion

**Table 1:** Summary of related work on Design of GW traffic controls

| Cycle Length | Split | Green Wave | GPS | Model | Efficiency | Algorithm | Ref |
|---|---|---|---|---|---|---|---|
| Fixed | Ad | √ | √ | | Not def | Green Route | [15] |
| Fixed | Ad | √ | | Poisson Distr | Not def | REDV | [25] |
| Ad | Ad | | | | Not def | | [2] |
| Ad | Ad | | | Poisson Distr | Not def | RHODES & DOGS | [31] |
| | Ad | √ | | | Not def | | [3] |
| Ad | | | √ | Bayesian | Not def | SURTRAC | [16] |
| Ad | | √ | | | | Fuzzy | [22] |

**Table 2:** Summary of related work on algorithmic models used in GW traffic controls

| Fish Swarm | MIP | Fuzzy | ML | Genetic | Markov | Monte Carlo | Ref |
|---|---|---|---|---|---|---|---|
| | √ | | | | | | [15] |
| | | | | | | | [25] |
| | | | RL | √ | MDP | | [2] |
| | √ | | | | | √ | [31] |
| √ | | | | √ | | | [3] |
| | √ | | | | | √ | [16] |
| √ | √ | √ | RL | √ | | | [22] |

**Table 3:** Summary of related work on Performance Metrics on GW traffic controls

| Ref | Fuel Cost | Number of Intersections crossed | Delay | Travel times | Rate of Pollution | Performance Rate | Number of stops |
|---|---|---|---|---|---|---|---|
| [15] | √ | | | √ | | 40% | |
| [25] | | | √ | √ | √ | | |
| [2] | | | | √ | | | |
| [31] | | | √ | | | 50% | |
| [3] | | | √ | | | | √ |
| [16] | √ | | | √ | | | √ |
| [22] | | √ | √ | | √ | | √ |

## 4. Conclusion/ Recommendations

Although quality researches have been conducted on the optimization of Green wave Traffic Control Systems, there are traceable research gaps in the standardization of the performance metrics, and also in the possibilities and capability of combining Machine Learning types to achieve optimality.

**Acknowledgment**
We earnestly thank Dr. John Bush for his words of advice and guidance.

**References**

[1]. Chen, J., Yu, Y., & Guo, Q. (2019). *Freeway traffic congestion reduction and environment regulation via model predictive control. Algorithms, 12(10), 220.* doi:10.3390/a12100220

[2]. Junchen, J. (2018).*Advance Traffic Signal Control Systems with Emerging Technologies.* (Doctoral Dissertation). KTH School of Architecture and Built Environment. SE-100 44 Stockholm SWEDEN, Stockholm, Sweden 2018.

[3]. Ma, C., & He, R. (2019). Green wave traffic control system optimization based on adaptive genetic-artificial fish swarm algorithm. *Neural Comput & Applic* 31**,** 2073–2083. https://doi.org/10.1007/s00521-015-1931-y

[4]. Al-Turjman, F. &Baali, L. (2019). Machine learning for wearable IoT-based applications: A survey. Trans Emerging Tel Tech. 2019; e3635. https://doi.org/10.1002/ett.3635

[5]. Sabbani, I., Youssfi, M., &Bouattane, O. (2016). *A multi-agent based on ant colony model for urban traffic management. 2016 5th International Conference on Multimedia Computing and Systems (ICMCS).* doi:10.1109/icmcs.2016.7905551

[6]. Coello, C. A., González, B. S., Figueroa, G. J., Castillo, T. M. G., & Hernández, G. R. (2019). Evolutionary multiobjective optimization: open research areas and some challenges lying ahead. *Complex & Intelligent Systems.* doi:10.1007/s40747-019-0113-4

[7]. Li, K., Wang, R., Zhang, T., &Ishibuchi, H. (2018). *Evolutionary many-objective optimization: A comparative study of the state-of-the-art. IEEE Access, 6, 26194–26214.* doi:10.1109/access.2018.2832181

[8]. Jiang, M., Huang, Z., Qiu, L., Huang, W., & Yen, G. G. (2017). *Transfer Learning based Dynamic Multiobjective Optimization Algorithms. IEEE Transactions on Evolutionary Computation, 1–1.* doi:10.1109/tevc.2017.2771451

[9]. Zang, W., Zhang, W., Wang, Z., Jiang, D., Liu, X., & Sun, M. (2019). A novel double-strand DNA genetic algorithm for multi-objective optimization. *IEEE Access*, vol. 7, pp. 18821-18839.

[10]. Ahn, H., & Del Vecchio, D. (2018). Safety Verification and Control for Collision Avoidance at Road Intersections. IEEE Transactions on Automatic Control, 63(3), 630–642. doi:10.1109/tac.2017.2729661

[11]. Lee, S., Younis, M., Murali, A., & Lee, M. (2019). *Dynamic local vehicular flow optimization using real-time traffic conditions at multiple road intersections. IEEE Access, 7, 28137–28157.* doi:10.1109/access.2019.2900360

[12]. Monti, F., Boscaini, D., Masci, J., Rodol`a, E., Svoboda, J., & Bronstein, M. M. (2017). Geometric deep learning on graphs and manifolds using mixture model CNNs. 2017 IEEE Conference on Computer Vision and Pattern Recognition DOI 10.1109/CVPR.2017.576

[13]. Alsrehin, N. O., Klaib, A. F., &Magableh, A. (2019). Intelligent transportation and control systems using data mining and machine learning techniques: A comprehensive study. *IEEE Access,7,* 2169-3536.

[14]. Oblakova, A., Al Hanbali, A., Boucherie, R. J., & van Ommeren, J.C.W. (2017). Green Wave Analysis in a Tandem of Traffic-Light Intersections. Memorandum 2062 (Aug 2017). ISSN 1874−4850. Available from: http://www.math.utwente.nl/publications Department of Applied Mathematics, University of Twente, Enschede, The Netherlands

[15]. Antonio, M. R. A., Jose, L. A. L., Jose, A. F. M., &Javam, C. M. (2017). GPS2GR: Optimized urban green routes based on GPS trajectories. In *Proceedings of 8th ACM SIGSPATIAL Workshop on GeoStreaming, Los Angeles Area, CA, USA, November 7–10, 2017 (IWGS'17)*.

[16]. Khattak, Z. H., Magalotti, M. J., & Fontaine, M. D. (2019). *Operational performance evaluation of adaptive traffic control systems: A Bayesian modeling approach using real-world GPS and private sector PROBE data. Journal of Intelligent Transportation Systems, 1–15.* doi:10.1080/15472450.2019.1614445

[17]. Cao, W., Yan, Z., He, Z., & He, Z. (2020). A Comprehensive Survey on Geometric Deep Learning. *IEEE Access, 8, 35929–35949.* Doi: 1109/access.2020.2975067

[18]. Wang, Q., & Abbas, M. (2019). Optimal urban traffic model predictive control for NEMA standards. transportation research record: *Journal of the Transportation Research Board, 036119811984185.* doi:10.1177/0361198119841851

[19]. Kentaro, W., Kento, U., Tsubasa, T., & Masao, K. (2017). An optimization modeling of coordinated traffic signal control based on the variational theory and its stochastic extension. 22nd International Symposium on Transportation and Traffic Theory Transportation Research Procedia 23 (2017) 624–64

[20]. Zhao, N., Li, B., Wu, K., Yang, Y., Wu, X., & Huang, S. (2019). *Turning Green Wave Signal Control Optimization Based on Route-Choice Model. CICTP 2019.* doi:10.1061/9780784482292.226

[21]. Alaeddini, A., & Klein, D. J. (2019). *Parallel Simultaneous Perturbation Optimization. Asia-Pacific Journal of Operational Research.* doi:10.1142/s021759591950009x

[22]. Wang, Y., Yang, X., Liang, H., & Liu, Y. (2018). *A Review of the Self-Adaptive Traffic Signal Control System Based on Future Traffic Environment. Journal of Advanced Transportation, 2018, 1–12.* doi:10.1155/2018/1096123.

[23]. Chen, D., Yan, X., Liu, F., Liu, X., Wang, L. & Zhang, J. (2019). Evaluating and diagnosing road intersection operation performance using floating car data. *Sensors, 19(10), 2256.* doi:10.3390/s19102256

[24]. Dong, C., Huang, S., & Liu, X. (2011). Comparative study of several intelligent optimization algorithms for traffic control applications. *2011 International Conference on Electronics, Communications and Control (ICECC).* doi:10.1109/icecc.2011.6066641

[25]. Cano, M. D., Sanchez-Iborra, R., Freire-Viteri, B., Garcia-Sanchez, A. J., Garcia-Sanchez, F., & Garcia-Haro, J.(2017). A self-adaptive approach for traffic lights control in an urban network. 19th International Conference on Transparent Optical Networks (ICTON), Girona, pp. 1-4, 2017. DOI**:** 10.1109/ICTON.2017.8025051

[26]. Karagiannis, G., Altintas, O., Ekici, E., Heijenk, G., Jarupan, B., Lin, K., & Weil, T. (2011). Vehicular Networking: A Survey and Tutorial on Requirements, Architectures, Challenges, Standards and Solutions. *IEEE Communications Surveys & Tutorials, 13(4), 584–616.* doi:10.1109/surv.2011.061411.00019

[27]. Péres, M., Ruiz, G., Nesmachnow, S., & Olivera, A. C. (2018). *Multiobjective evolutionary optimization of traffic flow and pollution in Montevideo, Uruguay. Applied Soft Computing, 70, 472–485.*doi:10.1016/j.asoc.2018.05.044

[28]. Zhou, A., Qu, B.-Y., Li, H., Zhao, S.Z., Suganthan, P. N., & Zhang, Q. (2011). Multiobjective evolutionary algorithms: A survey of the state of the art. Swarm and Evolutionary Computation. *1(1), 32–49.*doi:10.1016/j.swevo.2011.03.001

[29]. Farhangi, H. (2017). Multi-objective combinatorial optimization problems in transportation and defense systems. Doctoral Dissertations. 2559. Missouri University of Science and Technology https://scholarsmine.mst.edu/doctoral_dissertations/2559

[30]. Bronstein, M. M., Bruna, J., LeCun, Y., Szlam, A., and Vandergheynst, P. (2017). Geometric deep learning: going beyond euclidean data. IEEE Signal Processing Magazine, 34(4):18–42.

[31]. Warberg, A., Larsen, J., & Jørgensen, R. M. (2008). Green Wave Traffic Optimization - A Survey. *Informatics and Mathematical Modelling. D T U Compute. Technical Report, No. 2008-01*. https://backend.orbit.dtu.dk/ws/portalfiles/portal/3050157/tr08_01.pdf

[32]. Cao T. P., Duy, D. P., Phuong, M. N., & Hoang, V. T. (2018). Green Wave - based Solution for Intelligent Traffic Lights System Control in Vietnam Urban Areas *2018 4th International Conference on Green Technology and Sustainable Development (GTSD)*