International Journal of Computers and Informatics

Journal Homepage: https://www.ijci.zu.edu.eg

Int. j. Comp. Info. Vol. 5 (2024) 85–95

Paper Type: Original Article

Fog Computing-Based Multi-Criteria Decision-Making for Evaluating Traffic Light Control Systems: Ensuring Safety, Efficiency, and Environmental Standards

Alaa Salem [1,*] and Mona Mohamed [1]

[1] Faculty of Computer and Informatics, Zagazig University, Zagazig 44519, Egypt; as.ata23@fci.zu.edu.eg.

[2] Higher Technological Institute, 10th of Ramadan City 44629, Egypt; mona.fouad@hti.edu.eg.

Received: 05 Sep 2024 **Revised**: 20 Nov 2024 **Accepted**: 18 Dec 2024 **Published**: 20 Dec 2024

Abstract

Due to increasing mass of automobiles on the road, is making traffic efficiency a global issue. Intelligent traffic signal control is a key component of intelligent transportation systems, which seek to increase traffic efficiency. Several approaches to reduce urban traffic accidents, congestion, and other issues have been put forth by intelligent traffic. It is unable to control the traffic signal cycle in real time to match the flow of traffic, which can further lead to traffic jams that lengthen travel times and increase vehicle range. Also, there are difficulties faced by the intelligent traffic signal management systems e.g. avoiding dense roadside sensors, fending off hostile cars, and preventing single-point failure.To overcome the drawbacks of conventional traffic light control, this research proposes an intelligent fog computing-based traffic light control system. Fog computing offers several benefits for traffic light control systems. It a perfect solution for traffic light control systems that need real-time responses to ensure it meets safety, efficiency, and environmental standards. Thus, unitization fog computing for evaluating traffic light control systems is crucial. Also, utilizing the appropriate system of traffic light control is an obstacle. In turn, this study contributes to constructing innovative decision-making methodology. To achieve the study's objective, Opinion Weight Criteria Method (OWCM) of Multi-Criteria Decision Making (MCDM) techniques are utilized for weighting criteria. The generated criteria weights are harassing in Weighted Sum Product Method (WISP) for ranking systems and recommending optimal. The utilized techniques of MCDM collaborate with single value Neutrosophic Numbers (SVNs) for supporting decision makers (DMs) in perplexing situations and ambiguity as well as eliminating prejudice. The appraiser model's findings indicated that A2 was the optimal candidate based on its ranking. In contrast, A4 is the worst one.

Keywords: Traffic Light Control; Fog Computing; MCDM; Opinion Weight Criteria Method; Weighted Sum Product Method; WISP.

1 | Introduction

Traffic congestion on urban transportation networks is getting worse due to urbanization, growing global populations, and automobile ownership with serious repercussions, such as delays in travel, irritated drivers, higher emissions, and worse safety [1]. Injuries from automobile accidents are a major cause of death worldwide. The World Health Organization's 2015 Global Status Report on Road Safety states that 1.2 million people lose their lives to traffic-related injuries every year [2]. According to the organization's later

Corresponding Author: as.ata23@fci.zu.edu.eg

publications, this figure has been rising year. The major factors to high traffic accident rates are Low safety standards, a lack of law enforcement, fast urbanization, driving while intoxicated or under the influence of narcotics, failure to wear seat belts and helmets, and exhausted drivers [3]. Road traffic accidents have an influence on the direct victims, their families, and the nation as a whole health, financial, and social consequences. Survivors of automobile accidents experience chronic physical and mental health issues. Furthermore, compared to the norm for the general population, people's overall quality of life is considerably lower following injuries sustained in traffic accidents [4]. Therefore, traffic management is an essential part of smart cities since it directly affects public safety, economic productivity, environmental sustainability, and urban adaptability [5]. Since there are more automobiles worldwide, especially in major cities, traffic efficiency is becoming a global issue [6]. Although laws and traffic regulations are in place to make sure that drivers behave in a way that is convenient for all, maintaining smooth traffic flow is not an easy job. Lights are the signaling systems that are used to direct traffic on a multi-way lane [7]. At road intersections, pedestrian crossings, and other locations, traffic lights, also known as traffic signals, are signaling devices that alternate the signal phase to maximize traffic efficiency. Conventional traffic lights typically have fixed cycles, meaning they change on a regular basis. Given how frequently the traffic situation changes, this is inefficient [6]. All intersections and crossroads have traffic lights installed to guide all vehicles entering from all directions. These traffic lights serve the dual aims of (1) preventing accidents from occurring due to uncoordinated traffic from all directions and (2) preventing congestion that may arise due to the high volume of cars or traffic density [8]. Although the installation of sufficient traffic lights, heavy congestion may still happen because of improper timing in relation to traffic volume at different times of the day. For example, sometimes the green light duration is too short during busy hours, but the traffic is heavy, resulting in a long line in one direction; other times, the green light duration is too long during vacant hours, resulting in less-than-ideal lane/direction utilization [8]. With the use of intelligent traffic lights, intelligent transportation systems (ITS) are designed to regulate traffic flow in an adaptive manner based on current traffic conditions [6]. To fully realize the benefits of transportation and integrate the system of real-time, accurate, and environmentally friendly automated information exchange among people, vehicles, and roads, ITS aims to essentially eliminate the effects of road traffic safety, automobile congestion, environmental pollution, and other factors on cities [9]. It does this by successfully combining advanced information, communication, electronic, sense, and dimension technologies with other technologies and implementing them into the transportation management system [10]. More real-time traffic flow data is available because to improved sensing and collection capabilities. Therefore, there must be a method for effectively optimizing the phase time using the collected traffic data. Furthermore, current control systems must overcome the lengthy reaction and decision latency caused by data processing. The traffic signal controller may see a significant shift in traffic flow by the time the optimization decision's outcome is given back. Therefore, the traffic flow status quo cannot be accommodated by the resultant optimal signal control technique on traffic light scheduling. Data processing and adaptive signal control systems' requirement for an instantaneous reaction present a problem for centralized compute infrastructure. To overcome this problem, the newly proposed fog computing paradigm, is a potential solution [11]. The idea of fog computing was first presented in 2011 by Dr. Flavio Bonomi, the president of the Cisco Global R & D Center. Fog computing's core idea is "intelligent front end," which refers to the use of a network system or specialized device to provide computing related to the terminal equipment between the cloud server and the terminal system. This lowers the cloud server's computing and storage overhead, improves the application system's reaction time and network bandwidth, and even continues to provide data and computing services even in the absence of Internet-connected areas [9]. Fog computing is a cloud computing extension that reduces latency by bringing network, storage, and computing services closer to the user's area. This decentralized computing infrastructure is characterized by position awareness , low latency, a wide geographic dispersion, mobility support, a large number of nodes, heterogeneity, and the dominance of wireless access [12]. Road status (such as wet or dry, under construction, traffic accidents), meteorological status (such as sunny or rainy), vehicle status (such as location, speed, acceleration, etc.), and intersection data (such as the length of the line waiting at the intersection) can all be gathered and processed instantly by fog nodes. Then, To reduce traffic congestion and further guarantee driving safety, the traffic signal controller can get an immediate response (for example, prolonging the green time or initiating new phase timing) [11].

1.1 | Fog Computing Features

Fog computing's appealing qualities make it a perfect solution for Intelligent Transportation Systems (ITS) that need real-time responses for traffic safety and other latency-sensitive applications [12].

Table 1. Important criteria's of fog computing.

Criteria	Description
Real-time interactions (C1)	A preponderance of wireless access, support for online analytics, and interaction with the cloud.
Location awareness and geo-distribution (C2)	Unlike cloud computing, fog computing is not centralized. Instead, it offers dispersed services and applications and may be implemented anywhere. Because fog nodes can be placed in a variety of locations, fog computing thus facilitates location awareness.
Mobility Support (C3)	With fog-enabled services, mobile devices can travel between locations without experiencing any disruptions.
Scalability (C4)	Fog computing can accommodate a growing number of end devices because it is a multilayered distributed environment. The service that fogs servers offer is more scalable when they communicate with one another.
Heterogeneity (C5)	Clients and fog servers have varied forms and are made by different vendors. However, fogging is designed to function on various systems.
Interoperability (C6)	Various providers' collaboration is required for heterogeneous devices. Numerous domains and service providers can collaborate and work with fog nodes.
Reliability (C7)	Compared to centralized computing paradigms, fog computing is more dependable since it doesn't depend on a single failure of the fog environment.
Low latency and reduced network traffic (C8)	Large volumes of raw data generated by low-level devices shouldn't be sent to distant servers. Data processing and filtering by fog servers significantly lowers the volume of data transmitted to cloud servers. Applications such as augmented reality, safety, e-health, gaming, antilock brakes on cars, etc., need real-time data processing. For these kinds of applications, fog servers must be close to end users to satisfy latency requirements.

2 | Related Work

Reviews and surveys of traffic light control architecture have been published by several researchers. Nevertheless, the research survey works do not provide detailed information regarding the benefits and drawbacks of each technique [7]. The goal of most recent studies is to establish real-time traffic light control to reduce traffic flow. These studies concentrate on optimizing traffic signal configurations, which involves adjusting phase timing intervals and sequences [11]. With the use of microscopic traffic flow simulators (such as SUMO and PARAMICS), many previous studies assess the effectiveness of smart traffic control algorithms and strategies. Their optimization goals typically include the average travel time, average number of stops, and waiting queue length at the intersection [6]. To reduce both the queue length at intersections and the total delay minimization, Feng et al. [13] provide a real-time and adaptive signal phase scheduling approach using V2I/V2V communication protocols. For example, Priemer and Friedrich [14] suggest using V2I communication protocols to gather vehicle speed, acceleration, and heading to increase the effectiveness of traffic control strategies at intersection. However, there are other challenges that must be resolved, making the creation of an effective traffic management plan hard [11]. Among the difficulties and problems are, for instance, the unpredictable nature of traffic patterns and the combination of IoT and traffic data (considering the diversity of automobiles and V2X communication methods) [11]. Furthermore, Wang et al.'s review paper [15] on self-adaptive traffic signals examines global advancements in widely used self-adaptive signal control systems. The research survey only included a self-adaptive strategy, which is regarded as a restriction. To accomplish traffic signal control, academic research primarily focuses on creating real-time, adaptable algorithms [16]. For example, Intelligent traffic light control systems are the urban traffic control system [17] and TRANSYT [18]. We point out that these kinds of systems are not real-time and are only useful in situations when demand is largely constant over time. When there are unexpected shifts in traffic patterns brought on by emergencies or accidents, they are ineffective [6]. Shinde and Jagtap summarizes a review of the various strategies applied to the intelligent traffic management system's implementation [7]. Kotwal et al.'s research [19] provides a thorough grasp of modern technology in the United States by analyzing and synthesizing data on a wide range of signal systems, detection devices, and communications elements. The investigation of postmodern technologies and the comparison of emerging technologies were conducted by looking at current signal system practices. Additionally, suggestions for additional research on traffic signal systems were given. Souza et al. [20] published an article on the current traffic management system, which included a classification, analysis, problems, and possible perspectives. However, Jensen et al. in [21] outline the difficulties that remain in traffic light identification research and give a summary of recent efforts. The objective is to clarify which domains have been extensively investigated and which have not, consequently identifying avenues for additional enhancement. Krajzewicz et al. [22] describe an agent-based traffic signal control method to reduce traffic congestion at crossings. Depending on how long the queues are for various lanes, they start the optimization. They raise the phase length one at a time if the queue length is beyond the predetermined threshold. The model has no mathematical formulation and is straightforward. It lacks the necessary qualifications to handle scenarios involving more complex smart traffic. Guo and colleagues [23] introduce a plan for optimizing traffic scheduling in the context of user equilibrium traffic. They use a genetic algorithm to simulate the optimization in PARAMICS, modeling it as a multi-dimensional search problem. In research published by Hawi et al. [24], the authors investigate the motivations for the development of the many kinds of traffic control systems that are currently in use. Among them are wireless sensor networks, fuzzy expert systems, and artificial neural networks (ANN). Fog computing has recently been included in smart cities and smart transportation [11]. Fog computing is a new technique which was put forward by Cisco [25]. In fog computing, computation and storage are performed by a cooperative plurality of end-user clients or near-user edge devices. A traffic light may function as a fog device that communicates with surrounding cars and other traffic lights in fog computing-based traffic light control schemes [24]. The traffic light may execute a traffic schedule algorithm to modify the traffic signal in response to the information it has received [6]. Compared to the earlier approaches, this one has the advantage of minimal latency since the traffic light controls the traffic schedule algorithm [6].

3 | Research Methodology

In this sub-section, the proposed method has the three steps includes, Building Aggregate Matrix, compute the weights of criteria by the OWCM method, and rank the alternatives using the WISP method. The proposed approach is implemented using a single value neutrosophic scale.

3.1 | Building Aggregate Matrix

Step 1: Determining the alternatives to be candidates in the evaluation process as

An = {A1, A2, A3, … An}.

Step2: Determining the influenced criteria which candidates are evaluated based as

Cn = {C1, C2, C3, … Cn}.

Step 3: Communicating with decision makers who are related to our scope to form the panel of DMs to rate the traffic light control system based on determined criteria.

DMn= {DM1, DM2, DM3, DM4, DM5}. DMs utilized the linguistic terms presented in Table1 to assess the opinions of DMs about each criterion

Step 4: The various decision matrices are transformed into Deneutrosophicate a Matrix

through Eq. (1).

$$\boldsymbol{s}\,(\mathrm{Q_{ij}}) = \frac{(2+\mathrm{T}-\mathrm{I}-\mathrm{F})}{3} \quad (1)$$

Where: T, I, F refers to truth, indeterminacy, and falsity, respectively.

Step 5: Eq. (2) is employed in crisp matrices to aggregate it into single decision matrix.

$$x_{ij} = \frac{\sum_{j=1}^{N} Q_{ij}}{N} \tag{2}$$

Where: Qij refers to value of criterion in matrix, N refers to number of decision makers

Table 2. The linguistic scale is based on single valued neutrosophic scale.

Linguistic term	Abbreviation	SVNNs		
		T	I	F
Extremely Bad	EB	0.00	1.00	1.00
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	0.10	0.00	0.00

3.2 | OWCM Method

Step 1: Normalize the aggregate decision matrix to standardize it. the normalizing method involves using the following equation:

$$R_{ij} = \frac{x_{ij}}{\max\limits_{x_j}} \tag{3}$$

Step 2: Calculate the average score of the standardized decision matrix.

$$N = \frac{1}{N}\sum_{i=1}^{m} R_{ij} \tag{4}$$

Step 3: Determines the degree of preference variation and its corresponding value. According to this equation, the value of each attribute's preference variation (ϕ_j) is calculated:

$$\phi_j = \sum_{i=1}^{m} [R_{ij} - N]^2 \tag{5}$$

j = the value of each criterion

Step 4: Formulate the following equation to calculate the deviation in preference values:

$$\Omega_j = 1 - \phi_j \tag{6}$$

j = the value of each criterion

Step 5: Identify the criteria weight by using the following equation:

$$w_j = \frac{\Omega_j}{\sum_{j=1}^{n} \Omega_j} \tag{7}$$

The total weight for the criteria should be = 1.

3.3 | WISP Method

Step 1: Construct a normalized decision-making matrix calculated by implementing Eq. (8) in the aggregated matrix

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})} \quad (8)$$

Step 2: Calculate the values of utility measures, as follows:

$$U_i^{\mathrm{sd}} = \sum_{j\in \Omega_{max}} r_{ij}w_j - \sum_{j\in \Omega_{min}} r_{ij}w_j \quad (9)$$

$$U_i^{\mathrm{pd}} = \prod_{j\in \Omega_{max}} r_{ij}w_j - \prod_{j\in \Omega_{min}} r_{ij}w_j \quad (10)$$

$$U_i^{\mathrm{sr}} = \frac{\sum_{j\in \Omega_{max}} r_{ij}w_j}{\sum_{j\in \Omega_{min}} r_{ij}w_j} \quad (11)$$

$$U_i^{\mathrm{pr}} = \frac{\prod_{j\in \Omega_{max}} r_{ij}w_j}{\prod_{j\in \Omega_{min}} r_{ij}w_j} \quad (12)$$

where U_i^{sd} and U_i^{pd} denote differences between the weighted sum and weighted product of normalized ratings of alternative i, respectively, and Ω_{max} and Ω_{min} denote sets of maximization and minimization criteria, respectively. Like the previous one, U_i^{sr} and U_i^{pr} espectively

Step 3: Recalculate the values of utility measures:

$$\bar{U}_i^{\mathrm{sd}} = \frac{1+U_i^{\mathrm{sd}}}{1+\max U_i^{\mathrm{sd}}} \quad (13)$$

$$\bar{U}_i^{\mathrm{pd}} = \frac{1+U_i^{\mathrm{pd}}}{1+\max U_i^{\mathrm{pd}}} \quad (14)$$

$$\bar{U}_i^{\mathrm{sr}} = \frac{1+U_i^{\mathrm{sr}}}{1+\max U_i^{\mathrm{sr}}} \quad (15)$$

$$\bar{U}_i^{\mathrm{pr}} = \frac{1+U_i^{\mathrm{pr}}}{1+\max U_i^{\mathrm{pr}}} \quad (16)$$

Where $\bar{U}_i^{\mathrm{sd}}$, $\bar{U}_i^{\mathrm{pd}}$, $\bar{U}_i^{\mathrm{sr}}$ and $\bar{U}_i^{\mathrm{pr}}$ denote recalculated values of U_i^{sd} , U_i^{pd} , U_i^{sr} and U_i^{pr}

Step 4: Determine the overall utility U_i of the considered alternative as follows:

$$U_i = \frac{1}{4}\left(\bar{U}_i^{\mathrm{sd}} + \bar{U}_i^{\mathrm{pd}} + \bar{U}_i^{\mathrm{sr}} + \bar{U}_i^{\mathrm{pr}}\right) \quad (17)$$

Step 5: Rank the alternatives and select the most optimal one.

4 | Illustrative Case Study

4.1 | Comprehensive Overview

We applied the constructed evaluation model of this study in a real case study of traffic light control systems to validate the accuracy of the constructed model. Herein, five systems have contributed to this process embracing the technologies in their operations and practices for evaluating a traffic light control to ensure it meets safety, efficiency, and environmental standards. The evaluation of five alternatives is conducted through a fog computing features and obtained from utilizing contemporary and virtual technologies.

4.2 | Valuating Criteria: OWCM-SVNs

Five SVNs matrices are constructed and converted to crisp matrices using Eq. (1).

Using Eq. (2) to blend these matrices into an aggregated matrix as in Table 2.

Normalizing the aggregated matrix using Eq. (3) as in Table 3.

Final weights for As are generated after computing N, ϕ_j , Ω_j through deploying Eqs. (4), (5) and (6) as shown in Table 4. Figure 1 represents the valuation weights for Bs where B6 and B10 have highest weight but B2 has lowest weight.

Table 2. Aggregated decision matrix.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.3367	0.3367	0.3500	0.4567	0.4633	0.5433	0.6200	0.5033
A2	0.6433	0.6400	0.6633	0.4933	0.5700	0.4767	0.5433	0.5367
A3	0.6000	0.6133	0.6300	0.4133	0.6800	0.6100	0.6167	0.6533
A4	0.2967	0.5567	0.6433	0.7000	0.4800	0.3367	0.4967	0.7033
A5	0.7800	0.6133	0.6200	0.5800	0.5800	0.4333	0.6433	0.6433
Max	0.7800	0.6400	0.6633	0.7000	0.6800	0.6100	0.6433	0.7033

Table 3. Normalizing the aggregated decision matrix.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.4316	0.5260	0.5276	0.6524	0.6814	0.8907	0.9637	0.7156
A2	0.8248	1.0000	1.0000	0.7048	0.8382	0.7814	0.8446	0.7630
A3	0.7692	0.9583	0.9497	0.5905	1.0000	1.0000	0.9585	0.9289
A4	0.3803	0.8698	0.9698	1.0000	0.7059	0.5519	0.7720	1.0000
A5	1.0000	0.9583	0.9347	0.8286	0.8529	0.7104	1.0000	0.9147

Table 4. Average score and Preference variation.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
N	0.6812	0.8625	0.8764	0.7552	0.8157	0.7869	0.9078	0.8645
ϕ_j	0.2828	0.1505	0.1544	0.1056	0.0660	0.1173	0.0366	0.0575
Ω_j	0.7172	0.8495	0.8456	0.8944	0.9340	0.8827	0.9634	0.9425
w_j	0.1020	0.1208	0.1203	0.1272	0.1329	0.1256	0.1370	0.1341

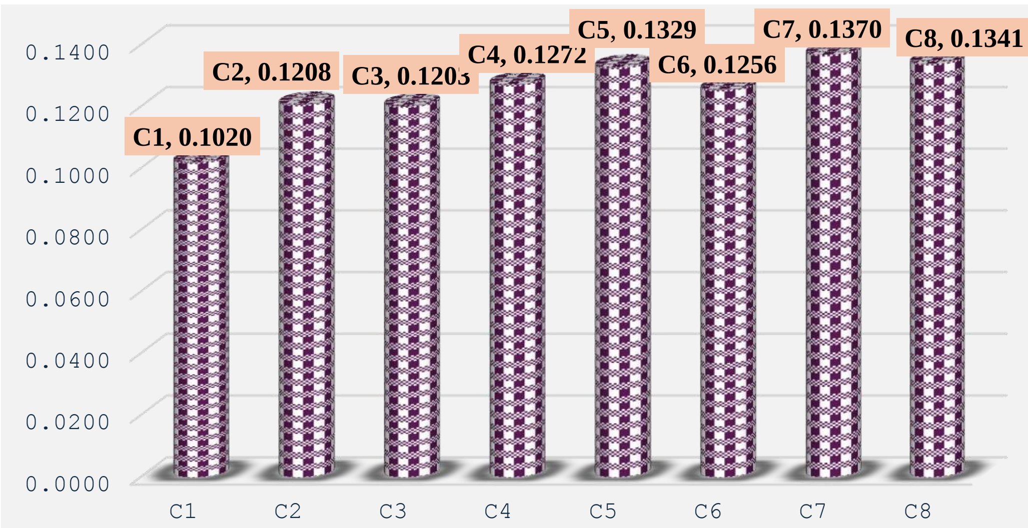

Figure 1. Final criteria weights.

4.3 | Ranking Alternatives: WISP

Normalizing the aggregated matrix for generating normalized matrix as listed in Table 5 based on Eq. (8).

Generating a weighted sum normalized matrix and weight product normalized matrix as in Table 6 and Table 7.

Then compute the values of utility measures of each alternative by using Eqs. (9-12).

Then recalculate the values of utility measures of each alternative by using Eqs. (13-16).

Then compute overall utility U_i of the considered alternative by using Eq. (17)

The final ranking of alternatives is represented in Table 8.

Table 5. Aggregate de-neutrosophic matrix.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.3367	0.3367	0.3500	0.4567	0.4633	0.5433	0.6200	0.5033
A2	0.6433	0.6400	0.6633	0.4933	0.5700	0.4767	0.5433	0.5367
A3	0.6000	0.6133	0.6300	0.4133	0.6800	0.6100	0.6167	0.6533
A4	0.2967	0.5567	0.6433	0.7000	0.4800	0.3367	0.4967	0.7033
A5	0.7800	0.6133	0.6200	0.5800	0.5800	0.4333	0.6433	0.6433
weight	0.1020	0.1208	0.1203	0.1272	0.1329	0.1256	0.1370	0.1341
max	0.7800	0.6400	0.6633	0.7000	0.6800	0.6100	0.6433	0.7033

Table 6. Normalized decision matrix.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.4316	0.5260	0.5276	0.6524	0.6814	0.8907	0.9637	0.7156
A2	0.8248	1.0000	1.0000	0.7048	0.8382	0.7814	0.8446	0.7630
A3	0.7692	0.9583	0.9497	0.5905	1.0000	1.0000	0.9585	0.9289
A4	0.3803	0.8698	0.9698	1.0000	0.7059	0.5519	0.7720	1.0000
A5	1.0000	0.9583	0.9347	0.8286	0.8529	0.7104	1.0000	0.9147

Table 7. Weight sum normalized.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.0440	0.0636	0.0635	0.0830	0.0905	0.1119	0.1321	0.0960
A2	0.0842	0.1208	0.1203	0.0897	0.1114	0.0981	0.1157	0.1023
A3	0.0785	0.1158	0.1142	0.0751	0.1329	0.1256	0.1314	0.1246
A4	0.0388	0.1051	0.1167	0.1272	0.0938	0.0693	0.1058	0.1341
A5	0.1020	0.1158	0.1124	0.1054	0.1133	0.0892	0.1370	0.1226

Table 8. Weight product normalized.

	C1 (+)	C2 (+)	C3 (+)	C4 (+)	C5 (+)	C6 (+)	C7 (+)	C8 (-)
A1	0.9178	0.9253	0.9260	0.9471	0.9503	0.9856	0.9949	0.9561
A2	0.9805	1.0000	1.0000	0.9565	0.9768	0.9695	0.9771	0.9644
A3	0.9736	0.9949	0.9938	0.9352	1.0000	1.0000	0.9942	0.9902
A4	0.9061	0.9833	0.9963	1.0000	0.9548	0.9281	0.9652	1.0000
A5	1.0000	0.9949	0.9919	0.9764	0.9791	0.9580	1.0000	0.9881

Table 9. Ranking alternatives.

	U_i^{sd}	U_i^{pd}	U_i^{sr}	U_i^{pr}	$\overline{U}_i^{sd}$	$\overline{U}_i^{pd}$	$\overline{U}_i^{sr}$	$\overline{U}_i^{pr}$	U_i	Rank
A1	0.4926	5.6909	6.1337	6.9520	0.9032	0.9680	0.8663	0.9801	0.9294	4
A2	0.6379	5.8960	7.2351	7.1138	0.9911	0.9977	1.0000	1.0000	0.9972	1
A3	0.6489	5.9015	6.2103	6.9601	0.9978	0.9985	0.8756	0.9811	0.9632	3
A4	0.5227	5.7337	4.8979	6.7337	0.9213	0.9742	0.7162	0.9532	0.8912	5
A5	0.6527	5.9121	6.3215	6.9832	1.0000	1.0000	0.8891	0.9839	0.9682	2

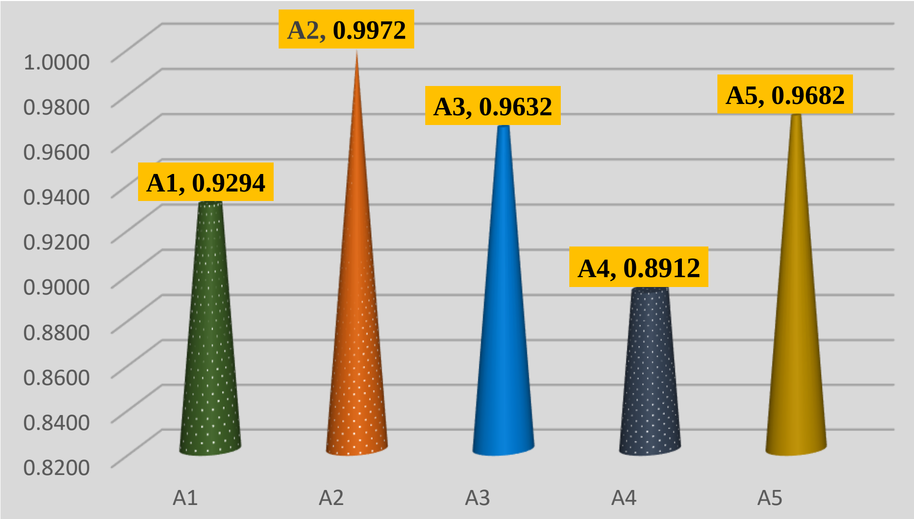

Figure 2. Ranking alternatives.

5 | Discussion

5.1 | Sensitivity Analysis

In this section we are applying the various scenarios of changing criteria weight through conducting sensitivity analysis method to o determine how the decision for final rank is affected by changing criteria. Hence, a sensitivity analysis model is presented by changing the weights of factors to show the rank of strategies under different cases in weights. Herein, we implemented the five scenarios of changing the weights of criteria as shown in Table 10. In the first case, the weights of criteria are equal. In other cases, we are changing the weight of two criterion and make other criteria are similar. According to Figure 3, all scenarios agree that A2 is the optimal while A4 is the worst as well as the findings of the proposed decision-making model.

Table 10. Five cases in the change of weights of criteria.

	Case1	Case2	Case3	Case4	Case5
C1	0.125	0.2	0.1	0.1	0.1
C2	0.125	0.2	0.1	0.1	0.1
C3	0.125	0.1	0.2	0.1	0.1
C4	0.125	0.1	0.2	0.1	0.1
C5	0.125	0.1	0.1	0.2	0.1
C6	0.125	0.1	0.1	0.2	0.1
C7	0.125	0.1	0.1	0.1	0.2
C8	0.125	0.1	0.1	0.1	0.2

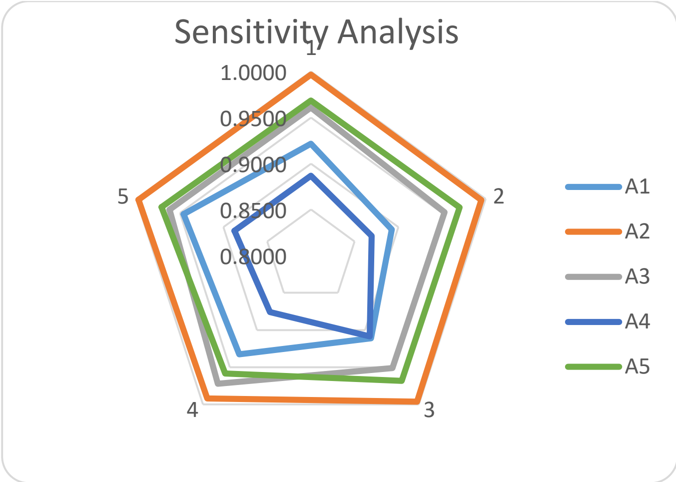

Figure 3. The rank of alternatives after changing weights of criteria.

6 | Conculsion

Fog computing provides a new method for intelligent traffic light control. The present study enhances our comprehension of the factors propelling the use of fog computing in traffic light control systems over the years. Fog computing offers several benefits for traffic light control systems. It a perfect solution for traffic light control systems that need real-time responses to ensure it meets safety, efficiency, and environmental standards. We present a methodology for the selection of the most suitable traffic light control system that is influenced by several factors and criteria. We used 8 criteria and based on 5 alternatives, A= {A1, A2, A3, A4, A5} for this work. The main criteria: Real-time interactions (C1), location awareness and geo-distribution (C2), Mobility support (C3), scalability (C4), Heterogeneity (C5), Interoperability (C6), reliability (C7), Low latency (C8). The proposed MCDM framework under single value neutrosophic scale. Also, this study combines the benefit of the OWCM Method—which determines the weights of criteria in MCDM problems—with WISP to evaluate and rank alternatives. Also, some analysis was performed to show the impact of the attribute of each criterion in choosing the best system, that shows how effective is the presence or absence of each of the criteria. All performed sensitivity analyses are used as the guide for the managers to analyze all statuses in calculating the scores of the strategies. The results show that the criteria weights and scores of the sustainable strategies are more reliable than results obtained from the same methods.

Acknowledgments

The authors are grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contribution

All authors contributed equally to this work.

Funding

This research has no funding source.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Ha, P., Chen, S., Du, R., & Labi, S. (2022). Scalable Traffic Signal Controls Using Fog-Cloud Based Multiagent Reinforcement Learning. Computers, 11(3). DOI:10.3390/computers11030038

[2] OMS. (2015). Global status report on road safety 2015. Injury prevention, 19(2).

[3] Commission, E. (2019). 2018 road safety statistics : What is behind the figures? European commission, (April).

[4] Rissanen, R., Berg, H.-Y., & Hasselberg, M. (2016). 593 quality of life following a road traffic injury: a systematic literature review [presentation]. DOI: 10.1136/injuryprev-2016-042156.593

[5] Puliafito, C., Mingozzi, E., Longo, F., Puliafito, A., & Rana, O. (2019). Fog computing for the Internet of Things: A survey. ACM transactions on internet technology, 19(2). DOI:10.1145/3301443

[6] Liu, J., Li, J., Zhang, L., Dai, F., Zhang, Y., Meng, X., & Shen, J. (2018). Secure intelligent traffic light control using fog computing. Future generation computer systems, 78. DOI:10.1016/j.future.2017.02.017

[7] Mohamed, N. E., & Radwan, I. I. (2022). Traffic light control design approaches: a systematic literature review. International Journal Of Electrical And Computer Engineering.

[8] Djuana, E., Rahardjo, K., Gozali, F., Tan, S., Rambung, R., & Adrian, D. (2018). Simulating and evaluating an adaptive and integrated traffic lights control system for smart city application [presentation]. IOP conference series: earth and environmental science (Vol. 106). DOI: 10.1088/1755-1315/106/1/012031

[9] Qiong, W. U., Fanfan, H. E., & Xiumei, F. A. N. (2018). The intelligent control system of traffic light based on fog computing. Chinese journal of electronics, 27(6). DOI:10.1049/cje.2018.09.015

[10] Li, Z., Liu, Y., Zhu, H., & Sun, L. (2015). Coff: Contact-Duration-Aware Cellular Traffic Offloading Over Delay Tolerant Networks. IEEE transactions on vehicular technology, 64(11). DOI:10.1109/TVT.2014.2381220

[11] Tang, C., Xia, S., Zhu, C., & Wei, X. (2019). Phase Timing Optimization for Smart Traffic Control Based on Fog Computing. IEEE access, 7. DOI:10.1109/ACCESS.2019.2925134

[12] Jalew, E. A. (2019). Fog Computing based traffic Safety for Connected Vulnerable Road Users. Université bourgogne franche-comté.

[13] Feng, Y., Head, K. L., Khoshmagham, S., & Zamanipour, M. (2015). A real-time adaptive signal control in a connected vehicle environment. Transportation research part c: emerging technologies, 55. DOI:10.1016/j.trc.2015.01.007

[14] Priemer, C., & Friedrich, B. (2009). A decentralized adaptive traffic signal control using v2i communication data [presentation]. IEEE conference on intelligent transportation systems, proceedings, itsc. DOI: 10.1109/ITSC.2009.5309870

[15] 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.

[16] Sattari, M. R. J., Malakooti, H., Jalooli, A., & Noor, R. M. (2014). A dynamic vehicular traffic control using ant colony and traffic light optimization [presentation]. Advances in intelligent systems and computing (Vol. 240). DOI: 10.1007/978-3-319-01857-7_6

[17] Wey, W. M. (2000). Model formulation and solution algorithm of traffic signal control in an urban network. Computers, environment and urban systems, 24(4). DOI:10.1016/S0198-9715(00)00002-8

[18] Robertson, D. I. (1969). "TRANSYT" method for area traffic control. Traffic engineering and control, 11(6).

[19] Kotwal, A. R., Lee, S. J., & Kim, Y. J. (2013). Traffic Signal Systems: A Review of Current Technology in the United States. Science and technology, 3(1).

[20] de Souza, A. M., Brennand, C. A. R. L., Yokoyama, R. S., Donato, E. A., Madeira, E. R. M., & Villas, L. A. (2017). Traffic management systems: A classification, review, challenges, and future perspectives. International journal of distributed sensor networks, 13(4). DOI:10.1177/1550147716683612

[21] Jensen, M. B., Philipsen, M. P., Møgelmose, A., Moeslund, T. B., & Trivedi, M. M. (2016). Vision for Looking at Traffic Lights: Issues, Survey, and Perspectives. IEEE Transactions On Intelligent Transportation Systems.

[22] Krajzewicz, D., Brockfeld, E., Mikat, J., Ringel, J., Rössel, C., Tuchscheerer, W., … Wösler, R. (2005). Simulation of modern traffic lights control systems using the open source traffic simulation sumo [presentation]. 3rd international industrial simulation conference 2005, isc 2005.

[23] Guo, J., Kong, Y., Li, Z., Huang, W., Cao, J., & Wei, Y. (2019). A model and genetic algorithm for area-wide intersection signal optimization under user equilibrium traffic. Mathematics and computers in simulation, 155. DOI:10.1016/j.matcom.2017.12.003

[24] Hawi, R., Okeyo, G., & Kimwele, M. (2015). Techniques for Smart Traffic Control: An In-depth Review. International journal of computer applications technology and research, 4(7). DOI:10.7753/ijcatr0407.1014

[25] Bonomi, F., Milito, R., Zhu, J., & Addepalli, S. (2012). Fog computing and its role in the internet of things [presentation]. MCC'12 - proceedings of the 1st acm mobile cloud computing workshop. DOI: 10.1145/2342509.2342513