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OPTIMIZATION

A hybrid traffic controller system based on flower pollination algorithm and type-2 fuzzy logic optimized with crow search algorithm for signalized intersections

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Abstract

In this study, a hybrid traffic signal control (HTSC) system based on phase and time optimization was developed. The Flower Pollination Algorithm (FPA) approach was used for phase optimization, while Type-2 Fuzzy Logic, optimized with the Crow Search Algorithm (CSA), was utilized for time optimization. The hybrid system's performance was investigated using nine different traffic conditions and four different intersection geometries. The hybrid system was compared with three controller systems which are a fixed-time signal controller, a signal controller based on the FPA approach (FPA_TSC), and the optimized Type-1 fuzzy logic signal controller (Type-1 FL-TSC). The HTSC approach achieved the best performance with about 32% improvement over the fixed-time traffic controller and it showed 5% and 6% better performance than the FPA_TSC and Type-1 FL-TSC, respectively. Considering the performance of the new hybrid system, it is effective in minimizing delays and driver dissatisfaction occurring from signalization. It also contributes to the reduction of emissions and fuel consumption. The HTSC approach can be used as an alternative signal control method in the control of intersections with high traffic volume due to its fast and effective performance.

Keywords Traffic signal controller · Flower pollination algorithm · Type-2 fuzzy logic · Crow search algorithm · Phase and signal optimization

1 Introduction

In Turkey and in the world, both the population and the number of vehicles tend to increase. This increase also causes an increase in the demand for transportation, a density in urban road networks and therefore an increase in vehicle delays (Cakici and Murat 2019). Vehicle delay is one of the important problems affecting daily life. For this reason, reducing vehicle delays and at the same time managing traffic safely has become an important study topic in traffic engineering. Different signal control approaches such as fixed time and traffic actuated have been developed to solve this problem. However, it is observed that these control systems are insufficient to provide the balance between both traffic safety and maximum intersection performance. This is the main reason why many researchers have been interested in investigating the applicability of different techniques based on particularly artificial intelligence in intersection control. A wide range of techniques such as artificial neural networks (ANN), fuzzy logic (FL), meta-heuristic algorithms have been implemented and effective results have been obtained compared to traditional approaches.

The researchers are focused on the development of control systems based on time or phase optimization for minimizing intersection performance indicators such as delay, number of stops, emission, queue length. Trabia et al. (1999) developed a control system that decides on the extension of the current signal timing based on the FL approach according to real-time traffic demands. They compared this system with the traffic-actuated controller and found that they could reduce the average delay by

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9.5%. Ceylan and Bell (2004) developed a system that optimizes signal timing based on genetic algorithm (GA) and determined the system performance index (PI) by means of TRANSYT software. Results of comparison with the mutually consistent (MC) solution approach showed that the GA approach is more effective. Chen and Xu (2006) applied the particle swarm optimization (PSO) algorithm to optimize both the membership functions and the rules of the FL. They showed that the optimized FL signal controller could significantly reduce the delay in time-varying traffic demands. Balaji and Srinivasan (2009) developed an urban traffic signal control system with Type-2 FL approach. They compared the developed system with the adaptive control and Type-1 Fl control systems according to 25 different intersection data in Singapore. They could reduce the delay value by approximately 66%. He and Hou (2012) determined the signal durations using the ant colony algorithm (ACO). Delay, number of stops, and intersection capacity values were used as the PIs. When compared with the Webster model and the GA approach, it was revealed that the proposed approach was superior to the Webster model and performed better than the GA approach. Thus, they were able to provide intersection control with lower delays and stops. Sabetghadam et al. (2012) developed a Type-2 FL traffic signal controller and made a performance comparison based on queue length. In their comparison with fixed-time control, they showed that they could reduce queue length by approximately 40%. Gacovski et al. (2012) developed a fuzzy traffic controller and used stop times and queue length as input parameters. By optimizing signal times and phase order, they improved intersection performance and reduced stop time, delays, and queue length compared to the fixed-time control. Araghi et al. (2014) determined green times by using the neural network (NN) and the FL approaches in traffic signal control. They used the queue length in each link as the input parameter. They compared the NN and FL approaches with the fixed-time control system and significantly reduced the total delay. Dell'Orco et al. (2014) determined the signal timing with the controller they developed using the artificial bee colony (ABC) algorithm. They compared the ABC approach with GA and hill climbing (HC). It was found that ABC had better performance and this method could reduce delays by 2.4–2.7%. Bi et al. (2014) developed a new controller via type-2 FL whose membership functions and rule base optimized by differential evolution (DE). They compared this approach with type-1 FL and fixed-time signal control. They improved intersection performance by decreasing delay, queue length, and stop rate. In addition, they were able to enhance the vehicular throughput rate. Odeh et al. (2015) developed an adaptive traffic signal system using the FLC approach hybridized with GA. They reported that the hybrid system performed 31% better than the conventional FLC approach and achieved a 34% improvement over the traditional traffic signal controller. Araghi et al. (2015) optimized the NN and adaptive neuro-fuzzy inference system (ANFIS) traffic signal controllers using the cuckoo search (CS) algorithm. They made a performance comparison with the Q-learning and fixed-time controllers and revealed the performance of the CS algorithm. They found that the NN, ANFIS, and Q-learning controllers showed 44%, 39%, and 35% improvement compared to fixed-time control, respectively. Long et al. (2015) developed a traffic controller based on queue lengths, delay, and stop times via Q-learning algorithm. when compared the developed model with fixed-time control according to two different scenarios, it was seen that the queue lengths, delay, and stop times were significantly reduced. Yu et al. (2016) determined the cycle length and effective green times by optimizing traffic capacity, delay, stops, and exhaust emission parameters with GA. They performed their analysis with the Vissim simulation program and revealed that the method could effectively reduce delays and stops and improve capacity. Doğan and Akgüngör (2016) developed a FL traffic controller and optimized the FL controller with the DE algorithm. In two levels of optimization, they determined the minimum and maximum points of the membership functions (MFs) in the first level and rearranged the MFs in the second level to achieve the lowest delay at specified intervals. They were able to improve intersection performance by 52%, 48%, and 14%, respectively, according to low, medium, and high traffic conditions. Araghi et al. (2017) improved the control system performance by optimizing the interval type2-FL traffic signal controller (IT2ANFIS) with simulated annealing (SA), GA, and CS algorithms. They achieved 31% improvement with the CS approach, 17% improvement with the GA approach, and 3% improvement with the SA approach compared to fixed-time control. Khooban et al. (2017) optimized the type-2 FL system with the modified backtracking search algorithm (MBSA) and determined the signal timing and phase. They demonstrated that the new system reduced queue length and average delays and thus is superior to the fixed-time and type-1 FL control approaches. Zargari et al. (2018) developed internal–external traffic metering strategy (IETMS) model for high-priority congested networks using the SA algorithm and imperialist competitive algorithm (ICA). After the application of the novel model where traffic lights are optimized according to queue length, average speed and delay could be improved by 14% and 19%, respectively. Cakici and Murat (2019) developed a traffic control system using the DE algorithm. This approach in which the signal duration and phase were optimized was compared with fixed-time and the adaptive control systems. The average vehicle delay was able to reduce by 28–42% compared to the fixed-time control and 3–38% compared to the adaptive control. Korkmaz and Akgüngör (2021a) developed a traffic control system using the FPA algorithm. This approach in which the signal timing and phase were optimized was compared with fixed-time and the fuzzy logic control (FLC) systems. The average vehicle delay was able to reduce by 12–30% compared to the fixed-time control and 0.77–3% compared to the FLC system.

Applications of artificial intelligence approaches on traffic signal control have been carried out for a long time and successful results have been obtained. Especially with the recent developments, studies on determining the signal duration and phase plan are continuing rapidly. Some recent studies are given in Table 1.

The main motivation of this study is the development of a dynamic control system that can respond quickly to changes in traffic and allows intersection control with lower delay value. With many studies in the literature, it is seen that different artificial intelligence-based approaches have achieved successful results in intersection control. However, in most of the existing control systems, the signal timing optimization approach has been used, but it is not sufficient by itself to increase the intersection performance. At the same time, the phase plan also has an impact on the intersection performance and it is very important to create a dynamic phase plan. Therefore, it is aimed to develop a dynamic traffic control system that can adapt to changing traffic conditions and optimize the signal duration and phase plan. For the proposed dynamic traffic control system to perform better than the existing systems, the phase plan and signal times have been optimized as well as the phase sequence has been provided to be changeable. With this system developed in a modular structure, the effects of phase and time optimization can be clearly demonstrated. Traffic contains uncertainties due to its stochastic nature. A fuzzy logic approach is preferred to develop a control system that will adapt to these uncertainties. It is also known that the type-2 FL approach exhibits an effective performance in traffic control where there are many uncertainties. At the same time, effective optimization methods are needed to optimize the signal duration and adapt the fuzzy logic approach to different traffic situations. Although many different optimization methods have been used in this problem, fast and effective performance algorithms have been preferred. Flower pollination and crow search algorithms have shown successful results in many engineering problems. These algorithms have performed better than the widely used algorithms such as GA, PSO, DE, and they are able to reach solutions quickly. FPA is used to determine the phase plan that reveals the minimum delay value in the phase optimization module. As the objective function, minimizing the delay per vehicle has been determined and the HCM 2000 delay formula has been preferred in the calculation of the delay per vehicle. At the same time, the determination of the optimum cycle length of the determined phase plan is carried out in this module. In addition to the phase optimization, phase selection is also provided and which phase will be prioritized is determined in the determined phase plan. The phase order has been determined according to the number of vehicles belonging to the phases and has been created in such a way that priority has been given to the phase with the highest number of vehicles. In the time optimization module, it is decided to increase or decrease the signal times of an isolated intersection with a certain intersection geometry, phase plan, and optimum cycle length by a Type-2 fuzzy logic approach. Optimizing the fuzzy logic method according to different traffic situations allows intersection control with lower delay values and allows the system to adapt to every traffic situation. For this reason, membership functions of the fuzzy logic approach are optimized using the crow search algorithm (CSA). In summary, the performance of a new hybrid traffic signal controller, which determines the phase plan and optimum cycle length with flower pollination algorithm (FPA) and the change in signal timing with Type-2 FL optimized with CSA, has been investigated in this

Table 1 Some artificial intelligence studies about traffic signal control systems

Authors	Opt. technique	Contribution
Lin et al. (2022)	Fuzzy logic and differential evolution algorithm (FASM-MDEA)	Optimization of phase plans and signal timing for six intersections
Zhang et al. (2022)	Multi-objective non-dominated sorting genetic algorithm (NSGA-III)	Signal cycle and green time optimization
Islam et al. (2022)	Convolutional neural network and long short-term memory (CNN-LSTM)	Signal phasing and timing optimization for seventeen intersections
Liu et al. (2022)	Mixed integer linear programming (MILP)	Signal timing optimization
Zhao et al. (2022)	Reinforcement learning (RL)	Optimization of phase duration of traffic signals for sixteen intersections

study. The most important contribution of this study and its distinction from other studies is that the signal timing, phase plan, and sequence are optimized together. In addition, the hybrid signal control system is the first control approach that can change the signal timing, phase plan, and sequence at the same time by constantly controlling traffic changes. On the other hand, FPA and CSA algorithms are not used alone or together in traffic control systems. Another innovative aspect of this study is to obtain better performance results by using both algorithms together and to examine the performances of the algorithms.

This section of the study provides a summary of the aims of the study and the review of the literature. In the second section, the FPA, CSA and Type-2 FL are explained and details of the developed traffic Simulation Program and hybrid traffic signal controller are given. In the third section, the performance indicators of the proposed approach are presented using statistical analyses. The results of the study are given in section four.

2 Materıal and methods

Minimizing the delay and maximizing the capacity in intersection control is the main objective. Therefore, due to the fact that the traffic is stochastic, an effective intersection control can be achieved by changing the signal timing or phase plan. Generally, optimization of the signal timing approaches is applied and the effect of the phase plan is ignored. Optimizing the signal timing, phase plan and sequence according to changing traffic conditions will create a more effective system than existing systems. A hybrid control system has been developed in order to reveal both the effects of signal timing optimization, phase optimization, and the performance of a dynamic control approach that can manage stochastic traffic. This system has been developed in a modular structure. Thus, the effects of phase and signal timing optimizations could be clearly demonstrated. FPA has been used to determine the phase plan that reveals the minimum delay value in the phase optimization module. At the same time, the determination of the optimum cycle length of the determined phase plan is carried out in this module. In the signal timing optimization module, it is decided to increase or decrease the signal timing with the Type-2 fuzzy logic approach at the isolated intersection whose geometry, phase plan, and optimum cycle length is determined. CSA is used to optimize the FL approach according to different traffic situations. The details of the FPA, CSA, and Type-2 FL approach and the literature summary of the algorithms are briefly explained in the 1st, 2nd, and 3rd subsections of this chapter. Information about the simulation program used is given in the 4th subsection. In the last part, detailed information about the developed signal control system method is given.

2.1 Flower pollination algorithm

The main aim of every living species in nature is to survive. For this purpose, animal and plant species reproduce in different ways and flowering plants continue to grow through their pollens. To produce the best populations in terms of number and quality, pollens need to be carried, and this process is called pollination. Yang (2012) was inspired by the reproductive behavior of flowering plants and developed the flower pollination algorithm (FPA) in 2012. Compared with many different artificial intelligence approaches, it has been shown that it has a competitive structure with superior results. This has enabled the algorithm to increase its popularity quickly and to be applied in many different fields. Pant et al. (2017) emphasized that the algorithm is effectively used in different fields such as medicine, energy, images, and structural design and can provide effective performance with flexible working in the solution of multi-purpose functions. Kayabekir et al. (2018) examined the applications of the hybrid FPA approach combined with different approaches to improve the performance of the algorithm. Emphasizing that the hybrid algorithm shows better performance than the classical FPA, the researchers stated that it is an effective solution method in fields such as chemical, civil, computer engineering and so on.

The main mission of reproductive behavior in flowering plants is to maintain optimal biological viability. It is necessary for pollens to reach the female organ of flowers both in nearby and distant places to increase the quality of biological vitality. Therefore, plant pollens are carried by biotic and abiotic pollination methods. In the biotic method, which provides 90% of the pollination of plants, pollens are carried with any living species such as butterflies, birds, and insects. The transport of pollen by an inactive carrier such as water or wind is called abiotic and is used for pollination at a rate of 10%. The FPA approach seeks the most appropriate solution within the framework of certain assumptions and operates according to four basic rules.

Rule 1: In global pollination, the transportation process of pollens is achieved with any living organism in accordance with the L'evy flight.

Rule 2: The spontaneous pollination is the local pollination.

Rule 3: The flower constant, which is proportional to the similarity of the flower species, expressed the probability of production.

Rule 4: Local and global pollination is controlled by the transition probability in the [0–1] range.

In fact, although plants have multiple flowers and millions of pollen gametes, for simplicity, the algorithm is assumed to have one flower and produce a pollen gamete. Thus, the point of the solution can be expressed with a flower. Since the Levy distribution allows the carriers to fly for a long time, it is possible to carry pollens to the plants far away. In this way, diversity is achieved to ensure the best reproduction. The mathematical expression of the global search is given in Eq. 1.

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_* - x_i^t) \tag{1}$$

Here, x_i^t is solution vector at iteration t and $g*$ is the current best. Here γ is a scaling factor to control the step size. Levy distribution (L), illustrated in Eq. 2, is the Levy flight-based step size that corresponds to the strength of the pollination.

$$L \sim \frac{\lambda\Gamma(\lambda)\sin(\frac{\pi\lambda}{2})}{\pi}\frac{1}{s^{1+\lambda}}(s \gg s_0 > 0) \tag{2}$$

where Γ (λ) is the standard gamma function and s is the step size (Fig. 1). This distribution applies to larger steps $s > 0$. In theory, $s_0 \gg 0$ is required, but in practice s_0 can be as small as 0.1.

Local pollination is effective in finding the optimum point in the neighborhood of the solution point. The expression of local pollination is given in Eq. 3.

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t) \tag{3}$$

Here, x_j^t and x_k^t are randomly selected pollen species from different flowers of the same plant species.

2.2 Crow search algorithm

Crow search algorithm (CSA) is one of the population-based heuristic optimization methods. Askarzadeh (2016) was inspired by the intelligent behavior of crow flocks and developed the algorithm. Being an algorithm that can be controlled by two parameters, it can easily be applied in different fields. Compared to different algorithms such as GA, PSO and HS, it shows superior performance and can reach the solution quickly. Zolghadr-Asli et al. (2018) reported that the CSA approach, which can be controlled by flight length and awareness probability (AP), can successfully be implemented in both simple and complex engineering problems. Although it is a new algorithm, due to its application to different fields and its modified versions, it is in high demand. Abdelaziz and Fathy (2017) applied the CSA method for optimal selection of conductor size in radial distribution networks. They determined the optimum conductor size to reduce power loss and total annual system operating costs. It was compared with evolutionary programming (EP) and HS methods to demonstrate the performance of the approach. The CSA approach, which outperforms EP and HS, provides 33.32% of savings in power loss and 24.48% of savings in annual cost in a 16-bus network, while in an 85-bus network, 19.53% of savings in power loss and 16.17% of savings in annual cost are achieved. Mohammadi and Abdi (2018) modified the CSA method and demonstrated that it is applicable to the economic load dispatch problem. They demonstrated superior performance in terms of solution quality, robustness, and calculation time compared with other approaches such as ABC, PSO, GA. Javidi et al. (2019) demonstrated the applicability of the enhance crow search algorithm (ECSA) approach, which shows better performance in the optimal design of structures problem. The ECSA method, which is better than the standard CSA method in terms of minimum weight, convergence rate and reliability, has achieved better or competitive results than other heuristic methods. Gadekallu et al. (2021) used CNN approach for Hand gesture classification in human–computer interaction (HCI) and optimized it with CSA. They compared artificial intelligence approaches such as PSO, GA, ABC with the CSA approach and revealed that the CSA approach performed faster and with less errors. Korkmaz and Akgüngör (2021b) used CSA, FPA, ABC, krill herd algorithm (KH), and the butterfly optimization algorithm (BOA) for passenger forecasting in air transportation. Among these algorithms, the CSA approach showed the best and fastest performance. In many different studies, it has been seen that the CSA approach performs effectively and provides fast solutions.

There are four basic principles in the CSA algorithm:

- Crows live in the form of flock.
- Crows memorize the position of their hiding places.
- Crows follow each other to do thievery.
- Crows protect their caches from being pilfered by a probability.

The CSA method works by modeling crows' ability to hide their food using their intelligence, to retrieve their food from the place they hid it, and to steal food from other crows. Therefore, in the CSA method, food searching behaviors of crows are modeled in two cases. The first case is that the crow which is going toward the hidden food source does not know that it is being followed by another crow. Thus, the following crow can easily reach the food source. In the CSA method, the new position of the following crow is determined using the mathematical expression given in Eq. 4.

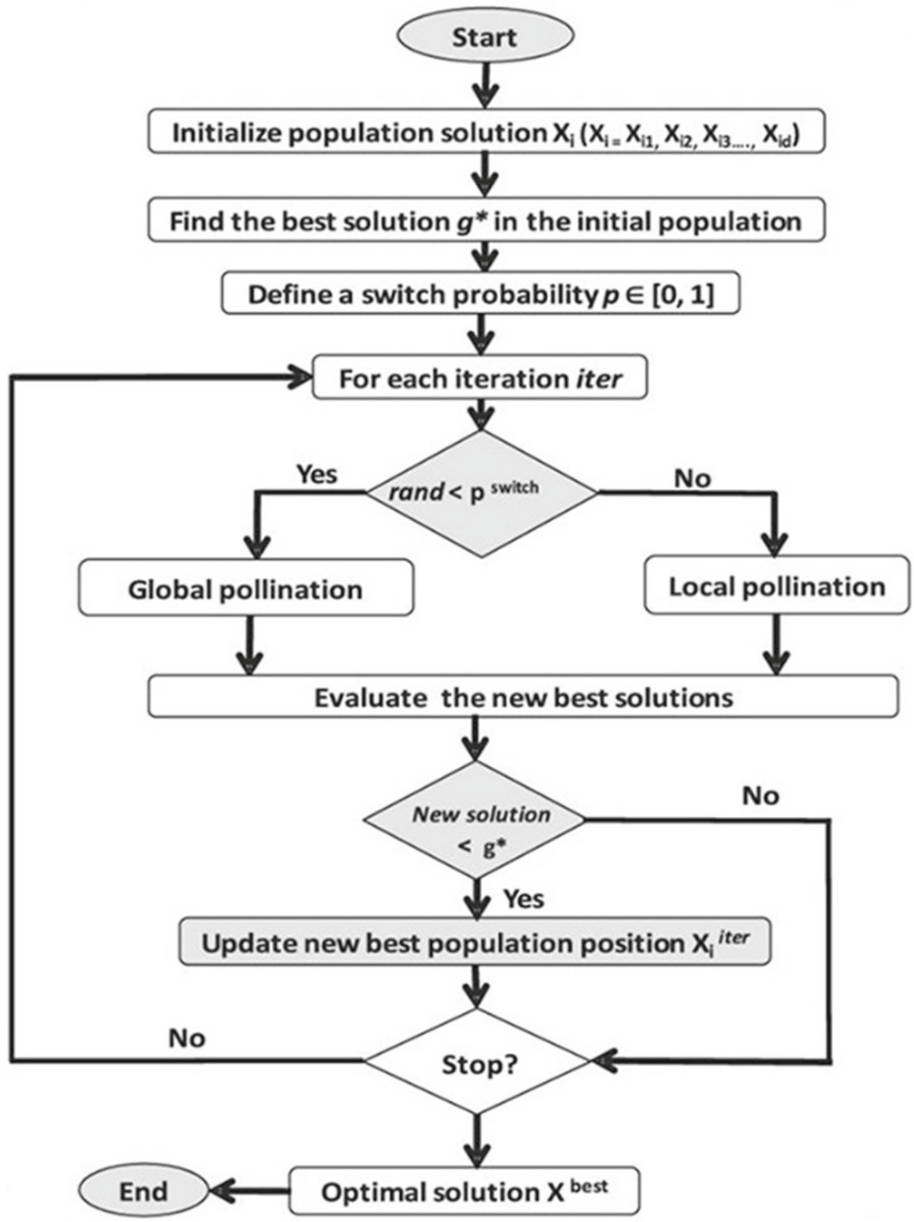

Fig. 1 Flow chart of FPA (Alyasseri et al. 2018)

$$x^{i,\mathrm{iter}+1} = x^{i,\mathrm{iter}} + r_i \times \mathrm{fl}^{i,\mathrm{iter}} \times (m^{j,\mathrm{iter}} - x^{i,\mathrm{iter}}) \tag{4}$$

where r_i is a random number with uniform distribution between 0 and 1 and $\mathrm{fl}^{i,\mathrm{iter}}$ denotes the flight length of crow i at iteration iter. $x^{i,\mathrm{iter}}$ is position of the crow i and $m^{j,\mathrm{iter}}$ is food place hidden by crow j.

The second case is that the crow that is going toward the food source knows that it is followed by another crow. In this case, the following crow is misled by the intelligence of the crow that is being followed and is taken toward another direction. Thus, the following crow moves to any position of the search space and moves away from the point of the solution. The new position of the following crow is determined using Eq. 5.

$$x^{i,\mathrm{iter}+1} = \begin{cases} x^{i,\mathrm{iter}} + r_{i \times \mathrm{fl}^{i,\mathrm{iter}}} \times (m^{j,\mathrm{iter}} - x^{i,\mathrm{iter}}) r_j \geq \mathrm{AP}^{j,\mathrm{iter}} \\ a\ random\ position\ otherwise \end{cases} \tag{5}$$

where r_j is a random number with uniform distribution between 0 and 1 and $\mathrm{AP}^{j,\mathrm{iter}}$ denotes the AP of crow j at iteration iter.

There are two important concepts that affect performance in heuristic algorithms: diversification and intensification. A good balance between these two concepts plays an active role in algorithm performance. The AP parameter is used for this purpose in the CSA approach. To increase diversity, the search space is expanded to a global scale by increasing the AP value, and density is increased by decreasing the AP value and by searching locally.

2.3 Type-2 fuzzy logic

The concept of type-2 fuzzy sets is an extension of the concept of type-1 fuzzy sets proposed by Zadeh (1975). As it is known, in type-1 fuzzy sets, the membership degrees of the elements belonging to that set have crisp values in the range [0,1]. However, if the degree of uncertainty in the problem is higher, then type-1 is insufficient. Type-2 fuzzy sets, on the other hand, are expressed by membership functions where the membership degrees of each element belonging to that set specify a fuzzy set. Thus, uncertainties can be better expressed with type-2 fuzzy sets depending on their extra degree of design freedom. The main difference between type-1 and type-2 fuzzy sets is that while the membership functions of type-1 fuzzy sets are two-dimensional, those of type-2 fuzzy sets are three-dimensional. Another important point is that type-2 fuzzy sets contain type-1 fuzzy sets because when all uncertainties on the type-2 fuzzy set disappear, the type-2 fuzzy set turns into a type-1 fuzzy set. This situation can be likened to the transformation of probability theory into deterministic theory when randomities disappear. Liang and Mendel (2000) developed an effective and simple method, interval Type-2 (IT2). In IT2, uncertainties are expressed as the footprint of uncertainty (FOU) in the region between the primary membership and the secondary membership. The membership functions (MF) are in the range [0,1] and they are represented by upper and lower MF. The MF is shown in Fig. 2.

The structure of the Type-2 FL system is similar to that of type-1, the only difference being the type-reduction process. The Type-2 structure is shown in Fig. 3.

As seen in Fig. 3, four different operations are performed in Type-2 structure. In the fuzzifier where the first operation is performed, crisp input values are blurred by creating fuzzy sets. In the second process, it is an essential operation in the FL structure. The outputs are obtained as Type-2 fuzzy sets by inferring according to the rule base. To perform defuzzification, type reduction must be performed. Type-2 fuzzy sets are converted to type-1 fuzzy sets with this process. Different reduction methods have been developed since it is an important process affecting the result. These include Karnik–Mendel (KM), enhanced Karnik–Mendel (EKM), iterative algorithm with stop condition (IASC), and Wu–Mendel uncertainty bound method (WM). Crisp output is obtained with the final process.

2.4 Traffic simulation program

In addition to having many advantages of existing simulation programs, there are also some negative aspects. Especially the lack of integration with programming languages such as MATLAB and C or the presence of some restrictions do not allow these simulation programs to be used in all conditions. Difficulties in combining traffic control systems developed with any programming language with existing simulations led traffic engineers to develop new simulation programs. Dogan (2014) encountered this problem in her doctoral dissertation and developed a microscopic simulation program called Kırıkkale University Traffic and Simulation (KU-Trsim). It proved the validity of the simulation program with 98% R^2 by comparing it with the delay data obtained from the field. The KU-Trsim consists of three main modules. These are the vehicle production module, the vehicle dynamics module, and the signal control module. In this study, KU-Trsim program has been revised according to the needs. No changes have been made to the vehicle production module. The vehicle dynamics module has been rearranged to obtain the queue length and number of vehicles lane-based. The signal control module was created according to the control systems developed within the scope of the study. In addition, input interfaces and output interfaces have been created to provide ease of use of the program via Graphical User Interface-GUI.

2.4.1 Vehicle creating module

This module enables the vehicles to enter the system and determines the entry intervals between vehicles and characteristics such as speed and vehicle type. In this module, the arrival intervals between vehicles are determined according to the exponential distribution. The speed and density relationship of Greenshields is used to determine the entry speeds of the vehicles. The free flow speed defined in the system is used as the highest speed. The expression of the Greenshields' speed and density relationship is given in Eq. 6. Vehicle type characteristics are given in Table 2.

$$v_s = v_f - \frac{v_f}{k_j} k \tag{6}$$

Here; v_s the mean speed at density k, v_f free flow speed ve k_j the jam density.

2.4.2 Vehicle dynamics module

It is the module controlling the movement of the vehicles that are added to the system. With this module, it is ensured that vehicles follow each other at a safe distance; the

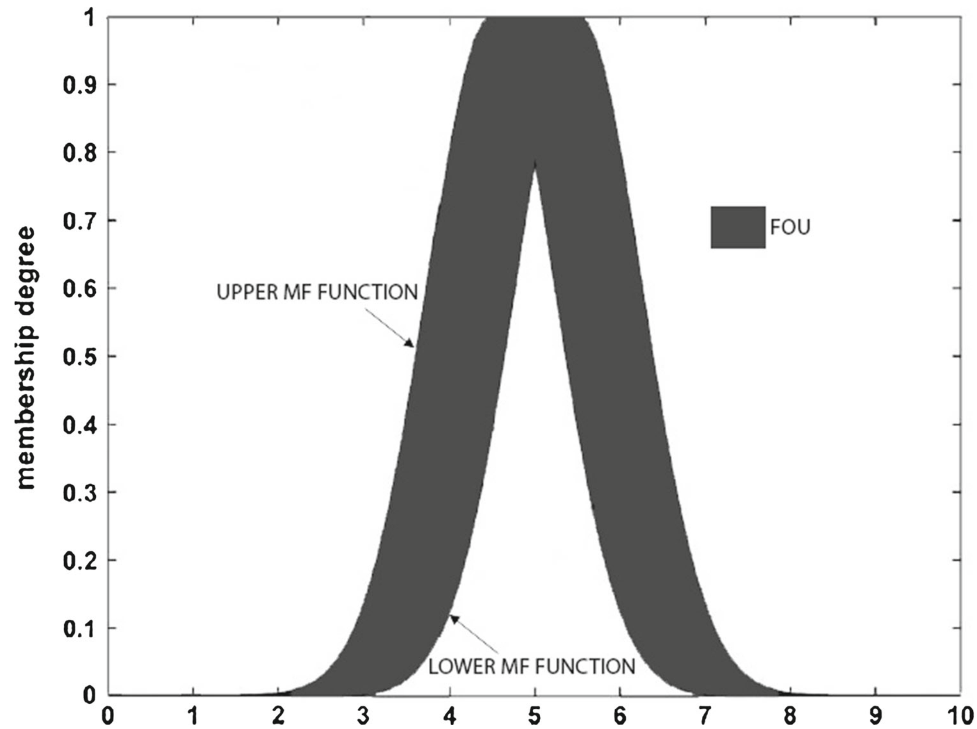

Fig. 2 Membership function of interval type-2

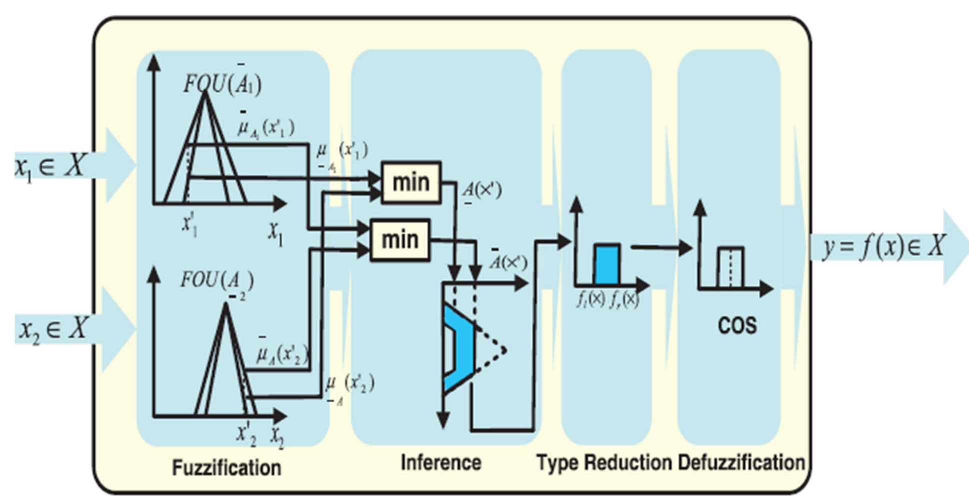

Fig. 3 Structure of type-2 fuzzy logic (Castillo and Melin 2014)

Table 2 Vehicle types and lengths

Vehicle types	Lengths (m)
Car	5,00
Minibus	6,00
Truck	8,50
Bus	12,00
Lorry	13,50

conditions of deceleration, acceleration, and stopping are controlled; and the dynamic parameters such as acceleration, speed, and coordinates are adjusted. The acceleration values of each vehicle type and changing depending on the speeds were determined according to the Synchro 7 simulation program (Husch and Albeck 2006). These values are given in Table 3.

The information regarding the movement directions of the vehicles (left, right, and straight) are kept in this module. Also, the information on the number of vehicles on lanes and queue lengths is traced in this module by means of detectors. In the measurement of the queue length, some assumptions were made and the CORSIM simulation program (Halati et al. 1997) was taken as a reference. Not only stationary vehicles (v = 0 km/h) but also vehicles with speed (v < 10 km/h) were included when determining the queue length.

Table 3 Acceleration values depending on speed ranges

Vehicle types	Speed Ranges									
	0–10	10–20	20–30	30–40	40–50	50–60	60–70	70–80	80–90	90–100
Car	2,44	2,74	1,83	1,52	1,52	1,52	1,22	0,91	0,61	0,61
Minibus	1,43	1,63	1,51	1,06	0,94	0,80	0,65	0,52	0,39	0,26
Truck	0,86	0,74	0,66	0,62	0,53	0,43	0,34	0,25	0,17	0,09
Bus	2,28	1,62	0,97	0,81	0,70	0,50	0,43	0,29	0,23	0,15
Lorry	0,75	0,65	0,43	0,34	0,26	0,19	0,13	0,09	0,04	0,00

2.4.3 Signal control module

This module comprises the signalization component of the simulation program. It activates the times set according to the intersection control systems (green, yellow, and red).

2.4.4 Graphical user interface

Geometrical properties and simulation variables of the intersection are entered through the data input interface. It is possible to enter parameters such as how many lanes an intersection will be designed, how many lanes will be on each lane, the traffic volume of each lane, vehicle distribution, turn rates, detector distance, from the intersection variables section. Simulation variables such as simulation time and seed number can also be entered. Phase changes and green times in phases are displayed on the output interface. In addition, cycle lengths, vehicle numbers, queue lengths, graphical display of the change in legs of the intersection, and delay values can be seen simultaneously.

2.5 Hybrid traffic signal controller

Since the aim of the study is to reveal the effects of phase plan, phase sequence and green time change, the system has been created in a modular structure. As the simulation program and control systems are developed with MATLAB, the desired module can be easily operated. It is sufficient to run phase optimization and phase sequence selection modules when only the effect of phase plan and phase sequence change is examined. In the phase optimization module, according to the intersection geometry, how many phases the intersection will be operated, that is, the phase plan is determined as 2, 3, or 4 phases. it is determined optimum cycle length and which lane will operate in which phase in this module with the FPA approach. In addition, the phase sequence within each cycle length varies according to the number of vehicles. The change of green time according to the number of vehicles and the length of the queue at the end of each phase makes the control system dynamic. Thus, unnecessary stops will be prevented as the green times, determined in the optimum cycle time, are increased or decreased. The signal timing optimization module using the CSA-optimized Type-2 FL approach will determine the green time change and reduce the delay. By operating all modules together, traffic signal control can be provided as a hybrid system. The system structure is shown in Fig. 4.

2.5.1 Phase plan optimization module

In this module, it is decided in how many phases the intersection will be operated and which lanes will receive the right of passage in which phases. The highway capacity manual (HCM) delay formula is used as the objective function when determining the phase plan according to intersection geometry and traffic volumes (TRB 2000). Thus, the phase plan which gives the lowest delay among all phase combinations can be determined. To operate an intersection with an appropriate phase plan, it is necessary to ensure that traffic safety is maximized and delay is minimized. Since the safety criterion is also taken into consideration in this module, the crossing of the traffic flows is not allowed when determining the phase plan, and only merging is allowed for the left and right turns. It is especially important whether the vehicles turning left will operate in a separate phase in terms of both delay and traffic safety. This works according to the module safety criterion. According to this criterion, if the multiplication of the left-turning traffic volume with the volume intersecting the left-turning traffic volume is less than 50.000 vehicles, merging of vehicles are allowed (Roess et al. 2004). If not, a separate phase is created for the vehicles that will turn left. Optimum cycle length can also be obtained according to the phase plan. While determining the optimum cycle length, constraints were used as minimum green time 8 s and maximum green time 60 s. Thus, the cycle lengths vary between 22 and 252 s. It is an important issue to determine that the phase optimization module will run in how many cycle lengths. To increase the efficiency of this module, it is necessary to ensure that phase optimization takes more tasks in the system. The determining factor in how many times the phase optimization module will run is the simulation time. For 900 s is used as the simulation time, there are at most 3 cycles

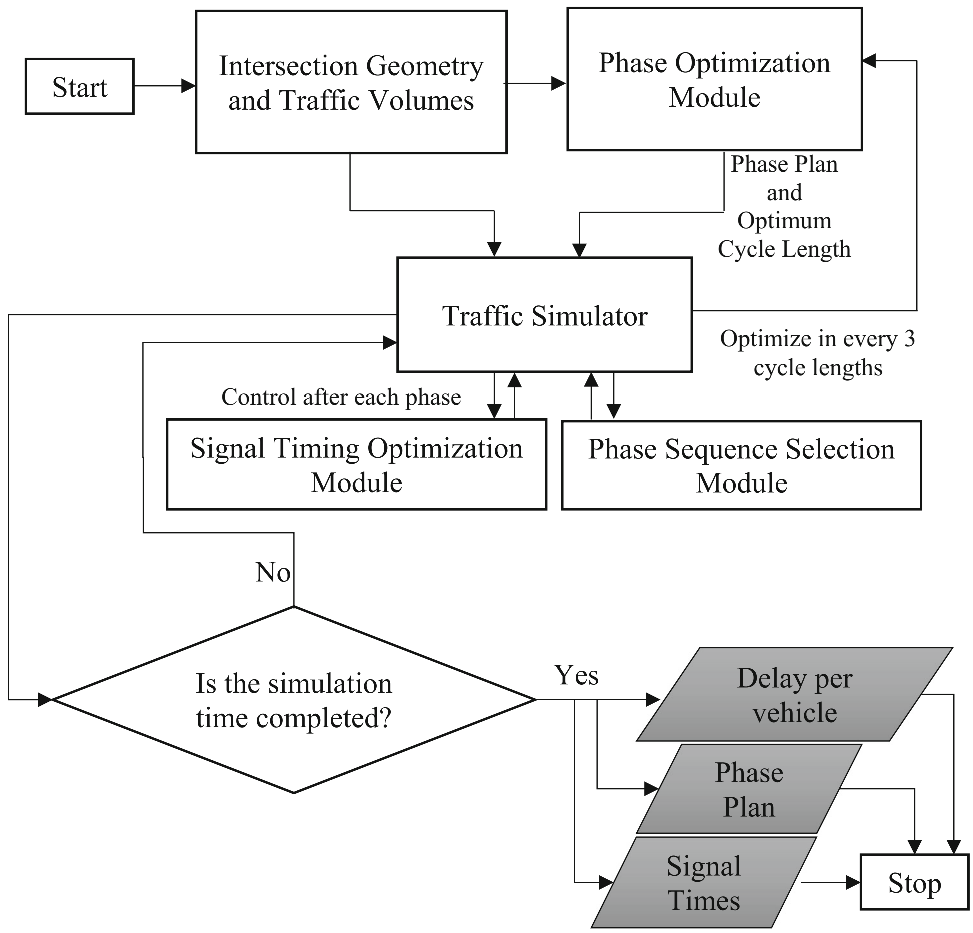

Fig. 4 Modular system structure

according to the highest cycle length. Thus, the optimization frequency is determined as 3 cycles for the phase optimization module to work at least once in the simulation period. To see the effect of the signal timing optimization module, the phase optimization module is not operated in every 1 or 2 cycle lengths. Thus, a longer period of time (3 cycle lengths) for the signal optimization module to work effectively is provided. For the phase optimization module, the objective function, decision variables and constraints set are presented in Table 4. The flow chart of the phase optimization module is given in Fig. 5.

While vehicles have to go at free flow rate, lost time such as deceleration, stopping and acceleration times caused by signaling constitute the delay time. The delay values specified in the objective function are obtained using the HCM delay formula in this system and given in Eq. 7.

$$d = d_1 \times (\mathrm{PF}) + d_2 + d_3 \tag{7}$$

Here d is the control delay per vehicle (s/veh), d_1 is the uniform control delay assuming uniform arrivals (s/veh), PF is the uniform delay progression adjustment factor, d_2 is

Table 4 Objective function, decision variable and constraints

Objective function	$f = \min\left\{\frac{\sum_{l=1}^{k} d_l}{\sum_{l=1}^{k} q_l}\right\}$	
	Figure 5: Flow chart of phase optimization module	
Decision variable	g_i	g is green light duration
		i is number of phase
Constraints	$8 \leq g_i \leq 60$	
	$0 \leq \frac{q_i \times C}{s \times g_i} \leq 1.4$	

d_l delay value on the lane, q_l traffic flow on the lane, k number of lanes in the intersection, s saturation flow

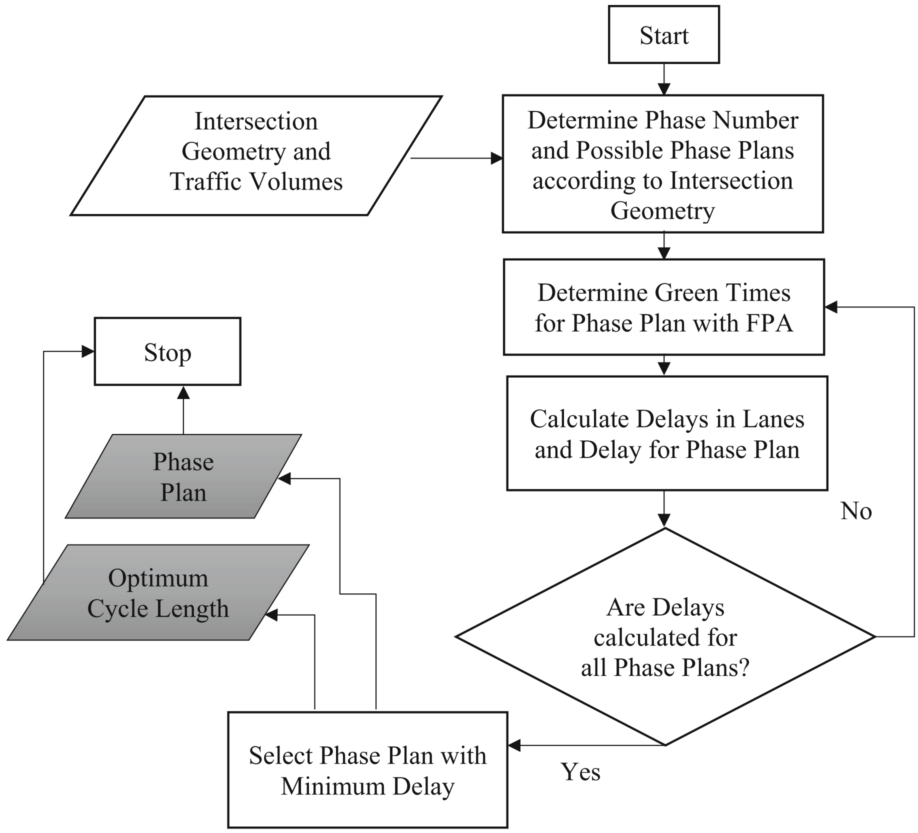

Fig. 5 Flow chart of phase optimization module (Korkmaz and Akgüngör 2021a)

the incremental delay (s/veh), $d_3$isthe initial queue delay (s/veh).

Equations 8 and 9 show the mathematical denotation of uniform control delay and incremental delay in the HCM delay formula.

$$d_1 = \frac{0.5 \times C \times (1 - \frac{g}{C})^2}{1 - [\min(1, X) \times \frac{g}{C}]} \tag{8}$$

Here C is the cycle length (s), X is the degree of saturation

$$d_2 = 900 \times T \times [(X - 1) + \sqrt{(X - 1)^2 + \frac{8 \times k \times I \times X}{c \times T}} \tag{9}$$

Here d_2 is the incremental delay (s/veh), T is the analysis period (s), X is the degree of saturation, k is the incremental delay factor, Iisthe upstream filtering/metering adjustment factor, c is the capacity (veh/h).

2.5.2 Signal timing optimization module

Optimizing the optimum cycle length obtained in phase optimization according to the traffic information in the intersection legs ensures the dynamism of the control system. In this module, at the end of each phase, it is decided whether to increase or decrease the green times according to the number of vehicles and the queue length for the next phase. The flow chart of the signal timing optimization module is given in Fig. 6.

As the number of vehicles and queue length vary according to the randomness of vehicle arrivals, uncertainties arise. At this point, these uncertainties can be expressed by using the fuzzy logic approach and appropriate solutions can be reached easily. In the system in which sugeno type-2 FL time optimization is performed as two input variables and one output variable, green times are changed between − 6 s and + 6 s. Thus, the required demand can be met in case there is a need for a time below or above the 8 s and 60 s constraints used to determine the optimum cycle length in the phase optimization module. Objective function, FL decision variables and constraints are presented in Table 5.

Different time intervals have been tried to determine at what intervals the green duration should be increased or decreased in the FL output membership function. Performance of each interval was obtained in 15 min simulation period according to 3 and 4-leg intersection geometries over low, medium, and high traffic volumes and is shown in Table 6. The effect of using different change times on the delay was examined by analysis of variance (ANOVO). In the variance analysis, h_0 and h_1 hypotheses are established.

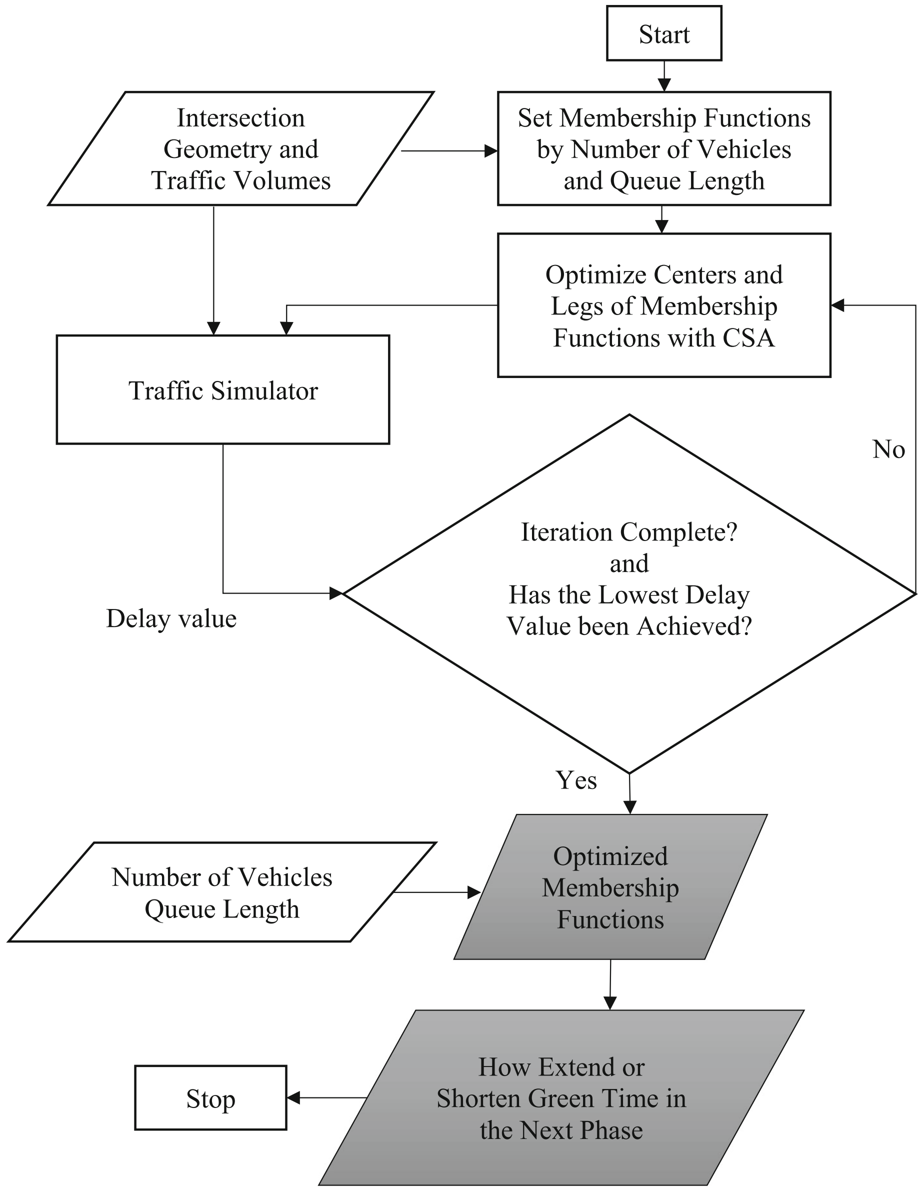

Fig. 6 Flow chart of signal timing optimization module

- h_0: No difference between averages.
- h_1: At least one average different from the others.

The results of the Levene test, which is the variance homogeneity test, and the ANOVO test are given in Table 7.

Since the significance value (0.992), calculated in the homogeneity test, is higher than the threshold value of 0.05, there is no significant difference between the four groups. Thus, the variances are homogenous. Since the significance value (0.962), calculated in the ANOVO test, is greater than the threshold significance value of 0.05, the h_0 hypothesis is accepted. Thus, it was deemed appropriate to use the interval between − 6 and + 6, which gives the lowest delay value.

Membership functions of the input variables in the Type-2 FL system are given in Figs. 7 and 8. The division of the number of vehicles membership function into 7 clusters was determined according to the maximum number of 35 automobiles in the measuring range 175 m. The queue length membership function is divided into clusters every 30 m. The determination of this range has been made according to the size of the lorry. The range in which two trucks are located at the same time has been determined. Since membership functions are divided into 6 and 7 sets, 42 rule bases are formed, and the rule base structure is expressed with “if–then” shown in Eq. 10.

Table 5 Objective function, decision variable and constraints

Objective function	$f = \min\left\{\sum_{l=1}^{k} d_n\right\}$	
Decision variables	g_{changes}	g_{changes} *is* green time change amount
	MFU_i	MFU_i is FL upper membership function center
	b_i	b_i is FL upper membership function left leg
	b_j	b_j is FL upper membership function right leg
	MFL_i	MFL_i is FL lower membership function center
	b_{ii}	b_{ii} is FL lower membership function left leg
	b_{jj}	b_{jj} is FL lower membership function right leg
Constraints	$-6 \le g_{\text{changes}} \le +6$	
	$\mathrm{MFU}_i \le \mathrm{MFU}_{i+1}$	
	$\mathrm{MFU}_i = \mathrm{MFL}_i$	
	$b_i \le \mathrm{MFU}_i$	
	$b_j \ge \mathrm{MFU}_i$	
	$b_i \le b_{ii} \le \mathrm{MFU}_i$	
	$\mathrm{MFU}_i \le b_{jj} \le b_j$	

d_n is the delay value on the lane, k is the number of lanes in the intersection

Table 6 Performance of green time change intervals

Traffic Situations	T	Traffic volumes			$-4+4$	$-6+6$	$-8+8$	$-10+10$
		V_1	V_2	V_3	Delay	Delay	Delay	Delay
Low	15	400	400	400	34.01	32.51	37.88	38.70
Medium	15	800	800	800	86.00	78.65	83.70	89.77
High	15	1200	1200	1200	97.82	95.60	98.18	101.09

Traffic Situations	T	Traffic volumes				$-4+4$	$-6+6$	$-8+8$	$-10+10$
		V_1	V_2	V_3	V_4	Delay	Delay	Delay	Delay
Low	15	400	400	400	400	71.33	66.53	76.13	79.59
Medium	15	800	800	800	800	86.81	84.88	86.35	88.50
High	15	1200	1200	1200	1200	108.68	103.13	105.44	109.84

Table 7 Levene and ANOVO test results

	Samples	Average	Standard deviation	Levene homogeneity test	ANOVO	
					F	P
$-4+4$	6	80.77	26.11	0.992	0.096	0.962
$-6+6$	6	76.88	25.22			
$-8+8$	6	81.28	23.71			
$-10+10$	6	84.58	24.83			
Total	24	80.88	23.46			

$$\text{If (Number of Vehicles is MF1) and} \\ \text{(Queue Length is MF1) then (green - change is EL)} \tag{10}$$

The membership function of output variables is divided into seven sets. Distribution and verbal expressions of output set are given in Table 8.

Running the type-2 FL approach used in this module according to a single membership function causes inefficiency in different traffic situations. Therefore, it is inevitable to optimize membership functions according to each traffic situation. The optimization of membership functions for each traffic situation is provided by the CSA approach. The center and legs of each membership set are

Fig. 7 Membership function of number of vehicles

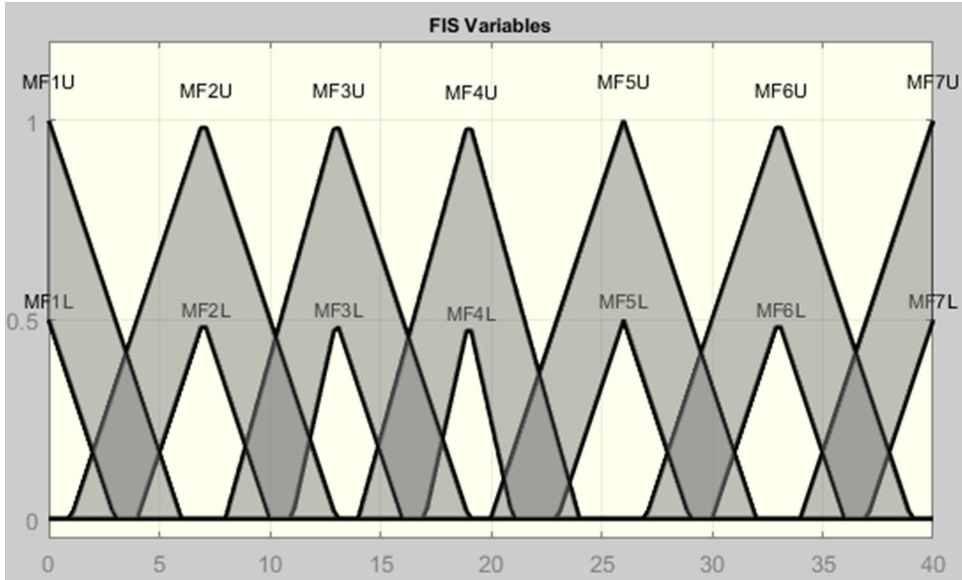

Fig. 8 Membership function of queue length

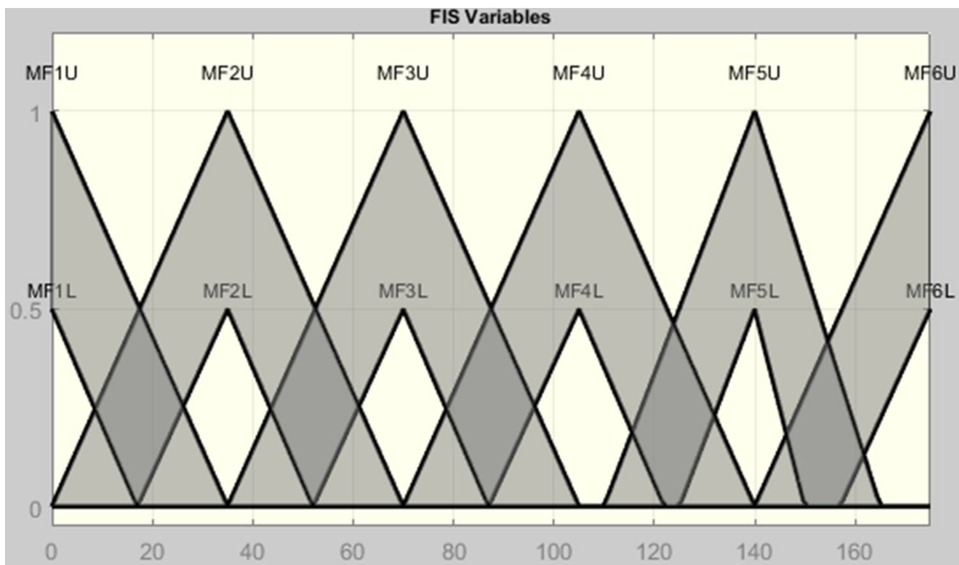

Table 8 Distribution and verbal expressions of output set

Membership function	Verbal expression	Value
MF1	Extreme low (EL)	− 6
MF2	Very low (VL)	− 4
MF3	Low (L)	− 2
MF4	Normal (N)	0
MF5	High (H)	2
MF6	Very high (VH)	4
MF7	Extreme high (EH)	6

optimized according to the CSA method, in which it is intended to achieve the lowest delay value. The membership functions of the optimized input variables are given in Figs. 9 and 10.

2.5.3 Phase sequence optimization module

The optimization of both the phase sequence and the phase plan has a positive effect on intersection performance. Therefore, in addition to the optimization of the phase plan and signal times, the phase sequence optimization module has been created. In this way, it can be determined which phase takes priority. At the end of each phase, priority is given to the phase with the highest number of vehicles compared to the number of vehicles in the lanes of other phases. Thus, the creation of the dynamic phase sequence

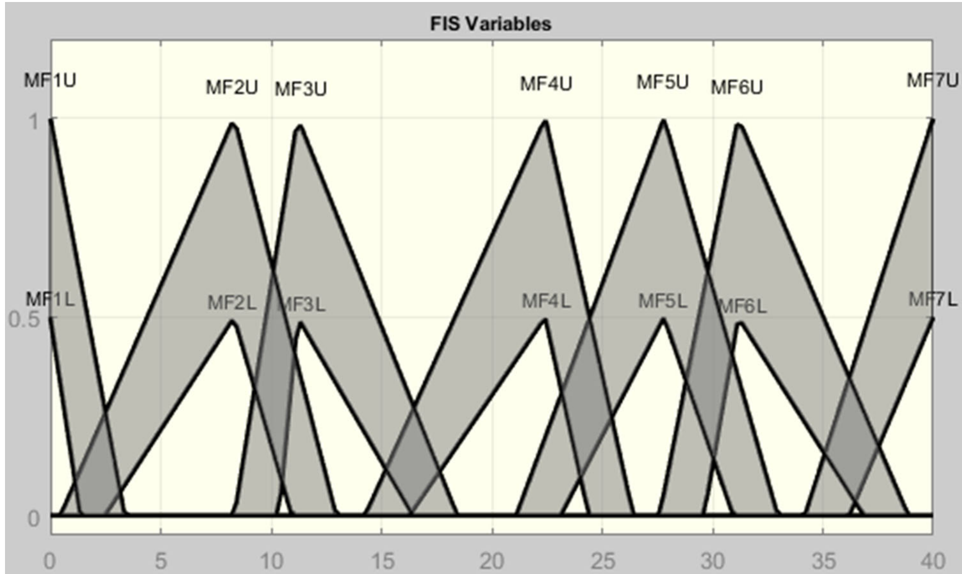

Fig. 9 Optimized membership function of number of vehicles

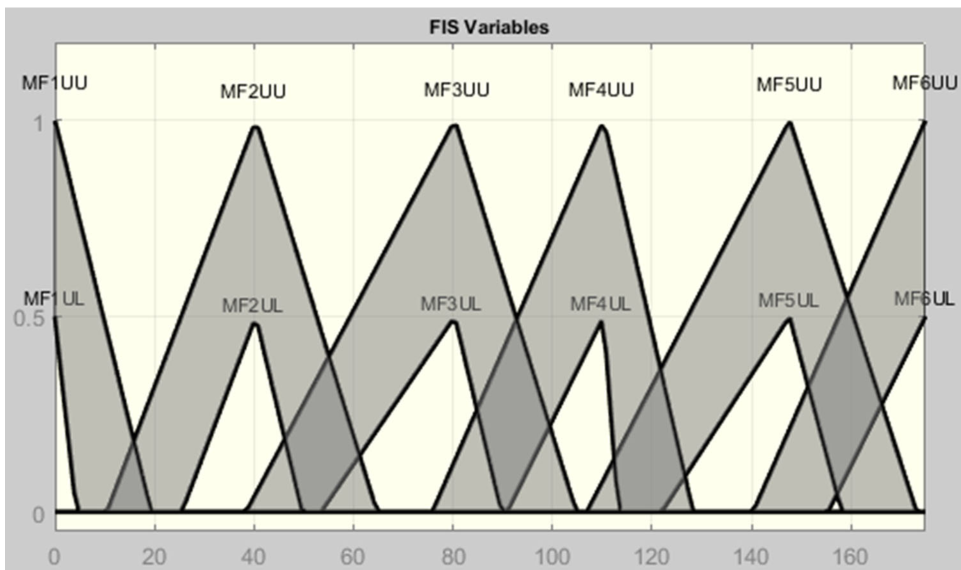

Fig. 10 Optimized membership function of queue length

instead of the fixed phase sequence allows the delay to be reduced.

3 Intersections parameters for simulations and results

Performance comparison was made according to different traffic situations and intersection geometries. Nine different scenarios including low, medium and high traffic volumes were constructed. In addition, delay values were obtained by performing simulations according to four different intersection geometries including three legs and four legs. Intersection geometries are given in Figs. 11, 12. Assumptions for simulations are as follows.

- Each leg has two lanes, with 3.6 m lane width and 0 slope.
- Start-up lost time is 3.6 s.
- Free flow speed is 50 km/h.
- Lost time for yellow light is 2 s and for all-red is 1 s.
- Right turns and left turns were determined to be 10% and 20%, respectively.
- Saturation flow was set at 1800 veh/h/lane.

In the simulation of traffic situations, the effect of different vehicle types on the delay was also taken into account by considering five different vehicle types. Cars, minibuses, buses, lorries and trucks with different lengths and acceleration–deceleration speeds were used. When creating traffic situations, 80% cars, 10% minibuses, 5%

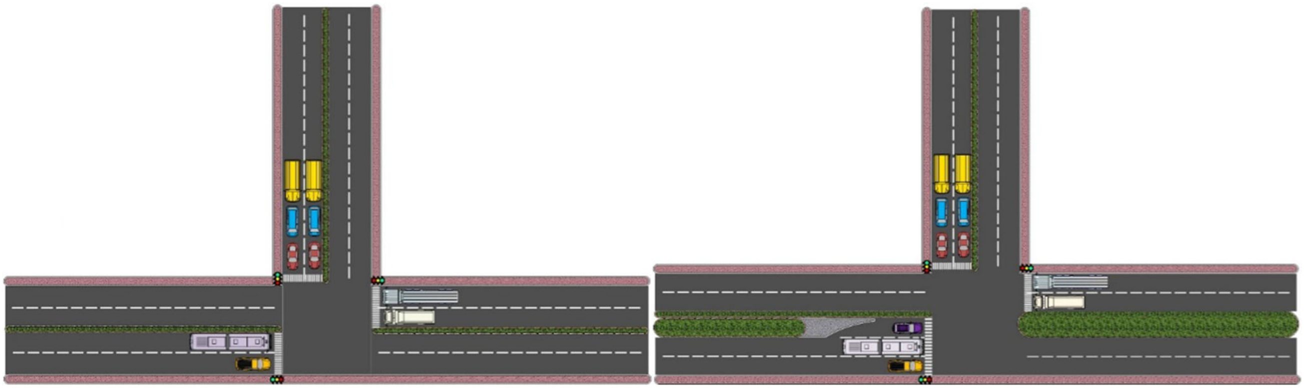

Fig. 11 Three-leg intersection and three-leg intersection with left turn pocket

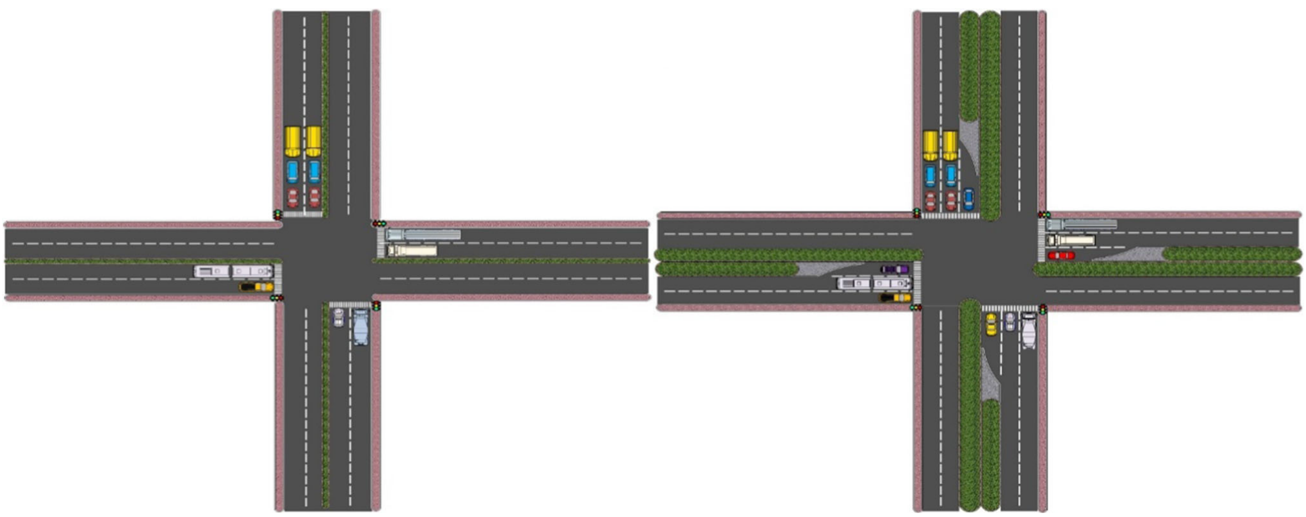

Fig. 12 Four-leg intersection and four-leg intersection with left turn pocket

Table 9 Traffic scenarios for three-leg intersection

State	Approach pattern	West (veh/h)	East (veh/h)	North (veh/h)
Low	All-equal	100	100	100
	All-equal	400	400	400
	Mixed	100	250	400
Medium	All-equal	500	500	500
	All-equal	800	800	800
	Mixed	650	800	800
High	All-equal	900	900	900
	All-equal	1200	1200	1200
	Mixed	900	1050	1050

buses, 3% lorries and 2% trucks were identified as vehicle type distribution. The traffic conditions used for 3 and 4-leg intersections are given in Tables 9 and 10.

The control parameters of the algorithms are important for performance. A constant value (2000) was used in the number of iterations for algorithms, and all algorithms were run accordingly. In the FPA approach, two different control parameters are used: population size (*N*) and probability switch (*P*) parameters. Yang (2012) showed that the probability switch between 0.05 and 0.95 and population size between 10 and 50 was available, and examined the performance of different values. He stated

Table 10 Traffic scenarios for four-leg intersection

State	Approach pattern	West (veh/h)	East (veh/h)	North (veh/h)	South (veh/h)
Low	All-equal	100	100	100	100
	All-equal	400	400	400	400
	Mixed	100	250	400	400
Medium	All-equal	500	500	500	500
	All-equal	800	800	800	800
	Mixed	650	800	800	500
High	All-equal	900	900	900	900
	All-equal	1200	1200	1200	1200
	Mixed	900	1050	1050	1200

that 25 for N and 0.8 for P were the most suitable operating conditions. There are three control parameters in the CSA approach: population size (N) and awareness probability (AP) and flight length (fl). (Askarzadeh 2016) stated that the AP parameter should be between 0.05 and 0.3 and the fl parameter should be between 1.5 and 2.5. By comparing the performances of different values, it showed that 0.05 for AP and 2 for fl were the best results. The control parameter values of the algorithms are used according to the suggested ones. Simulations of the HTSC, Fix-Time, Type-1FL-TSC (Doğan and Akgüngör 2016) and FPA-TSC (Korkmaz and Akgüngör 2021a) systems in which used only the phase optimization module were performed according to the traffic conditions created in four different intersection geometries. Since vehicle arrival in the simulation environment varies by seed number, obtaining delay values by a single seed number will result in misleading results. Therefore, each traffic situation was simulated according to 20 different seed numbers randomly selected, and the average of 20 different delay values obtained was determined as the delay value for each traffic situation. The distribution of delay values for traffic situations according to the simulation results is given in Figs. 13, 14, 15 and 16.

As can be seen in Figs. 13, 14, 15, 16, the fixed-time control approach performed intersection control with the highest delay values. The Type-1 FL-TSC approach outperformed fixed-time controls, but fell behind although it showed closer delay values to the FPA-TSC and HTSC approaches. Although the FPA-TSC and HTSC approaches showed very close performance to each other, the HTSC performed intersection control with the lowest delay values. The performance comparison of the control systems was made according to nine different traffic conditions and evaluated in terms of mean percentage errors (MPE) which is given in Eq. 11. Comparisons were also made with the non-parametric test. Friedman test, one of the post-hoc tests, was used to determine the location of differences between control systems. Descriptive statistics of control systems are given in Table 11. Friedman test statistics are given in Table 12. The hypotheses of the equality of the medians are rejected by p values that are smaller than 0.05, and there is a significant difference between the ranking of

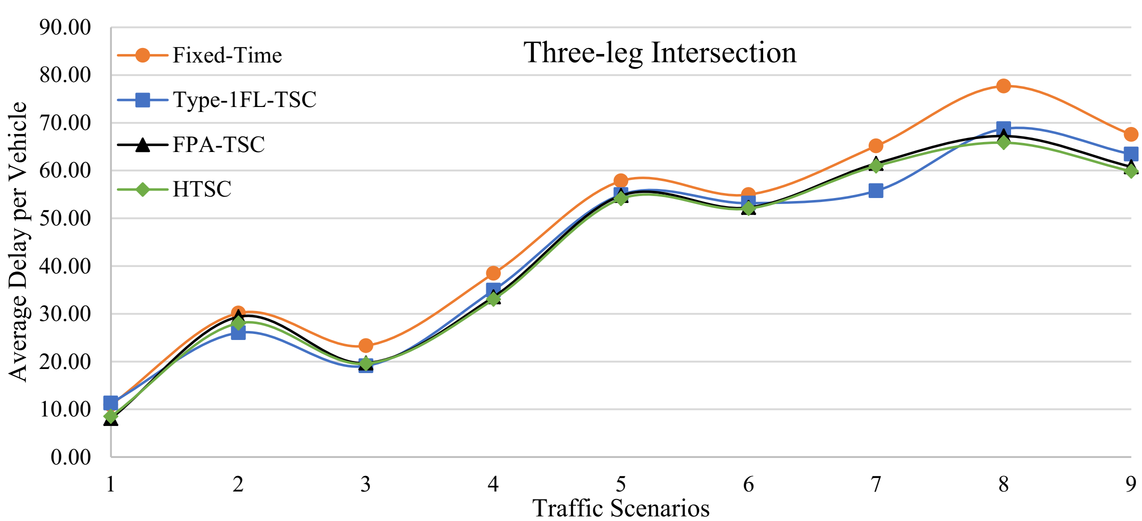

Fig. 13 Average delay distribution of control systems for three-leg intersection

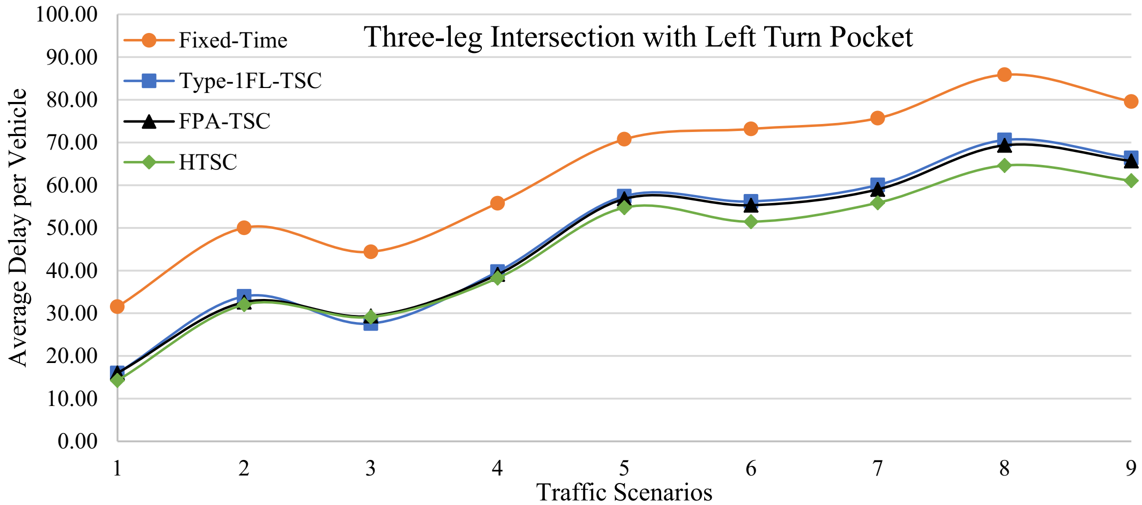

Fig. 14 Average delay distribution of control systems for three-leg intersection with left turn pocket

Fig. 15 Average delay distribution of control systems for four-leg intersection

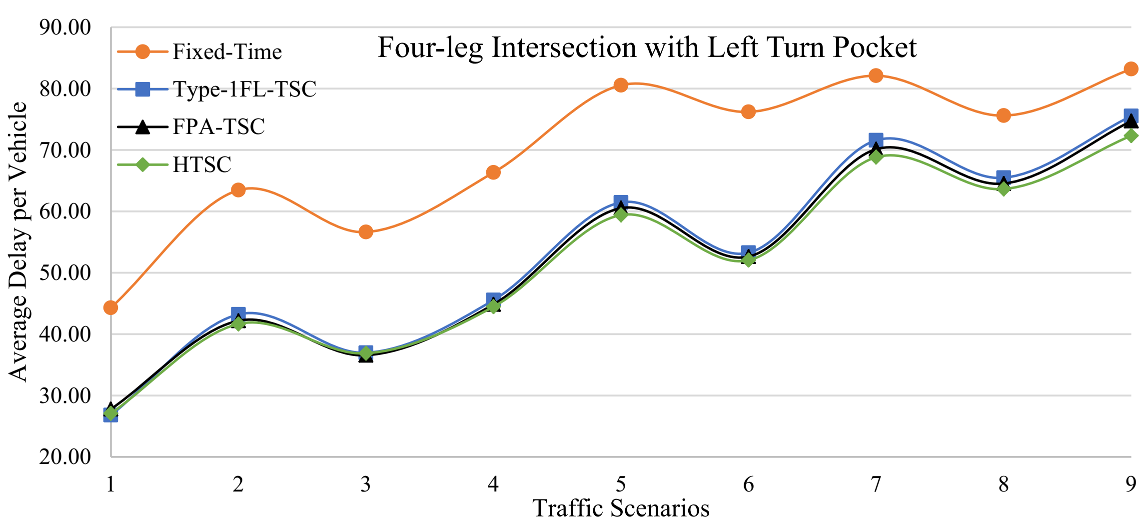

Fig. 16 Average delay distribution of control systems for three-leg intersection with left turn pocket

Table 11 Descriptive statistics

Algorithm	Three-leg				
	N	Mean	Std. deviation	Minimum	Maximum
Fixed-time	9	47.3293	22.61072	10.95	77.67
Type-1FL-TSC	9	43.0452	20.66746	11.30	68.74
FPA-TSC	9	43.0172	20.94332	8.05	67.23
HTSC	9	42.4345	20.59502	8.50	65.85
Algorithm	**Three-leg with left turn pocket**				
	N	Mean	Std. deviation	Minimum	Maximum
Fixed-time	9	62.9787	18.29680	31.56	85.87
Type-1FL-TSC	9	47.5462	18.88301	16.00	70.58
FPA-TSC	9	47.0178	18.36277	16.02	69.34
HTSC	9	44.5993	16.97585	14.27	64.61
Algorithm	**Four-leg**				
	N	Mean	Std. deviation	Minimum	Maximum
Fixed-time	9	61.8995	18.66233	31.09	81.53
Type-1FL-TSC	9	50.9896	19.99126	18.06	79.15
FPA-TSC	9	50.5641	19.48156	18.66	77.75
HTSC	9	48.5330	19.57509	16.93	75.43
Algorithm	**Four-leg with left turn pocket**				
	N	Mean	Std. deviation	Minimum	Maximum
Fixed-time	9	69.8196	13.21182	44.30	83.19
Type-1FL-TSC	9	53.3215	16.47929	26.82	75.53
FPA-TSC	9	52.6630	15.97809	27.79	74.71
HTSC	9	51.8187	15.40894	27.08	72.34

the observations. The MPE values for four different intersection geometries are given in Table 13.

$$\mathrm{MPE} = 1/n \sum_{i=1}^{n} \frac{\mathrm{Delay}_r - \mathrm{Delay}_c}{\mathrm{Delay}_r} \times 100 \tag{11}$$

Here, n is the number of samples, Delay_r is the delay value of the control system to be referenced, and Delay_c is the delay value of the control system which is calculated the percentage error.

According to the descriptive statistics and Friedman test statistics in Tables 11 and 12, the HTSC has the lowest delay (objective function) value for all type intersections. The FPA-TSC has better delay values than fixed-time and Type-1FL-TSC, and it remains in second performance place. Fixed time controller has the lowest performance and it has been seen that artificial intelligence approaches and control systems show better results. Thus, it has been observed that the HTSC performs better than other control systems.

As can be seen from Table 13, compared to fixed-time, the Type-1 FL-TSC, FPA-TSC and HTSC approaches could achieve 8.64%, 10.73% and 11.59% improvement at three-leg intersection, respectively. The FPA-TSC approach achieved 1.67% improvement over Type-1 FL-TSC, and the best performing HTSC improved intersection performance by 2.70% and 0.80% respectively compared to Type-1 FL-TSC and FPA-TSC. The fact that there is a left turn pocket at the three-leg intersection affects the performance of the control systems. At the intersection geometry with approximately three-fold improvements, the delay value was reduced by up to 30%. The best performing HTSC approach decreased the delay value by 5.70% and 5.04%, respectively, compared to Type-1 FL-TSC and FPA-TSC approaches. Although Type-1 FL-TSC

Table 12 Friedman test statistics

Algorithm	Three-leg		Three-leg with left turn pocket		Four-leg		Four-leg with left turn pocket	
	Mean rank	*p* values	Mean rank	*p* values	Mean rank	*p* values	Mean rank	*p* values
Fixed-time	3.89	0.001	4.00	0.000	4.00	0.000	4.00	0.000
Type-1FL-TSC	2.44		2.67		2.78		2.78	
FPA-TSC	2.22		2.22		2.22		2.00	
HTSC	1.44		1.11		1.00		1.22	

Table 13 MPE values for different intersection geometries

Intersections	MPE					
	Fixed-time / Type-1FL-TSC	Fixed-time / FPA-TSC	Fixed-time / HTSC	Type-1FL-TSC / FPA-TSC	Type-1FL-TSC / HTSC	FPA-TSC / HTSC
Three-leg	− 8.64	− 10.73	− 11.59	− 1.67	− 2.70	− 0.80
Three-leg with left turn pocket	− 27.23	− 27.86	− 31.45	− 0.71	− 5.70	− 5.04
Four-leg	− 19.81	− 20.27	− 23.99	− 0.42	− 5.26	− 4.83
Four-leg with left turn pocket	− 25.17	− 25.97	− 27.11	− 0.95	− 2.42	− 1.47

and FPA-TSC approaches show performance close to each other, 0.71% improvement shows the effect of phase optimization on intersection performance. Type-1 FL-TSC, FPA-TSC and HTSC approaches control the intersection with less delay in low and medium traffic conditions in four-leg intersection geometries, while their performance and delay values reach the fixed-time values in high traffic conditions. The main reason for this situation is the saturation of the intersection due to the high levels of traffic and the decrease in the effect of the control systems. The HTSC approach showed the best performance in four-leg intersections and achieved 4.83% and 1.47% better results than the FPA-TSC approach, which shows the closest performance to it. Statistical results obtained by applying different artificial intelligence methods and control approaches showed that better intersection performance can be achieved than fixed-time control approach. Optimizing and dynamizing the signal duration together with phase and sequence optimization has been found to have a significant impact on intersection performance, with a performance improvement contribution of up to 5.04%. In addition, according to the Type-1 FL-TSC approach, which shows an effective performance, the hybrid system developed using type-2 FL and algorithms provides an improvement between 2.5 and 5.7%.

When the effectiveness of the developed control approaches is compared according to the variance and standard deviation statistics, the HTSC system showed the lowest values in four intersection types. The combination of signal timing and phase optimization approaches provide intersection control at the lowest delay values. Also, using different algorithms together and optimizing the FL approach according to traffic conditions have been effective in obtaining the best results. The control system, which only performs phase optimization with the FPA approach, also produced better results than fixed-time and Type-1 FL-TSC systems.

4 Conclusion

In intersection control, it is important to operate the intersection quickly and effectively. Therefore, the main mission of the intersection control problem is to develop a system that can adapt to any traffic condition and to improve intersection performance indicators such as minimum delay and maximum capacity. It is known that traditional methods fail to accomplish this mission and new approaches based on artificial intelligence play an effective role in achieving this goal. In particular, when intersection control systems based on pioneering approaches of artificial intelligence methods such as GA, ACO and the FL are inadequate, new approaches are applied to intersection control and the deficiencies of the existing systems can be eliminated, thus improving performance. The main objective of this study is to develop more effective intersection control and to obtain effective results in intersection control using the FPA, CSA and Type-2 FL approaches among the current and high-performance algorithms. The applicability of the hybrid control system developed by combining the unique advantages of the FPA and CSA algorithms and the Type-2 FL approach was demonstrated, and the hybrid control system was compared with Type-1FL-TSC, which has a successful performance. The following conclusions were drawn from this study.

1. The phase plan and sequence affect the performance of an intersection as well as the cycle length in signalization. In this respect, a new control system based on the optimization of cycle length, phase plan, and phase sequence was developed using the FPA approach and the effectiveness of this system was demonstrated. The results revealed up to 30% improvement over the fixed-time control system. The new system also achieved 1–3% better results than the Type-1 FL-TSC approach, which has an effective performance. Thus, it was shown with statistical results that the FPA approach can be used as an effective method for intersection control. Another point is that the approach used can adapt to changing traffic situations as quickly as possible. The Type-1 FL-TSC approach yields good results in the intersection control problem but requires long operation time for optimization. In addition to the superior performance of the FPA-TSC approach, another advantage is that it can adapt to traffic situations in a very short time and make effective decisions in intersection control.
2. Optimizing the cycle length makes a significant contribution to reducing the delay but does not reach a sufficient level due to the change in traffic situation at the end of each phase. Therefore, re-optimizing the green times at the end of each phase, the cycle length is made dynamic, which contributes to a superior performance in intersection control. The signal time optimization module developed based on the CSA-optimized Type-2 FL approach plays an important role in further reducing delays and improving intersection control performance. The HTSC system, which was created using the FPA, CSA and Type-2 FL approaches together, showed the best performance among the other systems and enabled intersection operation in all intersection geometries with the lowest delay values. In addition, as the new approach led to an improvement between 3 and 6% compared to the Type-1 FL-TSC approach, it has been effective in both reducing emissions and fuel consumption and minimizing driver dissatisfaction resulting from signaling.
3. It was seen that the fixed-time system showed the lowest performance in intersection control and artificial intelligence approaches were found to be effective. According to the Friedman test results, optimizing the signal timing with the type-1 FL approach, approximately a 35% performance increase was achieved while a 40% improvement was achieved in the phase plan and optimum cycle length optimization with FPA. In the proposed hybrid system, on the other hand, the greatest improvement was achieved and approximately 60% improvement was achieved compared to the fixed-time system and approximately 40% compared to other systems. Thus, it is demonstrated that the most effective control system can be implemented by dynamically changing the phase plan, signal duration, and phase sequence.
4. Both the individual performance of the FPA approach and the combined use of the FPA, CSA and Type-2 FL approaches have led to an increase in intersection performance. In addition, it is thought that better results can be obtained by applying network optimization in which many intersections are controlled at the same time, except for isolated intersections. Studies are being conducted on this aspect.
5. In developing countries like Turkey, there is an increase in travel demand, and consequently, solving traffic control problems is of great significance. Especially when it is not possible to change intersection geometries, an effective signaling system is adopted by many organizations to solve these problems. The rapid and high performance of the developed HTSC approach increases the applicability of the system and provides an alternative method for the authorities responsible for intersection control such as directorate of highways and municipalities.

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Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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