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A Review of Expert Systems Integration in Signal Plan Optimisation

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ABSTRACT

In urban networks, periodic peak traffic congestion often occurs during the day, namely in the morning and afternoon hours. Due to spatial constraints and the inability to increase capacity through physical road expansion, modern traffic management increasingly relies on Intelligent Transport Systems (ITS) solutions. One such solution is the integration of automatic licence plate recognition, an expert system and microsimulation tools aimed at optimising the network performance of signalised intersections within a network. Based on real-time and historical data on individual vehicle trajectories, the system predicts the route of each vehicle through the observed segment of the traffic network, determines the network load and proposes optimal signal plans. This paper provides an overview of conducted research related to the optimisation of signal plans utilising expert systems. Mathematical models for capacity and load determination, as well as computational intelligence-based systems used for signalised intersection management strategies, are described. Finally, the paper proposes a basic framework and guidelines related to the suggested system, highlighting open questions and potential challenges in its development.

KEYWORDS

urban traffic management; automatic licence plate recognition; computational intelligence; prediction of vehicle trajectories; microsimulation tools.

1. INTRODUCTION

Through the development and implementation of advanced technologies enabling real-time processing of large volumes of traffic data, and with the application of sophisticated algorithms, it is possible to minimise the stochastic nature of the traffic system. Until recently, it was considered impossible to accurately predict the trajectory of individual vehicles through the traffic network of signalised intersections. With developed capabilities of vehicle tracking, along with the tools for interpreting these data, it is now feasible, with a certain level of confidence, to predict their route through a specific segment of the network.

Determining the route of an individual vehicle assumes that people use established routes from origin to destination, often during the same time of day with minor or negligible deviations. Although the research [1] pointed out that individual commuting trips are flexible and not fixed in terms of timing, travel mode choice, route selection or destination, the same study presented results indicating that commuting trips involving personal automobiles are the least flexible. Similar conclusions were also drawn in the study [2], where the results showed that when examining the same origin-destination points for individual personal vehicles, almost 59% of trips followed identical trajectories. When focusing exclusively on work-related trips, among all personal vehicle journeys, this percentage is even higher. By storing a large amount of vehicle data and appropriately interpreting recorded information, it is possible to determine individual vehicle trajectories through the network with a precision that meets acceptable standards. The statement above was validated in the research [3], where authors, based on a large dataset obtained through the automatic licence plate recognition (ALPR) system and an algorithm connected to a database, predicted individual vehicle paths through the traffic network with a minimum accuracy of 84%, even when 30% of the data was missing or unusable. When considering the data in real-time and comparing it with predefined trajectories of individual vehicles derived from historical data, the assumption is that it is possible to determine the current load of each traffic node (signalised intersection) with high precision.

To determine the current load of signalised intersections, systems based on computational intelligence (CI) are required, which can rapidly process large amounts of spatial-time data. Additionally, mathematical models are essential for determining the capacity of signalised intersections based on physical characteristics and fundamental traffic models describing intersection capacity. The development of data processing technologies accompanies the advancement in data collection technology. Depending on the context, intended purpose, scale, methods and data sources, various data processing approaches are employed [4]. On the other hand, mathematical models for determining intersection capacity are deterministic models derived from empirical measurements and utilise predefined calculations [5], which vary based on the physical characteristics of the road (number of lanes, group of lanes, number of approaches, etc.) and the saturation of traffic flows.

After successfully determining the load of each intersection, and consequently, the entire observed network, it is necessary to develop control strategies at both the local level (traffic intersections) and the global level (urban traffic system/traffic network). Modern management strategies rely on mathematical models embedded in knowledge-based expert systems (KBESes). These are systems developed in the field of artificial intelligence (AI), aiming to simulate complex societal problems and provide solutions based on human knowledge and experience [6]. The increasingly widespread application of information technology (IT) provides an opportunity to enhance expert system techniques, aiding in the management of systems operating in dynamic environments [7]. This is further affirmed by [8], where is explained that due to increased transport demand and the associated negative effects, the KBES application is increasingly focused on addressing issues related to urban infrastructure planning, traffic planning, timetable design, and traffic monitoring and control (especially in the field of urban traffic control and air traffic control).

To assess the effectiveness of proposed solutions obtained through expert systems, the solutions need to be tested and quantified before implementation. Microsimulation models are used for this purpose. These are dynamic, stochastic, discrete modelling techniques with the capability to simulate the movement of individual vehicles based on algorithms for vehicle following, lane-changing and accepting time gaps, which are updated several times per second. These computer models replicate the real state of the road network in the area to be optimised. They are applied in practical research related to modelling, planning, development and optimisation of traffic, traffic networks or transportation systems [9]. Although there are multiple levels of simulation tools (macro, meso and micro levels), due to the structure of this work, only microsimulation tools are analysed. The task of such tools is to evaluate quality indicators (flow, density, speed, time spent in the network, delay, queue lengthening, number of stops, harmful gas emissions, fuel consumption, etc.) and demonstrate the effectiveness of individual traffic network management solutions at the level of a single vehicle and intersection. After evaluating the results, the solution that indicates the best performance based on predefined objective functions (minimising time spent in the network, delay, number of stops, number of vehicles in the queue, fuel consumption, harmful gas emissions, maximising traffic flow, etc.) is transferred to the real traffic network management.

The organisational structure of the paper comprises six chapters. After the introduction as the first chapter, the second chapter provides a review of previous research in the areas of automatic licence plate recognition, KBESes and microsimulation tools. The third chapter presents an overview of basic mathematical models used to determine road capacity based on physical characteristics and traffic flow saturation. The fourth chapter outlines optimisation methods utilising CI, forming the foundation for the KBES discussed in this work. The fifth chapter introduces the architecture upon which the development of the system for optimisation of signal plans through expert systems will be based. Finally, the sixth chapter presents concluding considerations and discussions, emphasising open questions and guidelines for future research related to the construction and development of the proposed solution.

2. LITERATURE REVIEW

The system for optimisation of signal plans using expert systems, analysed in this paper, consists of three components. The first component (ALPR) is used to collect spatial-temporal data about individual vehicles for the prediction of vehicle trajectories and determination of a traffic load. The process of determining optimal signal plans (from trajectory prediction to signal plan calculation) is carried out through a KBES enhanced with CI. The third component, the microsimulation tool, is an extension of the expert system and serves as feedback on the effectiveness of individual solutions proposed by the expert system.

The first component is ALPR which presents a technological solution that captures images of moving vehicles and processes them using various image-processing techniques. In recent times, ALPR systems have found increasingly widespread applications, especially in the area of entrance/exit control for toll infrastructure (highways, bridges, garages, parking lots, etc.). ALPR is also used in monitoring border crossings, detecting traffic violations, and supporting traffic flow management systems [10]. With the advancement of technology and the processing power of computers, ALPR techniques continue to evolve. While the working principle is similar across most systems, the image processing and ALPR methods may vary depending on the used technology.

Generally, ALPR systems that isolate licence plate markings from images are composed of four steps [11]. The ALPR process is presented in *Figure 1*.

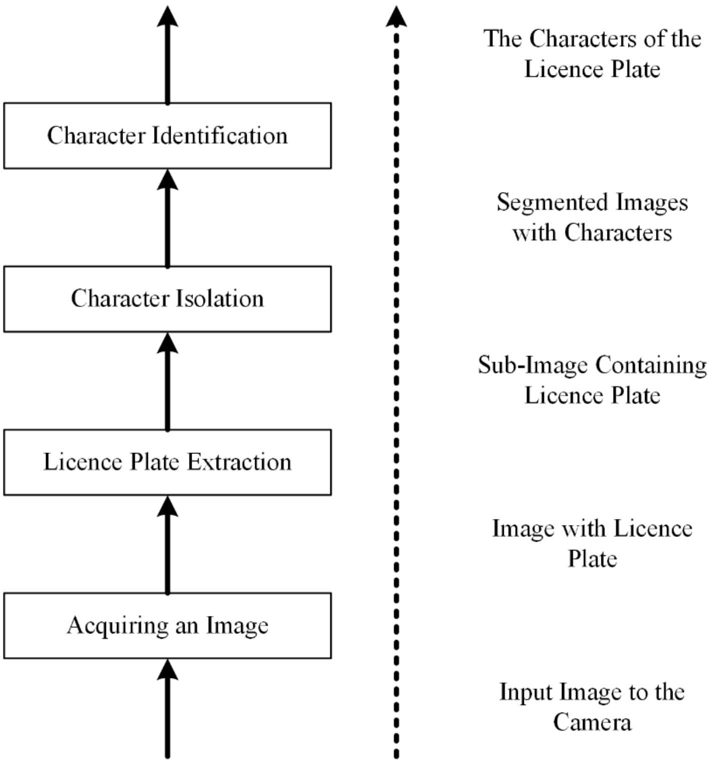

Figure 1 – The process of automatic licence plate recognition system

The first step is obtaining an image of the vehicle, taking into account camera parameters such as camera type, resolution, shutter speed, camera orientation and lighting conditions. In the second step, it is necessary to distinguish the licence plate based on features such as edges, colour or the presence of characters. The third step involves segmenting the licence plate and isolating characters by preserving their colour information and marking or comparing their location on the image with predetermined patterns. The final step is licence plate recognition using predetermined patterns or employing artificial intelligence-based classifiers such as neural networks or fuzzy classifiers. In the research [12], the authors summarised modern techniques used in the ALPR process, highlighting their advantages and disadvantages. In addition to summarising licence plate extraction, character isolation and character identification techniques, the authors emphasised potential obstacles related to licence plates and environmental factors as influences on licence plate recognition that need to be considered when designing ALPR systems.

In [13], various techniques used for licence plate detection from video footage were summarised. Also, an improved hybrid fuzzy technique used in the Malaysian automatic licence plate recognition (M-ALPR) system was developed [14]. The introduced technique led to a reduction in program complexity and processing time. Another study [15] proposed an ALPR method that recognises all licence plates in the field of view using classical template-matching methods, neural network-based methods and other AI-based pattern-matching methods. The results of applying these methods indicate improvements in response time, the ability to detect multiple licence plates in an image, and the capability to recognise plates from lower-resolution images. In the research [16], techniques based on open ALPR, k-neural network, and convolution neural network (CNN) were compared for licence plate recognition in still images and live streaming images. The comparison showed that CNN-based techniques are the most suitable for recognising licence plates with unconventional characters, such as those in India. Another research [17] presented a system where ALPR technology is used to estimate origin-destination (OD) matrices for rural traffic in Thailand. The proposed system uses algorithms for processing and linking images where vehicles with the same licence plates are detected, and it reliably estimates the OD matrix for each vehicle.

According to [12], a comprehensive study comparing techniques used in the automatic licence plate detection process is presented, where advantages and disadvantages are emphasised. Depending on the factors and specified constraints imposed on the system, which are often contradictory (such as speed and accuracy of processing), users must choose the optimal method that will meet their specified constraints. It is important to note that in the selection process, a balance must be struck between the ability to recognise non-uniform licence plates (plates with different fonts, colours, sizes and text tilts) and the robustness, speed and accuracy of recognition. The issue of recognition accuracy also needs to address problems caused by external influences such as glare from excessive brightness or adverse weather conditions (rain, snow, etc.), and the inability to distinguish between pairs of similar characters such as B-8, O-D-0, I-1, A-4, C-G, K-X.

KBESes use interactive computer programs aimed at providing a level of performance and expertise that only a few experts in a specific problem domain possess. Although expert systems have a wide range of applications, not all problems are suitable for solving them. Before constructing an expert system, it is necessary to determine if the problem can be solved using such a system. The authors in [6] identified criteria that can be used to assess the potential application of an expert system. According to the presented criteria, it can be concluded that KBESes are more flexible than algorithms designed to solve complex problems. KBESes surpass the issues of algorithm-based systems. Algorithms work with precise numerical data, and correct operation requires the representation of knowledge in sequential steps (which is often impossible or impractical in many problems). Furthermore, one of the problems encountered when using algorithm-based systems is the inability to detect and/or process incomplete data, while an expert system complements such data with conclusions from its database. Additionally, the flexibility of using KBESes compared to algorithm-based systems is evident in the ability to upgrade the system. Upgrading expert systems is simpler and almost limitless because knowledge is not hierarchically distributed nor is it spread throughout the entire algorithm; it is separated from the control process.

The architecture of expert systems is divided into the knowledge base process and the control process for the application and selection of knowledge, i.e. the inference machine. The general architecture of a KBES is illustrated in *Figure 2* [8].

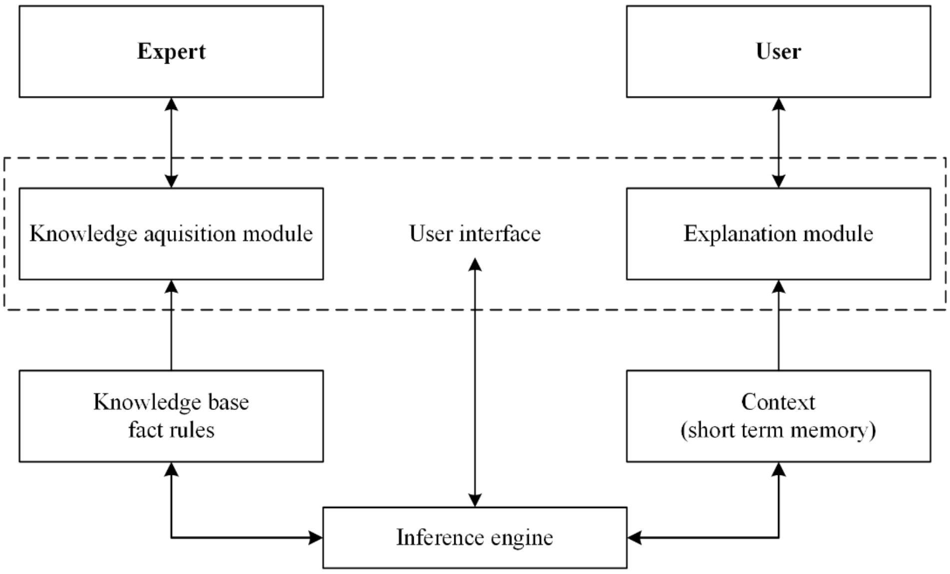

Figure 2 – Basic structure of knowledge-based expert system

According to *Figure 2* ***knowledge base*** is created by transferring expert knowledge from the problem domain by experts, representing the strength of the expert system (the larger the knowledge base covering a wide range of possible solutions, the stronger the expert system). The knowledge base contains all relevant information, facts or general knowledge about the domain, and rules used to determine which actions will be executed if the specified conditions are met. According to [18], there are several knowledge representation techniques, among which rules, frames and semantic networks are the most common. The method predominantly used in developing expert systems for solving transportation problems employs rule-based techniques composed in an IF “condition” THEN “action” format. When the IF part or the rule’s premise is satisfied by facts, the action specified in the THEN part is executed. The control level of the expert system is called the ***inference engine***. The goal of the inference engine is to find the conclusion of a subprocess or the entire problem-solving process. The inference engine searches the facts in the knowledge base and identifies new facts that serve for subprocess inference. According to [19], two common methods are used in inference: backward chaining and forward chaining. The difference between these two methods is that the first starts from a known result and looks for facts to support the result (goal-driven reasoning), while the second method uses facts and elaborates on the solution to reach a conclusion (data-driven reasoning). ***Context*** is the data level of the expert system. It includes all the data, symbols and facts that represent the current state of the solution. This information can describe the problem solution, the rules used in solving it and display the facts. Another term for context is short-term memory. Unlike traditional programs that are often conceptualised so that the user cannot see the logic behind the displayed result, an expert system has an ***explanation module*** that shows the problem-solving strategy to the user. ***Knowledge acquisition module*** is often the most challenging problem during the development of an expert system. Although there is the possibility of automatic knowledge acquisition, due to the specificity of each domain, collecting general knowledge that is not system-dependent does not provide acceptable solutions for most specific problems. The user accesses the system through a ***user interface*** that should be accessible and easy to use, enabling direct and efficient communication between the user and the system.

The description of the general architecture has outlined the components of an expert system that need to be considered during the system’s development. The foundation of building an expert system is the construction of a knowledge base. The main goal of building the knowledge base is to transfer knowledge and experience gathered from one or more experts into a computer program. The task of knowledge engineers is to facilitate the transfer of this knowledge and experience, ensuring that once entered into the computer, they are at a satisfactory level. The steps in building an expert system may vary depending on the characteristics of the problem, defined goals and the availability of development tools used for expert system development. However, according to [20], the construction of an expert system is generally composed of five steps:

1) *Identification* – the first step in building an expert system involves identifying the area, concepts and characteristics of the problem and its solutions. Additionally, it is desirable to identify participants and resources (such as time, labour and infrastructure) required during the system development.
2) *Conceptualisation* – the concepts needed to represent knowledge, and the overall structure of knowledge control strategies must be defined before the preliminary system design.
3) *Formalisation* – this step involves designing the formal organisation of knowledge using development tools or programming languages. The detailed design of the expert system is formulated by both the expert and knowledge engineers.
4) *Implementation* – in this step, the knowledge engineer transforms the formal knowledge into a computer program.
5) *Testing* – the performance and behaviour of the prototype expert system are iteratively tested and evaluated through comparisons with the capabilities of the expert. System revisions are made by the knowledge engineer with support from the knowledge provided by the expert.

There are two approaches to the construction of an expert system. The first approach involves writing the knowledge base from scratch, which requires using programming languages such as LISP [21], PROLOG [22–24], etc., specifically designed for applications in the field of AI [25]. The second approach is to use knowledge design and presentation tools, consisting of an inference engine, an empty knowledge base, contextual structures and supporting tools such as a knowledge base editor and an explanation module. This approach simplifies the process by reducing the number of steps required to build the knowledge base. In this case, the person developing the system is expected to input and formulate IF-THEN rules based on which the system makes conclusions. With the rapid development of AI, tools for developing expert systems have evolved. To increase task execution speed, these systems are often written in conventional programming languages (such as C, Java, Python, etc.) today.

One of the more widespread and commonly used tools is the integrated development environment written in the C programming language, known as the C language integrated production system (CLIPS). CLIPS is a tool for building expert systems that provides a complete environment for constructing expert systems, whether they are object-oriented or rule-based. It is a versatile tool managing a broad spectrum of knowledge with support for three different programming paradigms: rule-based, object-oriented and procedural paradigms [20].

An example of an expert system used for optimising traffic flow at signalised intersections is presented in [7] where a dynamic and automatic traffic signal control system to reduce traffic congestion is developed. The multi-part system comprises a radio frequency identification (RFID) detection system, a database system, a knowledge base and a control server. It successfully determines the duration of red and green lights based on information from the database and IF-THEN rules established in the knowledge base. In [26], the development of a traffic system based on fuzzy logic is presented. The system was tested at two bidirectional intersections, demonstrating its ability to adapt the duration of traffic signal intervals at signalised intersections depending on the congestion level of the roadway. In the research [27], a method for estimating the number of vehicles waiting in queue (NVWQ) based on a neuro-fuzzy system was presented. The accuracy of the system in predicting queues was reported to be higher than 90%. According to the authors, the neuro-fuzzy system can be successfully trained to predict queues in different intersection conditions, reducing the time required for experts to determine IF-THEN rules. In such a system, the fuzzy controller can adjust signal plans in real-time, reducing delay times and the percentage of stopped vehicles. Optimisation through an adaptive traffic signal control system based on fuzzy logic was proposed in [28]. The developed system utilised a simulation model of an adaptive fuzzy logic-based system embedded in the MATLAB programming package. The simulation model was used to assess the efficiency of the proposed system. When comparing the results of the proposed system with a fixed traffic control system, simulation results showed an improvement in reducing queues by 2.6 times and a 27% reduction in delays. In [29], the authors presented research results based on an expert system and a modern feature selection method (Bijective soft set-based feature selection BSSReduce), serving as assistance in traffic network management. The mentioned method enables the identification of key traffic congestion and assesses the importance of each congestion for the rest of the observed traffic network in two cities in China. The system's results indicate that among a total of 10,000 traffic nodes in Chongqing and 50,000 nodes in Beijing, less than 1% are identified as key congestions. Monthly, the system detects 75 key congestions in Chongqing and 300 key congestions in Beijing, allowing traffic management personnel to focus on the detected congestions rather than optimising the entire traffic network.

As mentioned before, the microsimulation models are the third component of a system for signal plan optimisation based on expert systems. Microsimulation software is used as a versatile tool that can vary depending on the size and complexity of the analysed area, ranging from individual roads, intersections or corridors to entire urban networks. For this reason, it is important to understand that each model is unique, and the function and appearance of the analysed area in each model may vary. According to [30], intersections and roads within the covered area must undergo thorough calibration and validation to ensure that the model best represents real-world conditions. Due to the complexity of traffic in urban areas and the representation of its characteristics and interdependencies of entities and parameters involved, it is often necessary to use two or more different tools to fully develop the model.

Numerous simulation tools are integral for the design and optimisation of signalised intersections, with notable solutions being Synchro Studio, AIMSUN, TRANSYT, SUMO and PTV VISSIM. Synchro Studio, developed by Trafficware, serves as a microsimulation tool for modelling unsignalised intersections, signalised intersections and roundabouts [31, 32]. It adopts the highway capacity manual (HCM) methodology for capacity calculations [5], ensuring a user-friendly graphical interface for quick data analysis. AIMSUN, known as the advanced interactive microscopic simulator for urban and non-urban networks, excels in representing real traffic data across diverse networks, offering microscopic, mesoscopic and macroscopic models [33]. Its integration with the generic environment for traffic analysis and modelling (GETRAM) enhances its capabilities. TRANSYT, or traffic network study tool, focuses on modelling and optimising signalised, unsignalised and roundabout intersections using the hill climbing algorithm [34, 35]. SUMO, the open-source simulation of urban mobility, provides microscopic multimodal simulation, modelling individual vehicles explicitly and offering diverse traffic management methods [36]. Noteworthy is SUMO's unique approach to external applications, allowing easier extension of applications within the tool. PTV VISSIM, a microscopic simulation tool, prioritises multimodality, enabling the simulation of all traffic modes in urban networks. Comprising a traffic simulator and a signal plan generator, PTV VISSIM collects data based on link and node evaluations [37, 38], using TRANSYT program formulas for optimising signal timings and emissions data from the National Laboratory Oak Ridge in the United States. Each of these tools plays a pivotal role in simulating and optimising traffic flow in diverse urban scenarios, contributing significantly to the field of transportation planning and management.

In recent decades, traffic simulation models have been widely used to assess new traffic solutions and ideas quickly and cost-effectively. Also, they can integrate with other software using various methods and tools for optimisation processes, making them extensively used for testing new traffic solutions. A study [39] presents the results of optimising traffic flows at a roundabout with 28 signal lanterns in Izmir, Turkey. Optimisation was achieved by integrating the VISSIM simulation model and the particle swarm optimisation (PSO) algorithm. The algorithm was used to find a signal plan that minimises the average travel time through the intersection, while the simulation tool was used to evaluate the results obtained from the PSO algorithm. The results indicate a 55.9% reduction in average delay time and a 9.3% increase in vehicle flow through the intersection. Another study [40] presents a simulation scheme for managing two interconnected signalised intersections in Beijing, China. Using a spillover queue detection algorithm and a simulation model, optimisation was performed resulting in a 40% reduction in individual vehicle delay and a 10% reduction in average delay. A signal plan optimisation system that collects data from the traffic network in Dhaka, Bangladesh, through video surveillance, based on which an expert creates a knowledge base was demonstrated in [41]. Signal plans are generated through the expert system and evaluated in VISSIM. This approach led to a 42% reduction in waiting queues on the most congested link and a significant decrease in traffic congestion, directly impacting the increase in the average travel speed through the traffic network.

3. DETERMINING THE CAPACITY OF SIGNALISED INTERSECTIONS

A theoretical model for finding the optimal signal plan, i.e. optimal allocation of green times for a group of lanes depends on a set of parameters that need to be incorporated into mathematical calculations. At signalised intersections, signal control is based on traffic demand, the volume of which (the size of the traffic flow for all signal groups) is determined by calculating the saturation of traffic flow. Saturation levels of groups of lanes and the intersection are derived from the degree of saturation of traffic flow, directly linked to the capacity of groups of lanes, approaches and the intersection.

3.1 Determination of saturated traffic flow

Saturated flow is the maximum volume of traffic that can pass through a traffic area under optimal technological conditions [5]. From the perspective of a signalised intersection, it is the number of vehicles for one hour that can pass through the observed group of lanes, considering factors that influence it, assuming that the green signal is active 100% of the time. The saturated traffic flow, represented by *Equation 1*, consists of the ideal traffic flow (flow without the influence of other traffic factors) and the saturation flow factors (factors that positively or negatively affect the ideal traffic flow):

$$S = s_o \cdot N_L \cdot f_W \cdot f_{HW} \cdot f_g \cdot f_P \cdot f_{BB} \cdot f_a \cdot f_{LU} \cdot f_{LT} \cdot f_{RT} \cdot f_{Lpb} \cdot f_{Rpb} \tag{1}$$

where:

s_o = base saturation flow rate per lane [pc/h/ln] (1900-2200),
N_L = number of lanes in a group of lanes (1,2,3...),
f_W = factor for lane width,
f_{HV} = factor for heavy vehicles in traffic stream,
f_g = factor for approach grade,
f_p = factor for the existence of a parking lane and parking activity adjacent to the group of lanes,
f_{BB} = factor for blocking effect of public transport vehicles that stop within the intersection area,
f_a = factor for area type,
f_{LU} = factor for lane utilisation,
f_{LT} = factor for left turns in a group of lanes,
f_{RT} = factor for right turns in a group of lanes,
f_{Lpb} = pedestrian-bicycle adjustment factor for left-turn movements,
f_{Rpb} = pedestrian-bicycle adjustment factor for right-turn movements.

The basic ideal traffic flow according to empirical measurements ranges between 1,900 and 2,200 [veh/h/lane/green]. According to the Handbook for the Design of Road Traffic Systems (German: Handbuch für die Bemessung von Straßenverkehrsanlagen – HBS [42]), the ideal traffic flow is considered to be 2,000 [veh/h/lane/green].

The factor for lane width represented by *Equation 2* is used for lane widths, *w*, ranging from 2.4 [m] to 4.8 [m]. A lane width exceeding 4.8 [m] is considered the width of two traffic lanes within the group of lanes.

$$f_W = 1 + \frac{(w - 3.5)}{9} \tag{2}$$

Empirically observed, the factor has no impact on the ideal traffic flow at a lane width of 3.5 [m], suggesting that the optimal lane width for the roadway is approximately this value. Widths greater than the ideal value increase the ideal traffic flow but allow higher traffic speeds, which may result in reduced road safety and, at saturated flow, lead to an increase in the number and intensity of shockwaves. A lane width smaller than ideal diminishes the ideal traffic flow and the capacity of the lane or group of lanes.

The factor for heavy vehicles in the traffic stream is described by *Equation 3*, illustrating the influence of the percentage of heavy-duty vehicles on the ideal traffic flow:

$$f_{HV} = \frac{100}{100 + HV * (E_T - 1)} \tag{3}$$

where:

E_T = The equivalent of passenger vehicles for a freight vehicle (2-3),

HV = Percentage of heavy-duty freight vehicles in traffic (0-100).

The percentage of heavy-duty freight vehicles in urban environments is usually around 2–5%, rarely higher (unless the area is located in an industrial zone or near a public urban transport terminal). The equivalent of passenger vehicles for one heavy-duty freight vehicle is usually considered to be 2–3 vehicles. By increasing the percentage of heavy-duty freight vehicles, the impact of the factors on the ideal traffic flow also increases. This decline is steeper when a higher number of passenger vehicles is considered as an equivalent to a freight vehicle. The factor for approach grade shown by *Equation 4*, is valid for the longitudinal gradient of approach *G* between the values of -6% and +10%, and it describes the influence of the longitudinal road gradient on the ideal traffic flow.

$$f_g = 1 - \frac{G}{200} \tag{4}$$

The longitudinal gradient does not have a significant impact on the ideal traffic flow and changes slowly depending on the gradient. The factor of the longitudinal gradient does not affect the ideal traffic flow when the longitudinal gradient is zero.

The factor for the existence of a parking lane and parking activity adjacent to the group of lanes represented by *Equation 5* is obtained through empirical measurement and is valid for the number of parking manoeuvres per hour Nm between 0 and 180 [manoeuvres/h]. The average duration of a manoeuvre affecting the ideal traffic flow is considered to be 18 [s].

$$f_p = \frac{N - 0{,}1 - \frac{18 \cdot N_m}{3600}}{N} \tag{5}$$

The maximum possible value of the factor is equal to 1, indicating that at this value, longitudinal parking does not exist. Considering a larger number of lanes (in the group of lanes), it is evident that parking has a smaller impact on the ideal traffic flow. The minimum value of the parking impact factor is 0.05 with a number of manoeuvres of 180 [manoeuvres/h].

The factor for the blocking effect of public transport vehicles that stop within the intersection area represented by *Equation 6*, is obtained through empirical measurements, illustrating the impact of the number of public transport vehicles on the ideal traffic flow. The maximum number of vehicles NB considered is 250 [veh/h].

$$f_{bb} = \frac{N - \frac{14{,}4 \cdot N_B}{3600}}{N} \tag{6}$$

A higher number of public urban transport vehicles reduces the factor of the influence of public transport and, consequently, the ideal traffic flow (especially if it involves a flow travelling on a single lane of the roadway). Empirical measurements have shown that the minimum factor of public transport is 0.05, corresponding to a quantity of 250 urban public transport vehicles per hour.

The factor for area type considers only the central urban area. If the area for which the calculation is performed is located in the central urban area, then the factor has a value of 0.9. For other areas, the factor is 1, meaning it does not affect the ideal traffic flow.

The factor for lane utilisation represented by *Equation 7* – illustrates the ratio of the traffic flow in a group of lanes (*q*) to the product of the maximum traffic flow in a single lane of the observed group of lanes (*q1*) and the number of lanes (*N*).

$$f_{LU} = \frac{q}{q_1 \cdot N} \tag{7}$$

The size of the factor of lane usage impact decreases with the increase of the maximum traffic flow in a single lane, ultimately reducing the ideal traffic flow. The factor of lane usage impact is calculated only for the traffic flow that travels through two or more traffic lanes.

The factor for left turns in a group of lanes at signalised intersections is considered in two conditions: for the permitted phase and the protected phase. The permitted phase is when left-turn movements coincide with a conflicting group coming from the opposite direction, while the protected phase is when left-turn movements coincide with a vehicle group with which they do not conflict. Calculating the factor of left-turn impact for the permitted phase is highly complex, and empirical values from the HCM [5] are usually used in such situations. For the protected phase, left-turn movements can have a dedicated lane, and in that case, the factor of left-turn impact is 0.95. For a shared lane in the protected phase, the factor of left-turn impact is obtained by *Equation 8*, which is valid for a pedestrian flow in collision ranging from 0 to 1700 [pedestrians/h]:

$$f_{LT} = \frac{1}{1 + P_{LT} \cdot [0.05 + (PJ/2100)]} \tag{8}$$

where:
P_{LT} = left-turn proportion (0-1),
PJ = pedestrian flow in conflict [pedestrians/h].

Empirically, a higher pedestrian flow in conflict does not have a significant impact on the decrease of the left-turning factor at a low percentage of left-turning vehicles. However, an increase in the percentage of left-turning vehicles significantly reduces the left-turning factor.

For the impact of right-turn vehicles, there are three mathematical models used to calculate the factor of impact of right-turn vehicles, models for a dedicated lane, for a shared lane and for an approach with a single lane. As with the left-turn factor models shown in *Equations (9-11)*, these models are valid for the pedestrian flow size in conflict up to 1,700 [pedestrians/h]. The mathematical model for the factor of impact of right-turn vehicles for a dedicated lane is shown in *Equation 9*.

$$f_{RT} = 0{,}85 * (PJ/2100) \tag{9}$$

In the dedicated lane model, the size of the right-turn factor does not depend on the percentage of right-turning vehicles but rather on the pedestrian flow size in conflict. The calculation for the factors of impact of right-turn vehicles in situations with a shared lane is shown in *Equation 10*, while the calculation for the approach with a single lane is represented by *Equation 11*.

$$f_{RT} = 1 - P_{RT} \cdot [0.15 + (PJ/2100)] \tag{10}$$

$$f_{RT} = 1 - P_{RT} \cdot [0.135 + (PJ/2100)] \tag{11}$$

The impact factor of right-turning vehicles in situations with a shared lane is somewhat lower than in the case of an approach with a single lane. As with left-turning vehicles, the pedestrian flow size in conflict has a greater influence on the right-turn factor than the percentage of right-turning vehicles alone.

The left-turn pedestrian-bicycle adjustment factor, f_{Lpb}, and the right-turn pedestrian-bicycle adjustment factor f_{Rpb} are shown in *Equation 12* and *Equation 13*:

$$fLpb{=}1{-}PLT{\cdot}1{-}ApbT{\cdot}\,(1{-}PLTA) \tag{12}$$

$$fRpb{=}1{-}PRT{\cdot}1{-}ApbT{\cdot}\,(1{-}PRTA) \tag{13}$$

where:
P_{LT} = proportion of Lts in a group of lanes
A_{pbT} = permitted phase adjustment
P_{LTA} = proportion of LT protected green over total LT green
P_{RT} = proportion of RTs in a group of lanes
P_{RTA} = proportion of RT protected green over total RT green.

The procedure to determine this factor consists of four steps. The first step is to determine average pedestrian occupancy, which only accounts for the pedestrian effect. Then relevant conflict zone occupancy, which accounts for both pedestrian and bicycle effects, is determined. Relevant conflict zone occupancy takes into account whether other traffic is also in conflict (e.g. adjacent bicycle flow for the case of right turns or opposing vehicle flow for the case of left turns). In either case, adjustments to the initial occupancy are made. The proportion of green time in which the conflict zone is occupied is determined as a function of the relevant occupancy and the number of receiving lanes for the turning vehicles. The proportion of right turns using the protected portion of protected – plus – permitted phase is also needed. This proportion should be determined by field observation, but a gross estimate can be made from the signal timing by assuming that the proportion of right-turning vehicles using the protected phase is approximately equal to the proportion of the turning phase that is protected. If P_{RTA} =1.0 (that is, the right turn is completely protected from conflicting pedestrians), a pedestrian volume of zero should be used. Finally, the saturation flow adjustment factor is calculated from the final occupancy based on the turning movement protection status and the percentage of turning traffic in the group of lanes [5].

3.2 Degree of saturation and congestion of a group of lanes

After calculating the saturated traffic flow for all groups of lanes, it is necessary to determine the degree of saturation for each group of lanes. This degree of saturation represents the ratio between traffic flow and capacity and is a fundamental parameter for the analysis of intersection capacity. According to *Equation 14* mentioned in [42], the degree of saturation for a group of lanes x_j can be obtained

$$x_j = \frac{q_j}{Q_j} \tag{14}$$

where:
q_j = traffic flow of the group of lanes [veh/h],
Q_j = capacity of the group of lanes [veh/h].

To calculate the capacity of the group of lanes Qj, it is necessary to know the saturated flow of the group of lanes Sj and the ratio of effective green time of the group of lanes g to the cycle time C. The previous sentence can be described by *Equation 15*.

$$Q_j = \frac{g_{i\in j}}{C} \cdot S_j \tag{15}$$

When *Equation 14* and *Equation 15* are considered together, the extension is obtained as shown in *Equation 16.*

$$x_j = \frac{q_j}{\frac{g_{i\in j}}{C} \cdot S_j} \tag{16}$$

Equation 16 can also be written as shown in *Equation 17* and *Equation 18*.

$$x_j = \frac{C \cdot q_j}{g_{i\in j} \cdot S_j} \tag{17}$$

$$x_j = \frac{\frac{q_j}{S_j}}{\frac{g_{i\in j}}{C}} \tag{18}$$

Equation 18 represents the ratio of the degree of saturation (utilisation) of the group of lanes y_j to the ratio of effective green time of the group of lanes to the cycle $\lambda_{i\in j}$ (Split). Through these defined parameters, the degree of saturation of the group of lanes is reached, which leads to the fundamental condition for sustainable traffic light control, as depicted in *Equation 19.*

$$x_j \leq 1 \leftrightarrow \frac{q_j}{S_j} = y_j \leq \frac{g_{i\in j}}{C} = \lambda_i \tag{19}$$

From *Equation 19*, it is evident that the degree of saturation (utilisation) of the group of lanes must be less than or equal to the ratio of effective green time to the cycle. In other words, for the observed group of lanes, the ratio of effective green time to the cycle is greater than the degree of saturation of the group of lanes only if the degree of saturation of the group of lanes is less than 1.

In addition to the fundamental condition for sustainable traffic light control, a significant parameter influencing traffic management at a signalised intersection is the critical degree of congestion of the group of lanes. The critical degree of congestion of the group of lanes, denoted as y_i represents the maximum degree of congestion among the group of lanes y_j in a specific phase. In the observed phase, the ratio of green time to the cycle is greater than or equal to the critical degree of congestion of the group of lanes if the basic condition of capacity is satisfied for all movements in that phase, as expressed in *Equation 20*.

The sum of critical congestion degrees Y for each phase yields the ratio of the difference between cycle C and the total lost time in cycle L to the cycle itself. The preceding sentence can be expressed with *Equation 20*.

$$Y = \frac{\sum_{i=1}^{n} g_i}{C} = \frac{C - L}{C} \tag{20}$$

The critical degree of congestion of a group of lanes determines the critical movement. By satisfying the basic conditions for capacity and traffic safety for the critical movement, the other movements in that phase are also satisfied.

3.3 Determination of intersection capacity

Capacity is the maximum volume of traffic that can traverse a roadway in a specified time, considering designated technological factors. At a signalised intersection, the intersection capacity, or junction capacity, depends on the approach capacity, which, in turn, is influenced by the group of lanes capacity [5]. In other words, the capacity of the intersection is the sum of the capacities of all approaches or groups of lanes. The capacity of a group of lanes can be determined according to *Equation 21*.

$$Q = S * \frac{g_{i\in j}}{C} \tag{21}$$

The interdependence of the presented traffic parameters forms the basis for calculating intersection capacity. These calculations are employed for determining capacity at an isolated intersection. For optimising traffic flows along a corridor or network of intersections, additional parameters are considered. These additional factors may have an impact on the traffic flow that is targeted for optimisation.

4. OPTIMISATION METHODS BASED ON COMPUTATIONAL INTELLIGENCE

In the last decades, researchers have conducted theoretical and practical studies related to CI in the management of signalised intersections. Many of the methods used in these studies could potentially become standards in signalised intersection control. Generally, traditional strategies for signalised intersection control based on mathematical models of traffic flow provide a useful foundation. However, the calculations are often very complex and challenging to meet the real-time computing demands [43]. The description of traffic flows using strict and explicit mathematical models loses the ability to generalise the traffic model.

To address this issue, intelligent computational methods for signalised intersection control are employed, such as fuzzy systems, artificial neural networks (ANN), and heuristic methods like evolutionary computation (EC) and swarm intelligence (SI). Due to the computational complexity, heuristic methods often lead to acceptable solutions only in an offline mode. Therefore, for online optimisation, methods like reinforcement learning (RL) and adaptive dynamic programming (ADP) are used. Building on this, to solve optimisation problems on a broader scale, agent-based approaches are employed. Research related to optimisation approaches and methods is outlined in the review [43] with the details provided in the next chapter.

4.1 Systems based on fuzzy logic

Fuzzy logic emerged as a contrast to the original two-variable logic of computer reasoning with "True" and "False" possibilities. Fuzzy theory developed from the concept of fuzzy rules introduced by Zadeh [44], based on reasoning in the area around crisp values. Fuzzy systems were proposed in the late 1970s and were among the first CI systems successfully implemented in traffic control systems. Despite being known for quite some time, many studies related to signalised intersection control are based on fuzzy systems. In the research [45] authors proposed signalised intersection control using fuzzy controllers. They designed a fuzzy system adaptable to real-time traffic demand. Based on data obtained from inductive loops and fuzzy logic, the green time of signal groups in two phases is extended or shortened. This method was expanded in [46], where authors presented a more complex method of adjusting phase schedules and the green-to-cycle ratio (Split) to increase flow and improve coordination between connected intersections. The method proved successful in all simulation scenarios, showing improvement ranging from 3.5% to 8.4% under normal conditions and 4.3% to 13.5% under varying traffic demand. In the study [47] authors demonstrated the results of a multi-phase signalised controller based on fuzzy logic and a phase sequencer. Simulation results showed an effectiveness improvement of almost 25% compared to traffic-dependent control in high traffic demand and variable traffic conditions. Authors [48] proposed a control model for two interconnected intersections using a trapezoidal membership function embedded in the Mamdani algorithm and the centre of gravity defuzzification method [49]. When comparing traffic-dependent control with fuzzy system control, simulation results indicate improvements in all proposed control scenarios. Authors [50] presented the use of a multi-agent system based on a more complex system that utilises second-order fuzzy logic for optimisation. The system was tested through simulations incorporating agents into the simulated network, which consisted of a total of 25 intersections, 330 links, 23 zones and 132 detectors, with 16 types of simulated vehicles. Simulation results suggest better performance in all scenarios using the proposed method compared to authoritative traffic control methods such as GLIDE and HMS [51–52].

Fuzzy systems are based on fuzzy reasoning, making them easier to apply in various scientific fields. Previous expert knowledge can be easily incorporated into a well-designed set of fuzzy rules, eliminating the need for mathematical models to describe objects. This ultimately makes the construction of a fuzzy controller more intuitive and straightforward. The low implementation cost of fuzzy controllers has attracted the attention of many traffic engineers. The development of CI technologies has further expanded the practicality of such controllers, enabling cooperation with other technologies and integration with expert knowledge [43].

4.2 Systems based on artificial neural network

An artificial neural network is a system that mimics the functions of biological neurons in the brain and the connections between them, simulating the way the brain processes data. By updating the "weights" of individual neurons, an artificial neural network learns and memorises input data to discover patterns or characteristics. Artificial neural networks are a promising technology in the field of AI and can be categorised into various types, such as single-layer networks, multi-layer networks, self-organising networks and networks with feedback. With diverse applications ranging from pattern classification, robotics, prediction, etc., control systems based on artificial neural networks are among the more effective methods [53]. Due to their ability to handle nonlinear, unreliable and time-dependent systems, they are widely applicable in traffic control in urban environments.

In the research [54], the operation of a controller based on ANN is presented. Using a system-wide traffic-adaptive control (S-TRAC) adaptive traffic control system spread across the entire traffic network, real-time optimal signal plans are proposed, and the signal plan database is updated for long-term traffic control. The main characteristic of ANN is learning based on input data, making it often used in conjunction with fuzzy logic systems described in the previous section. This type of CI is called neuro-fuzzy or fuzzy NNs. A traffic coordination control technique with priority assignment to buses was introduced in the research [55]. The coordination control is based on a back-propagation neural network system used to implement fuzzy rules. Simulation results showed a reduction in average delay time from 14.79% to 18.11% and a decrease in the average time spent in the network from 11.79% to 14.21% in all scenarios during peak conditions. For the same scenarios, the average delay time for buses decreased from 30.76% to 45.01%, while the average time buses spent in the network decreased from 16.4% to 17.17%. Similar research was conducted where they presented the possibilities of implementing a learning-capable fuzzy neural network [52]. Comparing simulation results of the fuzzy neural network and the GLIDE method [51], it was concluded that the presented method reduced the average delay time by 23% in the morning peak load scenario, 50% in the noon and afternoon peak load scenario, and 78% in the extreme scenario with multiple peak loads. In their research, authors [56] demonstrated the potential for optimising traffic flows on entry ramps of urban highways using an adaptive neuro-fuzzy inference system (ANFIS). A traffic model was created for the Zagreb city (Croatia) beltway, presenting the control system and integration possibilities of the proposed system with existing control algorithms. These techniques can be further enhanced with reinforcement learning techniques. The basic idea of reinforcement learning in a fuzzy neural network system was demonstrated in the research [57]. An isolated intersection controlled by a fuzzy controller formulated by a neural network was incorporated with a reinforcement learning algorithm that evaluates previous steps and system solutions based on reducing or increasing the average delay time. The feedback is then used for fine-tuning the membership function in the fuzzy controller.

4.3 Systems based on heuristic methods

Systems based on heuristic methods are inspired by nature and often incorporate algorithms such as genetic algorithms (GA) in evolutionary computing (differential evolution, cultural evolution, etc.) or algorithms of swarm intelligence. These genetic or evolutionary algorithms mimic natural processes such as natural evolution, based on the survival of the fittest individual. Technologies based on swarm intelligence principles have algorithms that mimic collective behaviour in nature, such as bird flocks, ant columns, bee swarms, etc. [58]. Both methods use heuristic search procedures to find optimal or sufficiently good solutions by simplifying nonlinear programming solutions [43]. Due to their adaptability, heuristic methods are applied in various scientific disciplines and for solving a wide range of computer problems.

In the study [59] authors demonstrated the optimisation of signal plans using a genetic algorithm, the TRANSYT simulation tool, and a path flow estimator (PFE). The program called GATRANPFE finds solutions using the performance index (PI) and a problem minimisation formulation embedded in the PFE algorithm. Results showing an increase in PI by 34% indicate that the presented approach is simpler and more effective than the mutually consistent (MC) approach, whose results were taken for comparison. In their work, authors [60] used GA to find optimal parameters for a hybrid multi-agent system based on fuzzy neural networks. The research [61] illustrates the possibilities of applying the particle swarm optimisation (PSO) algorithm as an enhancement to the fuzzy traffic control system. With the PSO algorithm, the fuzzy system gains the ability to learn from experience. Comparing simulation results of fuzzy control and fuzzy control with the PSO algorithm, the second scenario showed an improvement in reducing the average delay time by an average of 20.33% over six simulations. A comparison of results between scenarios with traditional fixed control and fuzzy PSO control showed an improvement in reducing the average delay time from 10% to 35%. In the study [62], the authors presented the results of research based on an intelligent real-time traffic network control approach. Using a four-phase multi-objective isolated intersection model, they demonstrated the optimisation effect using the differential evolution algorithm. The differential evolution algorithm served for the optimal configuration of phase distribution and cycle duration. Simulation results show that the proposed approach can select a better configuration scheme for traffic signalisation and has better real-time performance, considering parameters such as traffic network relief and reduction of the average time spent in the network.

From the presented research in this section, it can be concluded that heuristic methods are a good way to enhance CI technologies, such as fuzzy systems or neural network-based systems. In addition to heuristic methods, there are enhancement methods that reduce computation time, based on reinforcement learning techniques and dynamic programming. These techniques are described below.

4.4 Systems based on reinforcement learning and adaptive dynamic programming

Due to the computational complexity, heuristic methods are not suitable for real-time calculations, and often the results cannot be achieved within the time frames required for real-time network (online) management. Therefore, in network optimisation of traffic signal controllers as an enhancement to systems based on CI, reinforcement learning methods are used. According to [63], reinforcement learning is a machine learning method that attempts to find optimal steps in improving a system through interaction with a given environment using an “agent”. Reinforcement learning typically consists of three elements: state, action and reward [43]. The reinforcement learning agent responds based on predefined states and depending on the quality of the response from the environment, it receives a reward that serves as a learning element and helps the agent improve future steps.

States and actions can be summarised in discrete and continuous methods. The most commonly investigated discrete reinforcement learning methods are based on the application of the Q-learning algorithm [43]. Q-learning represents off-policy learning through a model-free RL algorithm. Off-policy means that in the iterative process of updating Q-values, the agent greedily selects the next action, which may not necessarily be the action of the current optimal control law. The function then defines the optimal control law, representing guidelines for selecting the optimal action for each system state. The model-free approach implies that it is not necessary to know the system model, i.e. the transition probabilities from the current state to a new one depending on the action taken. In Q-learning, the agent learns how to act in specific situations through trial and error, receiving feedback from the environment defined by the reward function.

Examples of using the Q-learning algorithm at the intersection level were demonstrated by the authors of the study [64]. Through three simulation scenarios of a four-legged isolated intersection, the effects of the implemented algorithm were presented. The research results showed that the presented algorithm can improve traffic conditions by timely shortening or extending green times depending on traffic demand. In their research, authors [65] presented a reinforcement learning method that uses a competition approach between multiple tasks (similar to the Q-learning algorithm) called W-learning. The method was used to reduce speed differences on fast roads with many junctions and thus harmonise traffic flow. The presented reinforcement learning approach shows the potential to improve traffic parameters by up to 18%. In [66], a reinforcement learning algorithm that makes decisions based on traffic volume in the area of several connected intersections is presented. Simulation results showed that the presented RL algorithm reduces average waiting time by more than 25% in congestion conditions compared to a scenario controlled by fixed non-adaptive traffic signal controllers.

Adaptive dynamic programming (ADP) combines dynamic programming (DP), reinforcement learning and function approximation method [67]. As shown in *Figure 3*, ADP consists of action, critic and model modules. According to historically collected data, the present traffic state $x(t)$ is obtained, which becomes the input of the action network. The output of the action network/module is $u(t)$ which becomes the input of the model module. At this point, the next system status $x(t+1)$ can be defined. The inputs of the critic module are both $x(t)$ and $u(t)$. The critic network's output $J(t)$ is the output performance index of the critic module.

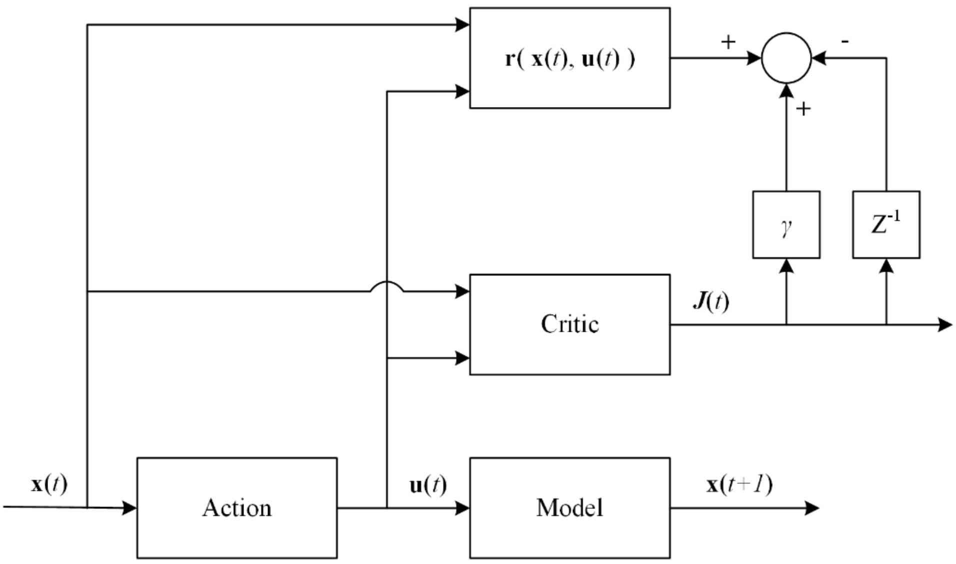

Figure 3 – Schematic representation of ADP

The parameter r represents the reinforcement signal which can be in the range $0 < r < 1$. The models of critic and action are not always based on neural networks but can be governed by any linear or nonlinear approximating form [43]. For instance, in [68], the results of a traffic control system based on adaptive dynamic programming that utilises a reinforcement learning controller were presented. With the presented system, it is possible to reduce vehicle delay time compared to fixed and dynamic traffic management while maintaining satisfactory computational speed. In another work, authors [69] introduced an ADP traffic intersection controller where the action model is based on a neuro-fuzzy system, while the critic model is composed of a three-layer artificial neural network. Simulation results indicate the potential for dynamic adjustment of parameters and achieving approximately optimal solutions. Compared to traditional ADP controllers, the presented controller enhances the learning efficiency with the neuro-fuzzy system, evident through a reduction in average vehicle delay.

4.5 Systems based on agents

Over the past few decades, agent-based technologies have become the preferred approach for developing distributed systems on a broader scale. Many agent-based methodologies have found applications in traffic management [70]. As defined by [43], an "agent" represents a technology that integrates various technologies. Essentially, it constitutes a physical and logical architecture encompassing all the technologies employed in the given system. The agent-based problem-solving approach facilitates the real-time resolution of traffic issues across a wider observed area, covering the entire traffic network.

Research [71] presents the results of traffic network management using a traffic model example. Traffic management for a model with six interconnected intersections is based on a multi-agent reinforcement learning approach. To minimise the computational load, each vehicle agent calculates its value function, while intersection agents manage only local "state-action" pairs embedded in the controller. In [72] the authors demonstrated a distributed multi-agent system for controlling a signalised traffic network. Each intersection is controlled by an agent that exchanges traffic information, coordinating decisions while retaining the ability to make autonomous decisions at the local level. The optimisation background involves the Q-learning algorithm, which computes distributed values for the desired functions. This system's advantage lies in its ability to scale larger problems at the local level while optimising locally to find a solution for the entire observed area. The authors also noted the necessity of applying a hierarchical architecture when managing heterogeneous systems. Such management was depicted, introducing a system based on a hierarchical distributed multi-agent approach [73]. The system's control is a complex hybrid evolutionary fuzzy neural network. Each agent, based on fuzzy system inference and learning facilitated by the neural network, can make real-time traffic management decisions. Additionally, the incorporation of reinforcement learning, based on the error backpropagation algorithm, allows weight and learning rate adjustments and the adaptation of fuzzy connections. In the research [74], the authors introduced a system for predicting traffic load and intersection control based on agents. The agent-based load prediction model estimates the load in the near future using a meta-model. Comparing the accuracy of data obtained from various sources (vehicle detectors, relevant meteorological systems, control systems at the strategic level, control centres, etc.) provides traffic loads, and if there is a lack of relevant data, they are supplemented using adjustment parameters. The intersection control model based on agents, through IF-THEN rules entered by an expert into the knowledge base and input data obtained from the traffic prediction agent, determines the cycle length and other parameters affecting the junction's capacity and the traffic network. In the research [75] authors divided a large group of networked agents into smaller groups. Using a hierarchical approach within smaller groups, with the help of algorithms based on Markov processes and game theory, learning between agents was enabled. In addition to learning between agents, supervision of divided agent groups by other agents was implemented, creating a system that mimics traffic management at both the local and "global" (micro and macro) levels. The supervision system consists of three phases. In the first phase, the supervising agent collects information (on states, actions and rewards) from the agent being supervised. In the second phase, considering data from other agents, the supervisory agent selects the best solution for a particular state and recommends an action to the supervised agent. In the third step, the agent being supervised continues to receive recommendations but does not take action if it can choose a better solution (re-evaluates the offered solution). Throughout the management process, each supervising agent updates its "case base", while the supervised agents update the "learning table". In an extensive study, the authors [76] provided an overview of research based on multi-agent deep reinforcement learning (DRL). The research presented best practices for selecting appropriate DRL, adjusting parameters and designing model architectures. Additionally, the authors discuss the importance of the concept of open traffic data for expanding the use of DRL in real-time adaptive signal plan control systems (ATSC). Systems based on agents, as shown, offer a potential way to reduce the time needed for executing optimisation computational operations. Traffic centres, control units, sensor devices and information devices were used in the research [77] to supplement tasks related to traffic management and functions that should be fulfilled by agent-based systems. This provides support in designing, developing and maintaining agent-based systems.

Based on the presented technologies used under the concept of CI, it can be concluded that each of these technologies has its advantages and disadvantages. Due to the complexity of problems arising from traffic flow theory and the interdependence of traffic parameters, it is almost impossible to solve complex traffic problems using a single approach. Therefore, a set of solutions based on fuzzy logic and neural networks is used as the foundation for CI or AI management. From the literature presented, it is evident that such systems are almost always enhanced with heuristic methods that mimic evolutionary processes or natural collective intelligence. The computational complexity of such systems is significant, and since traffic management systems must be able to make decisions based on real-time data and react in a relatively short time, a reinforcement learning approach is required.

Reinforcement learning is based on hybrid combinations of neural networks and fuzzy logic systems, often supported by heuristic algorithms. This approach reduces data processing time, and with fewer iterations, optimal solutions are reached. However, when considering traffic problems on a broader network, these hybrid systems are not able to propose an optimal traffic solution within a satisfactory time frame. To solve optimisation problems on a larger scale, it is necessary to use technologies based on hierarchical processes and managed by agents. This approach allows the optimisation of the traffic network based on the management of states and actions by agents distributed across multiple levels. Network optimisation is then possible at the micro-level while considering the overall management area or macro-level.

5. THE SYSTEM ARCHITECTURE

This chapter describes the integration and interconnection of previously mentioned subsystems into a system used for determining optimal signal plans through an expert system. The physical and communication architecture of the proposed system is integrated into the central control system for the network of signalised intersections as shown in *Figure 4*.

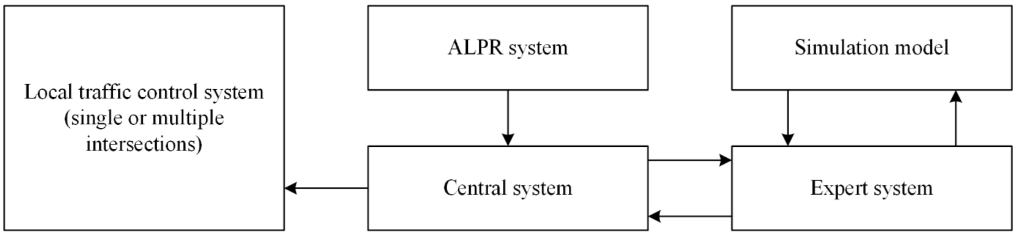

Figure 4 – Presentation of the architecture of the proposed system

In the system for optimisation of signal plans using expert systems, the function of the ALPR subsystem is to create reliable and accurate data. The reliability of the data depends on the quality of the hardware and regular maintenance of the system at a satisfactory level. On the other hand, the accuracy of the data largely depends on several parameters that can affect the proper recording of licence plates (environment, vehicle position, lighting, tilt or non-uniformity of characters on the licence plate or the non-uniformity of licence plates themselves, etc.). To mitigate or minimise the effects of these parameters, the system user must choose an optimal method that satisfies their specified constraints. As mentioned earlier, when making a choice, it is necessary to balance between the ability to recognise non-uniform licence plates (plates with different fonts, colours, sizes and text tilts) and the robustness, speed and accuracy of recognition. In other words, having a good understanding of the environment in which the system is implemented is crucial to increasing the system's success rate.

Based on reliable and real-time data, a KBES, along with methods of CI, determines the current network loads and optimally manages signal plans considering specific demands. To determine the current demand, it is necessary to enable the search of a large dataset stored in the database, containing pre-recorded data on vehicle trajectories through the considered segment of the traffic network. In other words, before optimising signal plans through expert systems, the ALPR subsystem should be connected to the database recording movement trajectories.

The foundation of the KBES relies on IF-THEN rules of fuzzy logic embedded in the knowledge base by experts. These rules are built on mathematical models describing the interdependence of traffic parameters, i.e. the impact of physical characteristics and saturation of traffic flow on the capacity of signalised intersections. The enhancement of the reasoning system based on CI aims to enable the expert system to learn through trial and error and, in a real and acceptable time, draw conclusions and propose optimal solutions. Therefore, for optimising broader areas such as urban traffic networks, the recommendation is to build a system based on multi-agent hierarchical processes. For a trial-and-error learning system, it is necessary to build a well-calibrated and validated simulation model that will, with a high degree of certainty, mimic the real state and provide relevant results. The simulation model serves as a learning platform for the expert system. The interconnection between the expert and microsimulation systems allows for the evaluation of the effectiveness of individual solutions, providing feedback based on which the expert system concludes that it has reached an optimal solution. The optimal solution is obtained in the form of signal plans that correspond to the traffic network management strategy for a particular load. After selecting the optimal solution, through communication links in the central system, signal plans are sent to the local control systems of signalised intersections in real-time.

6. CONCLUSION

Through a detailed review of relevant scientific literature, the possibility of integrating existing separate solutions in the field of Intelligent Transport Systems into one comprehensive innovative solution has been described. This work provides the conceptual and theoretical basis necessary for the development of a system for determining optimal signal plans using expert systems. The proposed concept consists of three interconnected modules that use innovative solutions to collect and process real-time data, based on which signal plans are determined with a prior assessment of success. The modules or components of the concept are ALPR, a KBES with computational intelligence and microsimulation software/tool. The integration of proposed models into one comprehensive system is a very complex process that must follow the system architecture which is also defined in this research. As clarified in the paper, the shift from traditional mathematical models of traffic flow towards intelligent computational methods was made. Fuzzy systems, ANNs, and other heuristic methods, leading to artificial intelligence, have emerged and can be used as an intuitive approach that leverages expert knowledge.

The integration of fuzzy logic with real-time traffic demand shows the adaptability and improvement achieved in coordination between signalised intersections. Also, the synergy of ANNs with traffic control systems points to their effectiveness in adapting to real-time traffic demands. Other presented expert system approaches such as reinforcement learning and ADP can also be used for real-time signal plan optimisation, especially with the application of Q-learning algorithms. The system architecture proposed in the paper integrates these computational intelligence subsystems into a unified solution for determining optimal signal plans through an expert system. The ALPR subsystem serves as a critical component for collecting reliable and accurate real-time data. The KBES, utilising IF-THEN rules of fuzzy logic, integrates CI methods to analyse and manage real-time traffic demand efficiently. The hierarchical multi-agent approach proposed in the system architecture offers a potential solution for optimising traffic networks on a larger scale, balancing computational complexity with real-time decision-making.

In conclusion, this paper provides a comprehensive overview of optimisation methods based on expert systems for the control of signalised intersections. By examining the possibilities of developed expert systems, fuzzy logic, and ANNs, this research proposes a methodology and system architecture for intelligent traffic control. The proposed system architecture integrates these methodologies, showcasing a holistic approach toward achieving optimal signal plans in real-time traffic scenarios. The synergy of these computational intelligence techniques offers a promising avenue for addressing the complex and dynamic nature of traffic optimisation problems. According to the presented, future research will be focused on selecting a test corridor or a network of intersections and creating a well-calibrated simulation model for traffic optimisation. After creating the test corridor, based on simulated data, the effectiveness and robustness of the proposed system will be examined in scenarios with different traffic loads.

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Luka Dedić, Miroslav Vujić

Pregled integracije ekspertnih sustava u području optimizacije signalnih planova

Sažetak

U urbanim mrežama, periodična vršna prometna zagušenja često se događaju tijekom dana, posebno u jutarnjim i popodnevnim satima. Zbog prostornih ograničenja i nemogućnosti povećanja kapaciteta putem fizičkog proširenja cesta, moderno upravljanje prometom sve više se oslanja na rješenja Inteligentnih Transportnih Sustava (ITS). Jedno od takvih rješenja je integracija automatskog prepoznavanja registarskih pločica, ekspertnog sustava i mikrosimulacijskih alata usmjerenih na optimizaciju performansi mreže signaliziranih raskrižja. Na temelju stvarnih i povijesnih podataka o putanjama pojedinačnih vozila, sustav predviđa rutu svakog vozila kroz promatrani segment prometne mreže, određuje opterećenje mreže i predlaže optimalne signalne planove. Ovaj rad pruža pregled provedenih istraživanja vezanih uz optimizaciju signalnih planova koristeći ekspertne sustave. Opisani su matematički modeli za određivanje kapaciteta i opterećenja, kao i sustavi temeljeni na računalnoj inteligenciji koji se koriste za strategije upravljanja signaliziranim raskrižjima. Na kraju, rad predlaže osnovni okvir i smjernice vezane uz predloženi sustav, ističući otvorena pitanja i potencijalne izazove u njegovom razvoju.

Ključne riječi

upravljanje urbanim prometom, automatsko prepoznavanje registarskih pločica, računalna inteligencija, predviđanje putanja vozila, mikrosimulacijski alati.