Traffic Signal Control with Autonomic Features

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Abstract Inspired by diverse organic systems, autonomic computing is a rapidly growing field in computing science. To highlight this advancement, this chapter summarises the autonomic features utilised in a traffic signal control in the form of an operational control system, not simply a simulation study. In addition, the real-time simulation is used to refine the raw sensor data into a comprehensive picture of the traffic situation. We apply the multi-agent approach both for controlling the signals and for modelling the prevailing traffic situation. In contrast to most traffic signal control studies, the basic agent is one signal (head) also referred to as a signal group. The multi-agent process occurs between individual signal agents, which have autonomy to negotiate their timing, phasing, and priorities, limited only by the traffic safety requirements. The key contribution of this chapter lies not in a single method but rather in a combination of methods with autonomic properties. This unique combination involves a real-time microsimulation together with a signal group control and fuzzy logic supported by self-calibration and self-optimisation. The findings here are based on multiple research projects conducted at the Helsinki University of Technology (now Aalto University). Furthermore, we outline the basic concepts, methods, and some of the results. For detailed results and setup of experiments, we refer to the previous publications of the authors.

Keywords Autonomic computing • Fuzzy control • Multi-agent systems • Optimisation • Real-time traffic simulation • Signal group • Traffic signal control

1 Introduction

Autonomic computing mimics self-sustaining organic systems, which are capable of self-protection, self-healing, self-adaptation, and so on. These features enable independent self-management in complex and uncertain environments. The goal

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here then is to demonstrate how various autonomic methods can be utilised in traffic signal control. Arguably, the first traffic signal control was carried out by traffic officers given that the human mind represents the ultimate capability in organic autonomic systems. Thus, the presented traffic signal control method attempts to capture some of those features of the human mind by mimicking these traffic officers.

There are several urban traffic control systems (UTCS) on the market. The most widely used systems are SCOOT [1], SCATS [2], MOVA [3], and UTOPIA/-SPOT [4]. These systems are based on a control loop, which minimises a cost function. The cost function can involve several aspects, e.g. delays, emissions, and public transport priorities. Therefore, these UTC systems have at least some autonomic features, such as being policy driven and adaptive. The aforementioned control systems are phase oriented, i.e. they have predefined phases.

Most of the research in traffic signal control focuses on the optimisation of phase-oriented systems. In these optimised systems, the parameters include the split, cycle, and offset, as well as the order of the phases. For example, in [5], a multi-agent approach with fuzzy control was studied by employing the type-2 fuzzy sets. Likewise, distributed W-learning was used to optimise a phase-oriented signal control [6]. In optimising the split, Shirai et al. [7] utilised the spring model, while Oliveira and Camponogara [8] used a model with predictive control.

To our knowledge, very little research exists on so-called signal group control, in which the phases are not predefined. Kronborg, Davidsson, and Edholm developed the SOS controller, in which Webster's delay calculation was used to determine the green extension of the individual traffic signals [9]. Wong et al. [10] studied group-based signal control; however, their definition for "group" denoted not the signal group but a group of traffic flows. In addition, Niittymäki [11, 12] and Kosonen [13] introduced the use of fuzzy logic with a signal group control. In a review of agent-based systems [14], no other examples of a signal group-based control were referred to, except the system proposed here.

In this chapter, we focus on the signal group control that has been adopted, especially in the Scandinavian countries. Unfortunately, the prevailing concept of a signal group remains somewhat confusing. In fact, the term "signal group" refers to one logical signal. The term "group" refers to the fact that often one logical signal can be represented by multiple physical signal heads in the field (i.e. primary and secondary signal heads). To avoid this confusion, we adopt the term "signal agent" instead of "signal group agent".

These signal agents behave in an autonomic way, pursuing to start green, but limited by other agents due to the safety factors. Here, the multi-agent approach is applied within a junction, not only between the junctions. The main benefit of the signal group control is that phases are composed on demand. As a consequence, unusual phases are possible, such as an all-red rest state and all-green state for pedestrian signals. The Swedish version of the signal group control is called LHOVRA [15].

The drawback of the prevailing commercial signal group controllers is the lack of real-time modelling and autonomic features like self-optimisation and self-calibration. The present systems rely on detectors for traffic actuation, but they do not have a cost function that can be optimised. Thus, this chapter aims to demonstrate how to improve the signal group control with various autonomic features.

The results of this effort are detailed across several sections. In Sect. 2.1., we apply a multi-agent real-time simulation to the processing of the sensor data, refining the detector occupancies into a microscopic traffic situation model. The self-calibration features related to this real-time simulation are presented in Sect. 2.2. Subsequently, Sect. 3 deals with the actual control algorithm; the signal agent and a multi-agent control with fuzzy logic are presented in Sects. 3.1–3.3. In Sect. 3.4, the self-optimisation with neural networks is explained, and an ongoing research project related to coordinated signal group control is introduced in Sect. 3.5. Finally, conclusions and future research are discussed in Sect. 4.

Due to the large number of simulations and field studies undertaken over the years, it is not feasible to present the detailed setup and results of each study within the constraints of this chapter. However, more detailed descriptions and results can be found from the references.

The basic architecture of the proposed control method is demonstrated in Fig. 1. The actual traffic as shown generates sensor data (samples), which is generalised by

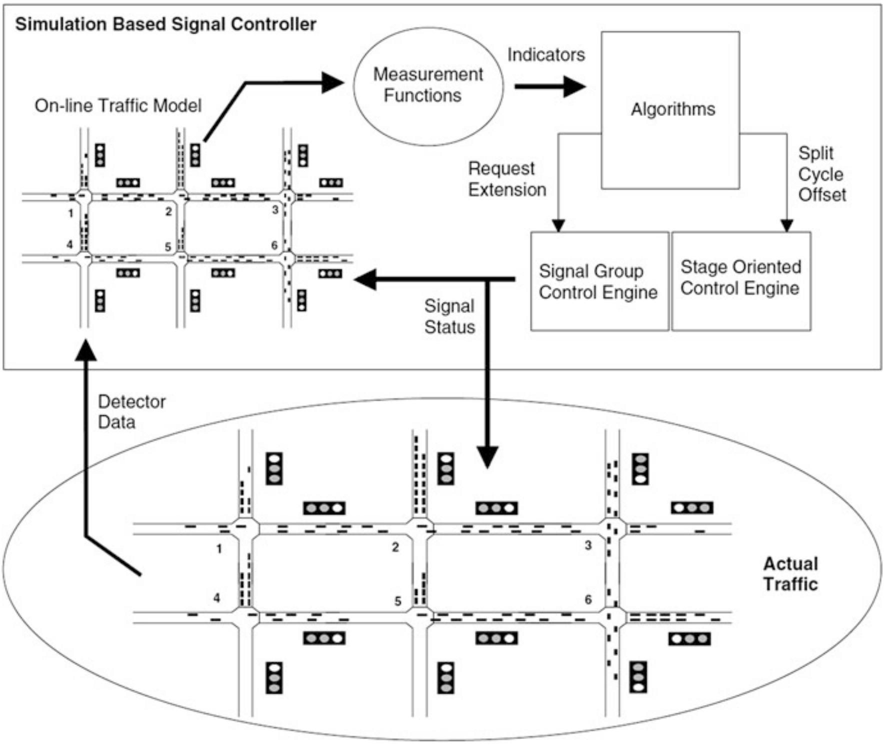

Fig. 1 The basic architecture of a signal control system based on a real-time simulation

using an online simulation. By using the microsimulation model, various indicators or measures of effectiveness (MoE) can be derived and applied as control input.

The artificial intelligence (AI) used for decision making here is fuzzy logic, but the architecture is not limited to any specific form of AI. The control decisions are delivered through a control engine, which can be phase oriented or signal group oriented. Subsequently, this chapter focuses only on the latter option, demonstrating the autonomic features related to this approach.

2 Sensory Processing

2.1 Multi-Agent Real-Time Modelling

Human operators are actually fairly adept at managing traffic flows through a junction. A human operator, such as a traffic officer, has a built-in modelling system, which converts the data from the senses into a comprehensive situational awareness. The human sensory processing system does not passively analyse data but rather acts more similarly to an active modelling and predicting system. During the control operation, previously acquired knowledge (cognitive model) is complemented with real-time information from the senses. The basic concept of applying a real-time simulation remains the same, i.e. to combine previous knowledge (the simulation model) with real-time detector input (the senses). This postulated real-time simulation approach provides an effective means for continuous and comprehensive situational observation.

Microscopic simulation is a form of multi-agent modelling, whereby the vehicle/driver functions as the agent with some degree of intelligence and autonomy. Only microscopic modelling embodies the capability of identifying individual objects (agents) and modelling their interactions. The simulation model is utilised to generalise the samples (detector data) over space and time. Through this dimension of time, the simulation model can also predict how situations will evolve in the short term. In the microscopic model, the previous knowledge involves all of the static features such as the detailed geometry, the lane topology, the detector positions, and so forth. This model may also include many statistical features like average driver behaviour and traffic composition.

The minimum requirement for this is that all vehicles have to be detected at least once (on arrival to the junction area). On arrival, each vehicle is detected and immediately inputted into the simulation model [16]. With additional sensor information, the accuracy of the model can be further improved with the self-calibration features described in Sect. 2.2. In principle, any type of additional sensor technology can be utilised to improve the accuracy [e.g. loop detectors, infrared (IR), radio-frequency identification (RFID), Bluetooth, video, radar, and the Global Positioning System (GPS)].

From the perspective of a seamless comprehensive picture, the simulation model can produce higher-order measures indicating traffic fluency, safety, economy, and environmental aspects. These refined indicators (e.g. delays, queues, stops, fuel consumption, and emissions) can be inputted for the reasoning process in the traffic signal control.

2.2 Self-calibration

Self-calibration is one of the key autonomic features. In a real-time simulation, calibration of the model is not simply a one-time event. The model itself needs to identify the discrepancies between its own state and the sensor data. Based on these differences, proper adjustments are undertaken to ensure the continued accuracy of the model.

The sensor system for traffic lights is usually based on stationary vehicle detectors, like the inductive loops. The sensory processing system relies on the detection of vehicles as they enter the junction area and then predicts the vehicle movements. This prediction tends to drift away from reality over time. Therefore, self-calibration features are necessary in order to correct the prediction using information from the other detectors.

One primary source of error is the vehicle speed, since a typical detector provides the occupancy information only. When detected and generated, the simulated vehicle is afforded its normal cruising speed. When both the actual and simulated vehicles have reached the next detector, the speed difference can then be calculated and the speed of the simulated vehicle adjusted accordingly. It is also important to recognise the vehicle types correctly. The length of the detection pulse indicates the length of the vehicle, given that the speed level is known.

The turning movements are another potential source of error. One approach for this is to maintain a table of turning probabilities. Unfortunately, this table needs to be updated periodically based on average detector counts. With this method, individual vehicles can be incorrectly predicted despite the accuracy of average turning flows. However, a more accurate approach utilises a detector at the beginning of the pocket lane. When a vehicle is detected, then the closest simulated vehicle in the main direction will be forced to change to the pocket lane.

The queue length is an important indicator of the traffic situation, but it is quite sensitive to cumulative errors. Even small errors in vehicle counts can accumulate to create large discrepancies in queue lengths over time. Therefore, the self-calibration features should focus on the detectors, which are occupied over a longer time than the normal vehicle passing time. These detections indicate that the end of the queue reaches the detector. If the simulated situation fails to reflect this, it may become necessary to add or remove vehicles in order to calibrate the queue length.

Moreover, other types of sensors can be employed to improve the calibration performance. For example, a vehicle with a positioning system can indicate the queue length as the moment of stopping. The measured travel times (via RFID or Bluetooth) can be compared to simulated ones in order to calibrate vehicle speeds and other parameters. Additional video or radar systems can provide detailed data about driving behaviour, which can be applied to calibrate the parameters of the vehicle dynamics.

It is worth bearing in mind that driving behaviour is not constant over time. For example, the density of the traffic can affect car-following gaps as well as the lighting, weather, and road friction. Ideally, a “perfect” self-calibration feature should learn these changes on a continuous basis.

2.3 Self-healing

The problems with the sensor systems are often hardware failures, and the physical self-healing capability may not be a realistic option. However, at the software level, it may be possible to replace actual data with the statistical equivalent. In this regard, the most common problem is often a broken detector. This can be diagnosed if there is no activity over a certain period. In the event of a malfunctioning input detector, one possible self-healing feature would be starting to generate vehicles randomly according to the average daily/weekly patterns.

Another type of error can occur with overly sensitive sensors. In this case, the sensor reacts to vehicles in adjacent lanes. By analysing the correlations between vehicle positions and sensor occupancies, it is possible to identify if a detector is not working properly. A self-healing action here would enable incorrect detections to be filtered out automatically.

3 Decision Making

3.1 The Signal Agent

In order to highlight the autonomic behaviour in a signal control, it is again worth considering the role of a human operator (e.g. the traffic officer in the junction). There are two levels of autonomy in the behaviour of the officer. On the conscious level, the officer is autonomous, i.e. no external agent is in direct control, and can thus freely perform tasks within the limits of the traffic rules.

The other autonomic level is subconscious. On this level, previously learned skills produce fast and detailed responses to various traffic situations without much effort on the conscious level. Over time, the traffic officer is also learning to perform better, so there is arguably self-optimisation in the control operation. These subconscious operations are in essence mappings between the inputs and outputs, so they can be implemented in multiple ways. Here, fuzzy inference is applied to produce the mappings and neural networks for the self-optimisation.

In the same fashion, we used fuzzy logic to provide the signal agent with the necessary intelligence. Fuzzy logic can be characterised as calculations with words. In fuzzy logic, all rules and inputs can affect the final output to some degree [17].

This differs significantly from binary logic (true/false), whereby only one branch of the decision tree is followed. As such, fuzzy logic is a deterministic algorithm without any autonomic features. While there exists plenty of literature about fuzzy sets in general, this chapter focuses on the application of fuzzy logic to signal controls.

We do not claim that fuzzy logic is the best of all options, only that it is suitable for signal controls. Generally speaking, fuzzy logic is suitable when the desired mapping can be described as explicit rules provided by a human expert. This is the case in traffic signal controls. The traffic officer or signal control planner's knowledge can be transformed into a form of rule sets, which are then implemented into the control algorithm.

Fuzzy logic as such involves no self-adaptation or learning. The self-adaptation can be included by adjusting the parameters of the algorithm, i.e. the fuzzy rule sets and fuzzy membership functions. This will be explained in Sect. 3.3.

The signal agent is basically making decisions about its own green time (Fig. 2). To enable this, the signal agent requests data from the real-time simulation model regarding the number of approaching vehicles. This input (APP) involves only those vehicles, which are controlled by this particular signal agent. Obviously, a high number of arriving vehicles shift the decision towards extending the green time.

The other input requested by the signal agent describes the number of queuing vehicles (QUE). These vehicles waiting behind the red signal(s) can belong to any number of conflicting signal agents (i.e. they cannot go green at the same time). A high value of QUE puts "pressure" on the signal agent to terminate its green signal early.

Once the signal has entered a green state and the minimum green time has elapsed, the signal agent starts using a fuzzy inference object to determine whether to extend or terminate the green. This decision is repeated after each extension

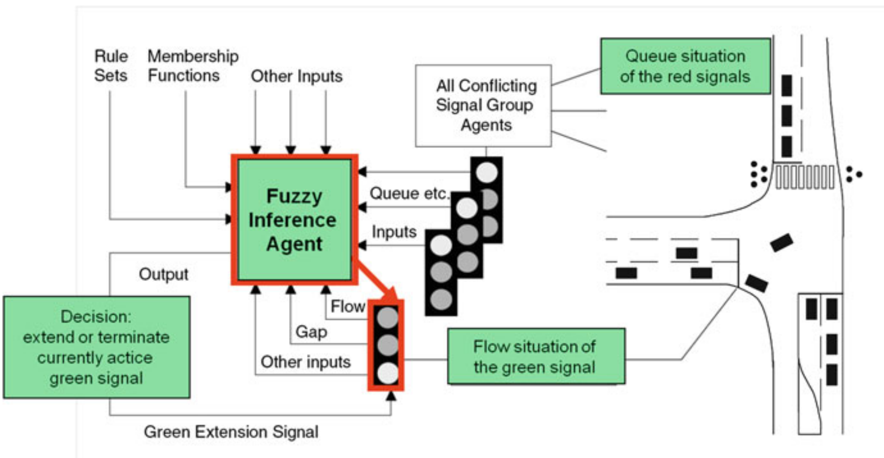

Fig. 2 The signal agent with the fuzzy inference object

(0–10 s), and zero seconds means termination of the green time. The fuzzy inference object is a general-purpose object that performs the fuzzy inference according to the fuzzy rules and the fuzzy membership functions (initialised from an input file). The fuzzy output has to be defuzzified into a strict value, before returning the result to the signal agent.

3.2 *Multi-Agent Process*

Human decisions are most often the result of a group process. This process can be simulated with a multi-agent control approach. In our case, rather than one traffic officer in the middle of a junction, we assume a group of officers each representing one traffic signal. While controlling their own signal, the agents also negotiate with each other to work out the optimal solution within the junction.

The general goal is to maintain the flexibility of phase sequences, while at the same time improve the decisions related to signal timing, phasing, priorities, and coordination. In a multi-agent approach, each signal agent has its own objectives. The basic objective of a signal agent is to obtain and maintain the green state, whenever there are vehicles requesting the green. Similar to those human groups, it is not always possible to act immediately but rather to adapt the behaviour or delay the action according to the states and objectives of the other agents.

In Fig. 3, the concept of a generic multi-agent control is demonstrated with a simple junction. In more complex junctions with plenty of dedicated lane signals, pedestrian crossings, and public transport priorities, the advantages of a flexible multi-agent control become more evident.

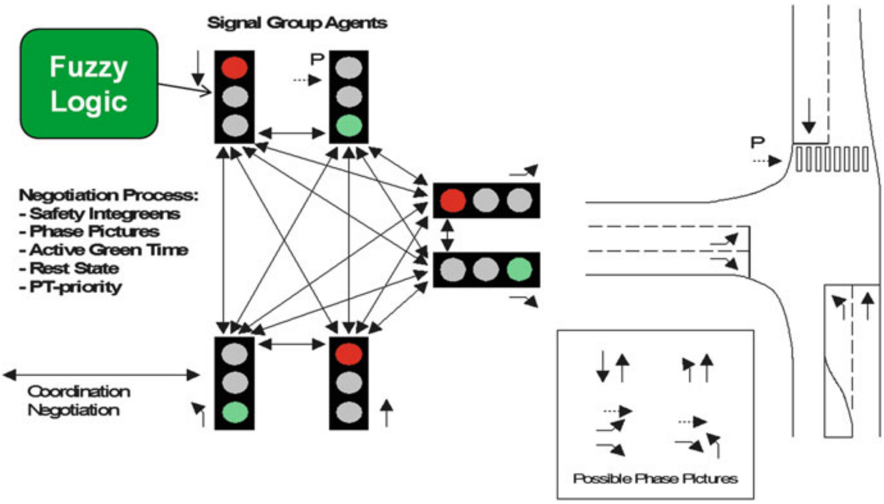

Fig. 3 Multi-agent signal group control in a simple junction [18]

A signal agent starts the transition to the green state through the intergreen and amber states. During the green signal, the other (conflicting) signal agents can create pressure (QUE) to terminate the active green. During the green extension, the APP value is decreasing because of the queue discharge, and the QUE value is increasing because of the queue build-up behind the conflicting signal agents. Depending on the traffic situation, the green extensions become increasingly shorter and finally reach zero, meaning the active green is terminated. After the active green extension, the signal agent can return to red or remain as passive green. If a signal is on passive green, any conflicting signal agent can terminate it immediately. During the green time, any other nonconflicting signal agent can start its own green state and green extension.

After termination of the green signal(s), the other conflicting signal agents have to decide which is next to start green. Obviously, if there is only one candidate with traffic demand, the choice is clear. However, there is often more than one pending signal agent. If they are not in conflict, they can start at the same time; conversely, if they are in conflict, they have to work out who is first in the queue. The agents have autonomy, but only within the limits of traffic safety, i.e. the safe intergreen time must be maintained at all times between conflicting signal agents.

To ensure some equality of opportunity to start green, we use a revolving priority order. The signal agent that had the last green receives the lowest priority (it can still get the green if there is no higher priority signal pending). The signal agent with currently the lowest priority gets the highest priority, and the others move down one step. If there is pending (traffic demand) for the highest priority signal agent, it can start green first. Otherwise, the signal agent(s) at the next priority level is offered the opportunity to start green. In this way, there are no fixed phases; instead, every agent receives an equal chance to start green, if it is pending to do so.

Within this framework, the signal agents have to negotiate and compose a mutual control strategy, which addresses at least the following objectives, listed in order of priority:

– Safety (intergreen management)
– Equality (assuring each direction has a possibility to get green and handling public transport priorities)
– Timing objectives (several objectives: delays, queues, stops, emissions, energy, etc.)
– Minimising transitions (find an optimal rest state when there is no demand)

3.3 Fuzzy Logic Green Extension

The presented methods and system were developed during the FUSICO project (FUzzy SIgnal COntrol) at the Helsinki University of Technology (HUT). The FUSICO software has some similarities to the object-oriented HUTSIM microsimulation software [13]. From signal timing point of view, the most crucial object type is the fuzzy logic green extender, which is connected to the signal agent as described in Sects. 3.1 and 3.2.

In the simulation studies and field testings, our main interest was to find out the performance of the detector logic (gap seeking) versus the fuzzy logic (Fig. 6). With the FUSICO software, we were able to replicate the operation of ordinary signal group controller, by applying the detector logic for green extension. The detector logic provides a simple gap-seeking method for the green extension of the signal agent. In the fuzzy control, we replace the simple detector logic with the fuzzy green extension. While the gap seeking uses the detector pulses only, the fuzzy green extension can utilise the situational awareness provided by the real-time simulation and the other signal agents in the same junction.

Our first step was to implement the fuzzy green extension method introduced by Pappis and Mamdani [19]. In this method the green extension can be 1–10 s. If the fuzzy logic results were equal to the maximum, then a new extension is started after 10 s. Otherwise the green signal will be terminated after the extension time has elapsed. This procedure will be repeated to the maximum of six times.

The Pappi and Mamdani version of the fuzzy logic green extension was found to be a bit inflexible and to cut the green short too easily. Therefore a new version (FUSICO) of the fuzzy green extension was introduced. In this mode, the green extension can get a value of 0, 3, 6, or 9 s. The green signal is terminated only if the result is 0 s; otherwise new extension will be started after the present one expires. The FUSICO version turned out to be more consistent with regard to the traffic situation and provides more sufficient amount of green time.

The basic approach is similar in both versions of green extension. For each consecutive green extension, a different set of fuzzy rules is applied. The membership functions remain the same all the time. In the beginning, the rules allow easy extension of the green time regardless of the queue(s) behind the conflicting red signal(s). After each completed green extension, the rules make it more and more difficult to extend the green; thus the pressure by the queuing vehicles starts to have an effect. Eventually the green will be terminated regardless of the traffic situation since there is a given maximum green time that cannot be exceeded.

The presented signal control method has been evaluated in simulations and tested with field installations. In Fig. 6, the results of a simulation study are shown. The average delay per vehicle is shown as the function of the overall traffic demand in the junction. Our base line here is the ordinary signal group control (gap seeking) since this is the prevailing controller type in Scandinavian countries. Despite the simple logic, the performance of a gap-seeking signal group control is fairly effective. Both types of fuzzy signal control perform better than the base line, but the FUSICO performs slightly better than the Pappis–Mamdani. The fuzzy logic can improve the performance by 10–20 % (see Fig. 4) when compared to gap seeking [20]. However, the gap-seeking algorithm can react more quickly to the arriving single vehicles, which explains the better performance in low-demand situations. These results presented here can be further improved with the self-adaptation feature described in the next section.

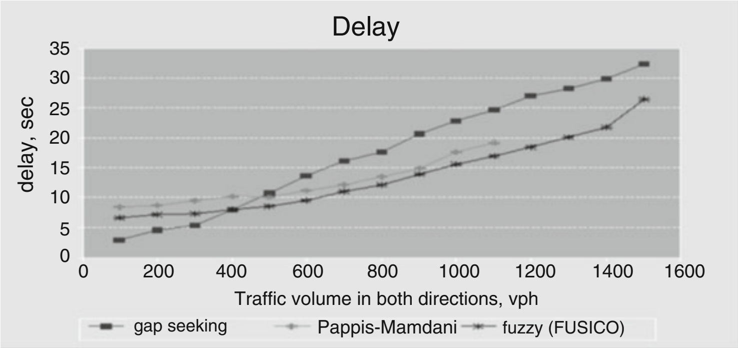

Fig. 4 Demonstration of performance of the fuzzy signal group control against the detector logic-based signal group control (gap seeking).

3.4 Self-adaptation

The fuzzy logic used for the signal control is based on transferring expert knowledge into the rule sets. A traffic signal control expert states the rules and membership functions for use in the control operation. The expert knowledge is generic and may not be optimal for all junctions with various traffic demands.

In this regard, self-adaptation can be implemented in different ways. The one presented here is based on neural networks [21]. Here, the performance is evaluated by delays only, but in more advanced versions, multiple objectives can be handled. At the moment, we are working on evolutionary algorithms for multi-objective optimisation [22].

The self-adaptation is used to fine-tune the membership functions. In this case, reinforced learning tunes the parameters of the fuzzy inference. After each round of a completed green extension, the simulation model provides feedback on the efficiency of the decision made by returning the delay caused by the signal control.

In neural network-based reinforced learning, the information regarding the inputs (APP, QUE) and the consequences (delay) are used to evaluate the performance of the control. Based on the evaluation, the membership functions of the APP and QUE will be modified gradually until no further improvement is achieved (Fig. 5).

With self-adaptation of the membership functions, the performance of the fuzzy signal control can be improved and adapted to various types of junctions or to long-term changes in traffic volumes. In Fig. 6, an example of the results is shown. About a 1-s decrease on the average delay was achieved with traffic flows of more than 400 vehicles per hour.

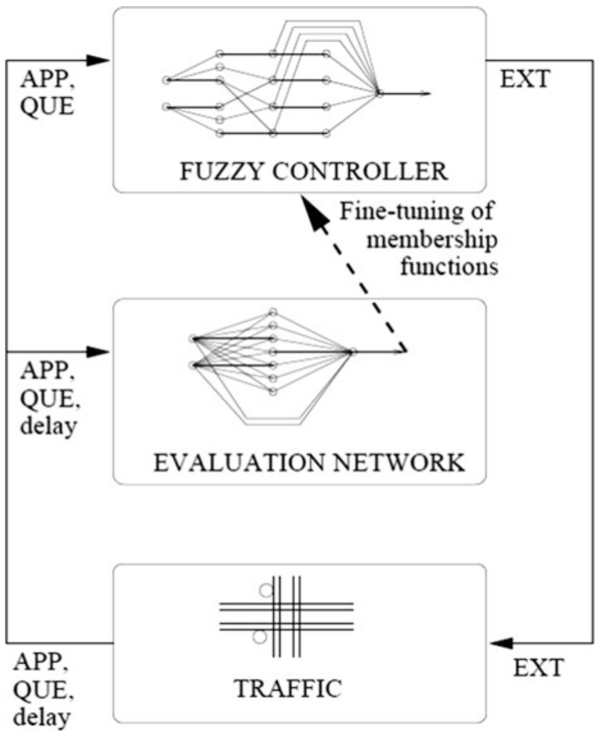

Fig. 5 Self-adaptation by reinforced learning

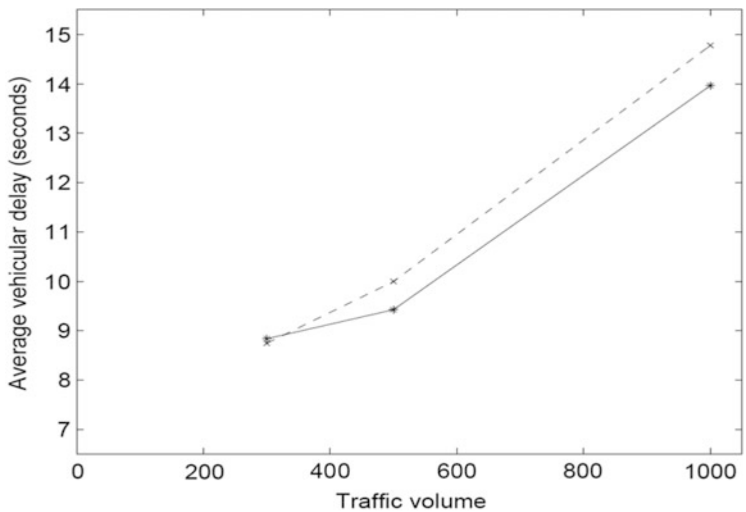

Fig. 6 The average delay before (*dashed line*) and after the self-adaptation

3.5 Autonomic Signal Coordination

In multi-agent area control, one agent is most commonly controlling one junction. However, we aim here to outline a multi-agent area control based on signal agents. The basic principle is the same as in a single junction case, but the negotiation process is extended to the neighbouring junctions. In the multi-agent signal group control, the agents aim to compose green waves for different directions in as flexible of a manner as needed. In addition to green extensions, the negotiation can be applied to phase sequencing and to public transport priorities. This research activity is currently ongoing; therefore within this chapter we can only demonstrate the basic concepts, but not the performance.

There are many possibilities for composing an area control strategy. One possible approach is proposed in Fig. 7. In this example, the signal agents in each junction negotiate regarding the green extensions, as in Fig. 3. In this coordinated operation, this negotiation process is affected by external signals from the neighbouring junctions.

Each signal agent generates two additional outputs for requesting or extending the green signal in the downstream junction. The basic concept is to increase the priority of a moving platoon especially on a main road where a green wave is desired. The increased priority has an effect through the fuzzy inference system. A moving platoon of a certain size and density can be compared to public transport vehicles. In this way, a moving platoon receives priority over other vehicles.

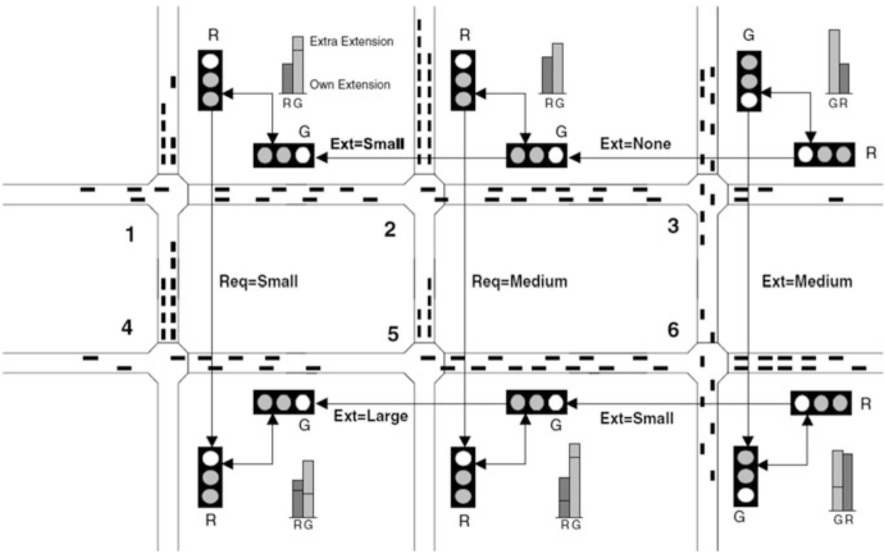

Fig. 7 Outlining a coordinated multi-agent signal group control [18]

This priority can lead to a green extension, early green, or extra phase. A green signal can be given an extra extension due to an approaching platoon. An early green (or red truncation) can be achieved by letting the approaching platoon put extra pressure on the conflicting signal groups to terminate their green signals. An extra phase can be arranged by affecting the priority order of pending signal agents. In this way, green waves can be created in an autonomic way on demand.

The benefit of this approach is that the actual bus priorities can be implemented in the same manner. In the case of buses, there can be additional inputs that affect the weight of the bus request. Factors such as the length of delay, the number of passengers, and the importance of the line could affect the bus priority decisions.

4 Conclusions

This chapter presents an intelligent traffic signal control method based on autonomic signal agents. Each signal agent is attached through a fuzzy logic controller, which handles the interactions with the other agents. The decision process in these interactions is improved with an autonomic self-optimisation feature. Moreover, a multi-agent approach is also used in the sensory processing in the form of a real-time simulation. Autonomic features also involve self-calibration of the simulation during the real-time operation.

The contribution of this chapter rests in the combination of three methods: multi-agent signal group control, real-time simulation, and fuzzy logic. To the best of our knowledge, the presented system or combination of autonomic methods is unique. In this chapter, we do not claim that fuzzy logic or neural networks as such are the best possible choices. The intelligence of the system is encapsulated into objects, which can be replaced with other types of artificial intelligence, while the basic architecture remains unchanged. This approach provides a basis for further research based on the presented system.

Plenty of studies have been carried out both in simulation and field studies. Several versions of fuzzy inference, defuzzification, etc., have been tested. The isolated signal control has already been tested in the field in many cities, especially in the city of Tampere in Finland. Moreover, public transport priorities have been implemented and tested with the presented method. Special features for high speed junctions have also been tested.

This research work has been carried out in several projects by the Helsinki University of Technology (now Aalto University). We aim to continue the research cooperation between Aalto University and the Royal Institute of Technology (KTH). As such, we will continue developing and evaluating the coordinated signal control presented here. In addition, the self-optimisation will be further improved with multi-objective optimisation and evolutionary algorithms.

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