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An intelligent control system for traffic lights with simulation-based evaluation

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Abstract

This paper introduces an intelligent control system for traffic signal applications, called Fuzzy Intelligent Traffic Signal (FITS) control. It provides a convenient and economic approach to improve existing traffic light infrastructure. The control system is programmed on an intermediate hardware device capable of receiving messages from signal controller hardware as well as overriding traffic light indications during real-time operations. Signal control and optimization toolboxes are integrated into the embedded software in the FITS hardware device. A fuzzy logic based control has been implemented in FITS. In order to evaluate the effects of FITS system, this study attempts to develop a computational framework to evaluate FITS system using microscopic traffic simulation. A case study is carried out, comparing different commonly used signal control strategies with the FITS control approach. The simulation results show that the control system has the potential to improve traffic mobility, compared to all of the tested signal control strategies, due to its ability in generating flexible phase structures and making intelligent timing decisions. In addition, the effects of detector malfunction are also investigated in this study. The experiment results show that FITS exhibits superior performance than several other controllers when a few detectors are out-of-order due to its self-diagnostics feature.

Key words: Adaptive traffic signal control, fuzzy control, embedded system, real-time traffic simulation.

1. Introduction

In urban traffic management and operations, signal control systems play a crucial role in mitigating congestion and traffic impact issues. The control scheme can be classified into non-adaptive and adaptive control approaches. The major difference between these two approaches is whether signal parameters can be adjusted in real-time with regards to detected traffic conditions. For both non-adaptive and adaptive systems, on-street detectors, such as in-pavement loop detectors, are deployed for the purpose of improving the performance of signal control systems.

Vehicle actuated (VA) control system is one of the most popular non-adaptive system with the aid of loop detectors. They are commonly seen in European countries. In the Nordic countries, LHOVRA (see Appendix I) and MOVA (Microprocessor Optimised Vehicle Actuation) belong to the earliest VA-based signal control systems initiated in the 1980s (Vincent and Peirce, 1988; Peterson et al., 1986). They are still widely used in Sweden, Finland, Denmark etc. Both LHOVRA and MOVA make extension decision based on time gaps between vehicles reported by detectors. Therefore, the signal timings vary continuously according to the latest traffic condition. In the US, actuated signal controllers, either in a stage-based or dual-ring manner, are widely deployed based on National Electrical Manufacturers Association (NEMA) standards (Tarnoff and Ordonez, 2004).

In the past decades, many transport planning agencies and researchers have attempted to improve the signal systems deployed through tuning control parameters. One of the most widely used methods in engineering application

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is to apply a simulation-based optimization approach with respect to the pre-determined strategies and policies. For example, Ma et al. (2014) applied a stochastic optimization approach (mainly genetic algorithm) to determine signal control parameters for the purpose of improving traffic mobility efficiency, enhancing energy and reducing vehicle wait-time as well as emissions exhausted by vehicles. However, the optimal signal parameters normally correspond to a certain level of traffic demand. Due to the system uncertainties and variation of demand levels, the tuning process for signal parameters should be continuously executed in operations. In practice, control parameters are required to be predefined in the controller hardware. It would be hard to frequently change control parameters under the existing architecture of traffic signal system in order to be in accordance with live traffic conditions.

In parallel to continuous development of non-adaptive signal control system, adaptive control strategies have attracted increasing research interests. For example, SCOOT (Split Cycle Offset Optimisation Technique) and SCATS (Sydney Coordinated Adaptive Traffic System) are among the earliest adaptive signal control systems respectively developed by Hunt et al. (1982) and Sims and Dobinson (1980). The ideas behind the two systems are similar: selecting the most appropriate signal plan from a look-up table according to the traffic condition detected. Alternatively, a number of other adaptive control approaches were, together with the development of vehicle detection methods, proposed by Gartner (1983); Henry et al. (1984); Luyanda et al. (2003); Boillot et al. (2006).

Along with the evolution of traffic signal system, applications of adaptive control methods have shown to be a promising direction for future traffic management. In the mean time, emerging information and communication technology has offered great opportunities for developing more efficient signal control systems. Recently, more innovative approaches, especially from computer science and machine learning, have been applied for the development of adaptive signal control. For example, Cai et al. (2009) formulate signal control as a sequential decision-making problem and solve it using the approximate dynamic programming approach. El-Tantawy et al. (2013) applies reinforcement learning approaches and equips signal system with the intelligence to carry out learning for control parameters. Nevertheless, most adaptive signal control systems focus on managing traffic at the network level using simplified fixed-time (FT) control logic to represent local operation.

In reality, signal systems often apply more advanced detecting and corresponding control technologies, and so there is great need to develop new approaches changing the parameters of the controller adaptively according to traffic conditions. The MOTION signal control system is a recent example, which optimizes the timing plans at the network level and applies vehicle actuated control at the local operation (Brilon and Wietholt, 2013). In addition, Jin and Ma (2015) developed an adaptive control approach based on the existing group-based traffic signal infrastructure. The approach has been evaluated in a microscopic traffic simulation environment. The study reveals that the current signal control system can be significantly improved, in terms of mobility, if control parameters can continuously adapt to real traffic conditions.

In practice, there are policy and economic barriers for deploying completely new traffic signal systems and control strategies. It is therefore convenient and more economic to develop an intermediate system capable of collaborating with current infrastructure and appending new functionalities including new control methods. Such a system should be able to communicate and work together with an already installed controller, receiving detection information and providing traffic light indications. Optimization algorithms and new control strategies should be implemented as software and embedded into the system. Fuzzy Intelligent Traffic Signal Control (FITS) is such an intermediate system dedicated for traffic signal control at urban intersections. It is implemented on an ARM single board computer capable of communicating with real signal controllers (such as LHORVA, MOVA and NEMA) as well as receiving detector information from the existing infrastructure.

Fig. 1 shows the hardware on which the FITS control system has been implemented. FITS applies real-time traffic simulation to predict live traffic states at the intersection being controlled. The simulation software embedded in the device determines traffic conditions using detecting data. The controller can take over the signal control tasks and apply its own control logic. Indeed, a fuzzy group-based signal control approach has been adopted in the control program. The pioneer development of the Fuzzy Control algorithm showed many advantages over conventional group-based signal controller in the FUSICO (FUZZY Signal COntrol) project (Niittymäki and Pursula, 2000). Currently, the control algorithm has been enhanced and implemented as embedded software in the new single board computing device with new functionalities such as automated signal optimization. The system has also been commercialized for real applications in several cities in the US and Europe.

This paper aims to introduce the basic principles of FITS system. Moreover, the effectiveness of FITS system is evaluated by using an integrated simulation framework in a laboratory environment, so called FITS-in-the-loop

Fig. 1. The FITS control device (left) with embedded software for fuzzy signal control and real-time traffic simulation (right).

simulation. The rest of the paper is organized as follows. Section 2 describes the basic principles of FITS signal control system. The following section illustrates the evaluation approach using FITS-in-the-loop simulation. A case study is then carried out using the SUMO microscopic traffic model and the results are presented in Section 3. Section 4 concludes the paper with summary and future work.

2. FITS system

2.1. Fuzzy control for signal timing

The original idea of the FITS controller was to mimic human policeman in controlling traffic lights at an intersection. Signal timing is generated by understanding the prevailing traffic situations using the detection information obtained. Here, vehicle detecting information has to be processed for representing the current state of the traffic system. Fuzzy Logic is therefore applied to approximate the reasonings of human mind while modeling uncertainty of the traffic conditions perceived. Indeed, a variational implementation of a microscopic traffic simulation model (Kosonen, 1999) is embedded as software in the controller to predict the states of the traffic system.

The microscopic model represents the states and interactions among vehicles as well as the status of signal controllers. The interaction between vehicles is modeled using a rule-based system. The speed and lane change of a vehicle are determined by a set of rules that are executed every time step. In addition, after receiving detection information, the simulation model has the capacity to adapt its prediction based on the current state. Simultaneously, it is also possible to derive from the simulation model some useful measures indicating, for example, the average delays, queues, stops, emission etc. In fact, these refined indicators can be used as inputs for the reasoning process in the controller. The sensors within this paper are limited to stationary vehicle detectors, although other types of sensory information are also adopted to FITS in real applications.

Since real-time simulation may predict the state of traffic system and effects at intersections, different types of traffic inputs and derivable measures can be applied in the fuzzy rules. In the current implementation, the fuzzy inference process is encapsulated into its own generic object in the object-oriented framework. In general, the standard Mamdani fuzzy inference system has been applied in the rule-based reasoning in FITS. It is based on the controller developed as part of the FUSICO project with modifications to the rule set. This section illustrates the basic principles of the fuzzy signal controller but more technical aspects are presented in the publication of the FUSICO study (Niittymäki and Pursula, 2000).

For the inference system, fuzzy membership functions and rules are the essential components. The input variables of FITS are mapped by sets of membership functions, converting them into fuzzy truth values between 0 and 1. Since group-based phasing and vehicle detecting information are applied for signal control, the inputs of traffic volume,

occupancy, queue length and waiting time for certain signal group are inferred when making control decisions. Although a general membership function is defined in the system, simple triangle membership functions are currently adopted for all input variables. For instance, queue length can be modeled by a number of fuzzy sets including "zero", "a few", "medium" and "long". The membership functions of the fuzzy sets can be described as follows:

- "zero"

$$f(q) = \max \left\{ \min \left\{ \frac{5-q}{5}, 1 \right\}, 0 \right\} \quad (1)$$

- "a few"

$$f(q) = \max \left\{ \min \left\{ \frac{q}{5}, \frac{10-q}{5} \right\}, 0 \right\} \quad (2)$$

- "medium"

$$f(q) = \max \left\{ \min \left\{ \frac{q-5}{5}, \frac{15-q}{5} \right\}, 0 \right\} \quad (3)$$

- "long"

$$f(q) = \max \left\{ \min \left\{ \frac{q-10}{5}, 1 \right\}, 0 \right\} \quad (4)$$

where $q \geq 0$ denotes the number of queuing vehicles. The membership functions here are triangle roof function.

Fuzzy rules in the original FUSICO project are developed for reasoning at three levels: traffic situation, phase and sequence selection, and green extension and termination. At the highest level, a control policy is determined according to the live traffic situations. For example, the control policy of over-saturation situation is the capacity maximization whereas low traffic situations apply the policy of First In First Out (FIFO). The purpose of second level is to enhance the capacity performance by reducing inter-green times based on the selection of next signal groups. The lowest level of control focuses on local timing decisions. The green extension and termination level is used to determine whether the controller should extend the current green according to the detected information. Examples of fuzzy rules below are, respectively, shown for the three different control levels.

- Traffic situation level:

$$(\text{VOL} = \text{low}) \oplus (\text{OCC}_{\max} = \text{zero}) \rightarrow (\text{TS} = \text{low}) \quad (5)$$

where $\text{VOL} \in \{\text{low}, \text{medium}, \text{high}\}$ denotes traffic volume of the past time interval (e.g. 5 minutes) at the intersection; $\text{OCC}_{\max} \in \{\text{zero}, \text{normal}, \text{high}\}$ represents the maximum occupancy of the detectors that are located at the stop line; TS means the traffic situation; $\oplus$ is the fuzzy "AND" operator; $\rightarrow$ is the fuzzy inference operator.

- Phase and sequence selection level:

$$\text{W}(B) = \text{high} \rightarrow (\text{NP} = B) \quad (6)$$

where $\text{W}(B) \in \{\text{very high}, \text{high}, \text{medium}, \text{low}\}$ denotes the weight of phase B ; NP denotes the next phase. The principle of phase generation is illustrated in the next subsection.

- Green extension and termination level:

$$(\text{W}_{\text{red}} = \text{low}) \oplus (\text{GRN} = \text{short}) \oplus (\text{GAP} = \text{long}) \rightarrow (\text{TD} = \text{extend probably}) \quad (7)$$

where W_{red} represents the weight for all red signal groups; $\text{GRN} \in \{\text{short}, \text{medium}, \text{long}\}$ denotes the running time of the green signal group; $\text{GAP} \in \{\text{short}, \text{medium}, \text{long}\}$ denotes the last observed gap between two approaching vehicles according to the detectors located at 80-100 meters away from the intersection; $\text{TD} \in \{\text{terminate certainly}, \text{extend probably}, \text{extend certainly}\}$ represents the timing decision.

In general, fuzzy inference system generates a crisp decision output given the crisp input values, consisting of the following three steps: fuzzification, rule-based inference and de-fuzzification. Fig. 2 gives an example of the fuzzy inference mechanism for green time extension. First, three inputs, W, GRN and GAP, are mapped into fuzzy degrees according to the membership functions in different rules (the left part in Fig. 2). The strength of each rule is computed by combining the antecedents according to the operators. For example, "AND" operator is mostly used in the system.

Fig. 2. Illustration of the fuzzy inference mechanism for group-based signal timing.

The strength of each rule is then computed by taking the minimum value from the fuzzy degrees of rule antecedents. The membership function of the consequence is clipped by the value of the rule strength. The output distribution is achieved by combining the outputs of all fuzzy rules (see right part of Fig. 2). Since the "OR" operator is used to combine all the rules, the final consequence is the aggregation of the clipped fuzzy sets derived by the rules.

The de-fuzzification function in the system is implemented through a general interface where various methods can be applied. The center of gravity method (COG) is the default de-fuzzification method for timing decision. The output is computed by

$$O_{cog} = \frac{\int x f(x) dx}{\int f(x) dx} \quad (8)$$

where O_{cog} denotes the crisp output for the extension ratio, $f(x)$ is the aggregation of the fuzzy sets derived by rules and x is the timing decision variable. The decision output of extension ratio is then compared with the preliminary extension criteria (e.g. 0.5 is used by default) to decide whether the signal group should extend its green time. In order to give readers an opportunity to evaluate the intelligent control approach of FITS, a set of fuzzy rules, developed and used in our university lab environment, is presented in the appendix. The rule set is simplified but the performance approaches the FITS controller according our evaluation.

2.2. Multi-agent model of group-based phasing

In addition to the timing decision, the phase generation has a direct impact on the performance of signal controls. FITS applies a group-based phasing technique that has been widely used in the Nordic countries, Germany, Austria, The Netherlands and elsewhere. It provides a flexible combination of traffic movements according to traffic demand. The signal group is defined as a traffic movement or a collection of a few traffic movements. It is possible for all of the compatible signal groups to form a phase. Hence multiple and dynamic phase rings can be applied to the signal cycle based on traffic situations. In group-based signal control systems, signal timings are directly assigned to each signal group. Each signal group can be modeled as an individual agent. Therefore, the multi-agent approach is used to model a group-based signal system.

Fig. 3 gives an example of the operation for group-based phasing. Assume that signal group agent SG1 is activated. Signal group agent SG1 (straight direction) is able to combine with SG2 (left turn) and SG3 (straight direction from the

Fig. 3. Multi-agent model for group-based signal control at one intersection.

opposite road). Thus, two possible combinations are represented by the phase PH1 and PH2. If PH1 is determined, the following phase might be either PH2 or PH3 depending on which one of the signal groups in phase PH1 is terminated.

In order to maintain the flexibility of group-based phasing, signal timing should also be a result of the group-based decision process. Therefore, the states of the competing signal groups that may turn green in the next phase should be considered in the decision making. For example, FITS adds the queue lengths of the signal groups that are conflicting to the current green signal group to the decision rules. This can be interpreted that signal group agents are negotiating with each other to figure out the "optimal" solution while controlling their own traffic light indications. Such a multi-agent control framework has already been proposed and illustrated in the previous study (Kosonen, 2003).

An agent-based approach has been implemented to represent a signal group in FITS. The system is decentralized such that each signal group agent operates individually. Specifically, without any central level of control, each signal group agent may still operate individually and locally. But the FITS system also introduces an intelligent agent playing the role as broker among the agents. The broker agent holds the information about which signal groups are conflicting and what is the necessary inter-green time between the signal group agents. In Fig. 3, the idea of generic multi-agent control is demonstrated for a simple intersection. The advantages of a flexible multi-agent control become more evident in more complex intersections. The complex intersection contains traffic signals for specific lanes, pedestrian crossings and dedicated lanes for public transport.

Within this framework, the signal agents have to negotiate and compose a mutual control strategy. The control strategy is required to fulfill at least the following objectives. In a priority order, they are summarized as safety (inter-green management), equality (that is, assuring each direction has a possibility to get green and handling public transport priorities), system performance (such as delay, queue length, stops and fuel efficiency) and minimal transitions (that is, finding an optimal rest state when there is no traffic). The priority order here means that lower-priority objectives can only be pursued within the limits of higher-priority objectives. This means, for example, that signal timing is subject to the limitations set by the minimum inter-green times between conflicting signals.

2.3. Autonomic features in FITS system

The FITS traffic signal system is designed as an autonomous system with the features of self-calibration, self-diagnostics, and self-adaptation. These properties have been illustrated in detail in Fig. 4. Currently, the detection system mainly considers stationary vehicle detectors, usually inductive loops, which provide lane occupancy information. The real-time simulation creates vehicles being detected once they enter the intersection area, and then predicting the vehicle movements continuously. Nonetheless, this prediction tends to drift away from reality over time. Therefore, self-calibration features are required in order to match the information from other detectors. For example, one primary parameter to be calibrated for each vehicle is speed characteristics. By using the given vehicle speed, the

Fig. 4. Illustration of the autonomic features and relations with FITS system.

simulated vehicle arrives to next detector. Meanwhile, as the real vehicle approaches the same detector, the vehicle speed is corrected based on the time variance between the real detections and the simulated ones. In addition, turning movement at an intersection is also calibrated by introducing pocket lanes. Pocket lanes are used for turning and a detector is located in the beginning of a pocket lane. All the vehicles are first directed to go straight ahead by default. However, if a detection is reported associated with the pocket lane, then the nearest simulated vehicle on the main road will be forced to make a lane change into the pocket lane.

The most important self-diagnostics feature of the system is to identify the malfunctioning detectors. This is done by monitoring the collected detector occupancy information. The real-time detection information posted from stationary vehicle detectors is stored in a detection database in FITS. If there is no activity reported by a detector during a configurable time period T_c (e.g., 15 minutes in morning peak hours), the diagnostic manager of the software will report that the detector is broken. In case of in-counting detector, a potential self-healing feature may start to generate vehicles in the real-time traffic simulator until the malfunctioning issue of the detector is addressed in the field. In this case, the vehicle generation in FITS is carried out with respect to the average daily patterns predefined for real-time traffic simulation. Fig. 5 illustrates how the self-diagnostics service works in details.

Self-adaptation is essentially to facilitate the FITS system in making its control decisions. The module has been recently under extensive research and development. The current FITS system applies essential prior knowledge obtained in advance. For example, the default parameters for fuzzy rules and membership functions are results of extensive simulation study and optimization for traffic mobility. For a new junction, different rule sets and membership functions have to be chosen for the primary and secondary roads. Therefore, lots of preliminary configurations are still needed to program the controlled intersection before real application.

However, the default values may not provide optimal performance under different traffic conditions. Hence a separate optimization software has been created for tuning signal control parameters using various machine learning techniques. For example, simulation-based optimization method in the tool can help find appropriate signal parameters (e.g. maximum green time, amber time, etc.) for different controls. The optimization is designed at two levels: offline and online. In the offline scenarios, an enhanced genetic algorithm is applied to optimize fuzzy rule sets and parameters of membership functions by global searching. The algorithm is modified based on a previous study (Jin et al., 2015). The technical details will not be covered in this paper. The recent development focuses on online learning in which the parameters of fuzzy membership functions are finely tuned according to estimated traffic demand. The major barrier here is the computational efficiency since the decision has to be fast enough to meet online requirement. An independent software component will be continuously extended to adapt signal parameters according to live detector information.

Fig. 5. Demonstration of the self-diagnostics feature.

3. FITS-in-the-loop simulation

This section depicts the evaluation process by using an integrated simulation framework, called FITS-in-the-loop simulation. As described previously, FITS is a traffic signal controller with a real-time traffic simulation model embedded for detailed traffic prediction. Both the real-time simulator and fuzzy controller are embedded as software components in the single board computing device. In principle, the performance of signal system can be evaluated by using high-resolution vehicle data (i.e. instantaneous speed, acceleration, position and so on) that is not practical to obtain from reality. Thus, in order to conduct a rigorous evaluation on FITS performance, this study has developed the FITS-in-the-loop simulation framework, where the FITS device is integrated with an external high-fidelity microscopic traffic simulator which generates mimicked traffic data.

Different from the conventional signal controller hardware that has to run in real time, the FITS device is simply an industrial computer capable of providing control decisions much faster than real time. So this results in an evaluation process that can be much more faster and efficient. Fig. 6 illustrates the running steps and information flow under the FITS-in-the-loop simulation framework. The external traffic simulation engine is based on Simulation of Urban MObility (SUMO), an open-source microscopic traffic simulator (Krajzewicz et al., 2012). FITS computing device is connected with the traffic simulation program that runs on desktop or laptop and the communication is via Ethernet.

FITS-in-the-loop simulation is achieved through distributed computing since FITS and SUMO are different programs running on different hardware. The communication is carried out through MQTT, a lightweight connectivity and messaging protocol. Fig. 6 shows the essential procedures how MQTT is used for message exchanging between

Fig. 6. The running steps for FITS-in-the-loop simulation (upper) and pseudo-code for information exchanges.

the two programs. MQTT is a publish-subscribe based protocol for use on top of the TCP/IP protocol. A MQTT client is specified for the purpose of connecting to the FITS device, where a MQTT message server is configured. The FITS device is connected by MQTT client by giving the IP address of the device (line 5 in the pseudo-code). A Python-based package, TraCI (Traffic Control Interface), is applied to get the on-line access to SUMO traffic simulator. Specifically, TraCI allows to retrieve values of simulated objects (e.g. detectors, vehicles and so on) and to manipulate the indications of traffic lights. TraCI uses a TCP based client/server architecture such that a port number is given to connect to the SUMO simulator (line 6 in the pseudo-code).

One-step evaluation process is illustrated in the flow chart in Fig. 6. First, the SUMO simulator carries out a simulation step. The states of the simulated objects (e.g. vehicles and detectors) are updated. The detection data are obtained from SUMO and then published by the MQTT client. The FITS system subscribes the detection data and uses the detection information to generate vehicles in the real-time simulator.

Table 1

Traffic flow and main signal parameters for each signal group in the case study.

Traffic movement ids	Simulation and control parameters			
	Traffic flow	Minimum green time	Maximum green time	Yellow time
SG1	242	6	30	3
SG2	220	6	30	3
SG3	75	4	30	3
SG4	63	4	30	3
SG5	198	6	30	3
SG6	298	6	30	3
SG7	63	4	30	3
SG8	63	4	30	3

The decision of fuzzy signal control, such as green time extension, etc., is correspondingly made by the FITS system. Traffic light indications (red, yellow and green) are obtained from the FITS system by subscribing a ticket by MQTT dedicated for receiving traffic light indications. In fact, the FITS system generates traffic light indications immediately according to the control logic and detection information, and thereafter sending them to traffic simulator. Meanwhile, vehicle trajectory data obtained from SUMO simulator via TraCI are recorded in a database, which will be used for estimating high-level performance indexes (e.g. travel delay, fuel consumptions, etc.) when a simulation run ends. Similarly, if a FITS device is connecting to real signal controller hardware, instead of traffic simulator, live traffic detection information will be sent to the FITS device which responds with realistic traffic control.

4. Case study

4.1. Experiment setup

In order to evaluate the performance and essential features of FITS, this section describes a case study performed for an isolated intersection (Heikkilänatu-Aitolahdentie) in Tampere, Finland. The FITS system has also been deployed at Heikkilänatu-Aitolahdentie intersection for test. Fig. 7 shows the layout of the study intersection. A separate lane is dedicated to each right-turn so that the right-turns are not regulated by traffic lights. Eight signal groups have been defined for this intersection (see Fig. 7). On each regulated lane, a long loop detector is located close to the stop line (D10 detector) and a short loop detector that is placed 50 meters away (D50 detector) from the stop line.

Four different signal control strategies, stage-based VA control, dual-ring VA control (NEMA), group-based VA control (LHOVRA) and FITS control, are tested in the simulation experiments. Both group-based VA and FITS are capable of on-line generating phase pictures according to the real-time traffic conditions. However, the mechanism of vehicle actuated control (so-called gap seeking algorithm) determines green time based only on traffic flow information behind the active green signal while FITS makes timing decision considering the traffic conditions at the whole intersection.

The conflict matrix of the intersection is presented in Fig. 7, and indicates the conflict conditions among signal groups represented by the minimum inter-green time between two signal groups. Note that dual-ring VA control is also able to generate flexible phase sequences according to the detection information. But the sequence of a phase in the dual-ring structure should be pre-determined (see Fig. 7).

Table 1 contains the traffic flow data for each traffic movement in the simulation. The traffic movement id corresponds to the signal group shown in Fig. 7. Signal parameters (minimum green time, maximum green time and yellow time) are identical for all of the signal control strategies (see Table 1). In addition, parameters of membership functions for fuzzy control in FITS system are calibrated in accordance with the traffic flows. To emulate real traffic conditions, parameters of driving behavior models are calibrated and validated. All traffic simulations are performed for a 60-minutes interval, excluding a warm-up period of 15 minutes to prevent from initial loading effects. Average travel delay (seconds per vehicle) and average number of stops are selected as the mobility indicators in this study. Here, a stop pertains to the situation that vehicle speed is below 2 m/sec or 7.2 km/h. Performance indicators are computed by using vehicle trajectory data obtained from traffic simulation.

Fig. 7. Intersection layout and control components for different signal control strategies.

Table 2
Performance measures of different signal control strategies.

Signal control strategies	Performance measures		
	Average travel delay (seconds / vehicle)	Average number of stops (times / vehicle)	Average cycle length (seconds)
Stage-based VA	27.41	0.756	73.85
Dual-ring VA	25.50	0.769	64.28
Group-based VA (LHOVRA)	24.27	0.759	62.08
FITS	23.26	0.710	NA

4.2. Effects of signal control systems

First, performance indexes on traffic mobility are investigated for all the signal control strategies (see Table 2). In general, FITS controller outperforms the other tested signal controllers with the result of the lowest values of travel delay and number of stops. That means, on average, drivers spend less time on driving through the intersection if FITS system is deployed compared to other signal control methods.

Among the tested signal control strategies, stage-based VA controller seems to be the worst signal controller in terms of the mobility efficiency. Dual-ring VA, group-based VA and stage-based VA controls apply the same timing logic, i.e. vehicle actuated timing. Stage-based VA control is not able to generate flexible phase structures according to traffic conditions whereas the other two are capable. For example, traffic flow associated with north-to-south (SG5 movement) direction is 198 veh/h and 298 veh/h for south-to-north direction (SG6 movement). It is natural that SG6 movement deserves more green times than SG5 movement. However, identical values of green time are always

Fig. 8. Average green time and the corresponding traffic flow for signal groups.

assigned to these two traffic movements if stage-based VA is used.

For the dual-ring VA or group-based VA controls, the SG6 movement could also be combined with another compatible traffic movement, i.e. SG8, so that the green time can be more efficiently utilized. In comparison to dual-ring VA controller, group-based VA controller is capable of constructing more flexible phase sequences in a cycle. Here, group-based signal control is able of generating the following scenario in the phase sequence that dual-ring based control cannot. That is, all of the traffic lights associated with both SG7 and SG8 are activated in a cycle before SG5 and SG6. The difference in their flexibility might be the main reason that group-based VA slightly outperforms dual-ring VA in terms of reducing average travel delay. This result shows that it is fairly important to provide efficient phase pictures with regards to traffic demands in traffic light control problem.

Except for the properties of group-based phasing, FITS makes timing decision by balancing the performances associated with all the lanes. However, group-based VA control decides the green time extension only based on traffic information behind the active signal group. Such timing decision of FITS leads to a better performance in traffic mobility compared with group-based VA control. For example, average travel delay is reduced by around 4% if FITS, rather than the group-based VA controller, is deployed at the intersection. In addition, the FITS controller is capable of skipping unnecessary signal groups in a cycle in practice. The phenomenon occurs when no vehicles are waiting on the lanes controlled by these signal groups. Consequently, the average cycle length for FITS is not available in Table 2.

To provide some insights into the operations among different signal control schemes, Fig. 8 demonstrates the average green time per minute for every signal group. The traffic flows associated with different signal groups are displayed at the top left corner of Fig. 8. As discussed before, stage-based VA underperforms when responding to various demands in different traffic turning movements. For example, the allocation of green time to SG5 is

Table 3

Average travel delay for different malfunction scenarios for different detection strategies.

Signal control strategies	Average travel delay (seconds / vehicle)					
	Baseline	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Stage-based VA	27.41	27.11	27.59	41.91	26.70	52.61
Dual-ring VA	25.50	25.58	25.60	67.80	25.70	65.54
Group-based VA (LHOVRA)	24.27	25.61	25.31	65.05	25.86	68.82
FITS	23.26	27.37	28.48	27.24	26.45	29.95

unnecessarily long whereas insufficient time is assigned for SG6.

Dual-ring VA control and group-based VA generate similar patterns in average green time for the eight signal groups. However, the patterns are not consistent with the patterns of traffic flows. For example, the traffic flow of SG8 is set as the same value as SG7. But the average green time of SG8 for both dual-ring VA and group-based VA are considerably higher than signal SG7. In addition, the high demand for SG6 might lead to the inefficient allocations of green time for SG8. The reason is as follows. The demand of extending the green time for SG5 is not as much as that for SG6, so it is highly possible to terminate SG5 first when it is in a phase with SG6. Thereafter, SG8 becomes the only possible signal group that can work with SG6 in a phase due to the conflict conditions in this case. Thus, the green time of SG8 is increased by operating together with SG6.

For the FITS control system, the distribution of average green time is generally in line with the pattern of traffic flows for turning movements. Moreover, the sum of average green time is significantly higher than other control strategies. Since FITS can skip unnecessary signal groups, the yellow time and inter-green time for the signal transition associated with negligible traffic demand can be avoided. Therefore, more green times can be allocated to the signal groups with high traffic demand.

4.3. Effects of detection system malfunctions

The performance of a signal control system might be significantly undermined if the loop detectors are malfunctioning. Hence, it is important to evaluate the negative effects of malfunctions in the detection system. In this study, five different scenarios of the detector breakdowns are simulated. Here, malfunction of a detector means that the detector does not send the detecting information to the corresponding signal controller. Scenario 1 to 4 presents respectively that one long detector is malfunctioning in left-turn direction, one short detector is malfunctioning in left-turn direction, one long detector is malfunctioning in the straight direction and one short detector is malfunctioning in straight direction. Scenario 5 is a combination of all four malfunctions. The detectors are randomly selected with respect to the scenario but are identically applied to different signal control systems for comparison purposes.

Table 3 shows the results of average travel delay for different scenarios of detector malfunction. In scenarios 1, 2 and 4, malfunction of the detector does not exert much influence on stage-based VA control or even dual-ring VA and group-based VA control. Traffic flow is low in the left-turn direction so that malfunction scenarios 1 and 2 do not significantly undermine the performance of the traffic system. The performance of the traffic signal control system using vehicle actuated timing, regardless of phasing techniques, is severely degraded if long detector in the straight direction does not report information to the signal controller. This indicates that short detectors play a supporting role in vehicle actuated timing, whereas long detectors play a crucial role in the decision-making process.

Another interesting finding is that the performance of FITS is superior to other controllers when detectors are not in proper modes due to its self-diagnostics feature. The increase of travel delay is less than 30% when four detectors are not working if FITS is in use while is around 100% for other signal control systems. This might be due to that the operation of FITS considering traffic states at the whole junction rather than the states on a few lanes. The useful detection information on other lanes might compensate the negative effects caused by detection errors. On the other hand, FITS applies real-time simulation as a predictive tool for traffic states of the coming future. So, with a proper traffic states estimation, the decisions on green extension can still be properly made even if detectors are broken.

5. Conclusion

This study introduces an innovative intelligent group-based traffic signal control system, FITS. The system is implemented on a single board computing device capable of applying its own control logic and taking over the decision by communicating with modern traffic signal controllers. Due to the economic and technical barriers in upgrading the signal control system based on the current architecture, the FITS system provides a great opportunity to improve the existing signal control system without changing the fundamental traffic management infrastructure. The critical capability of FITS lies in the principles of sensing and human-like reasoning as a group based process. In addition, FITS system includes several autonomic computing features, such as self-calibration, self-adaptation and self-diagnostics, designed for the real-world operation. The system itself is developed based on the concepts of distributed multi-agent control system. In particular, the controller uses fuzzy logic for the decision making associated with signal timing.

The FITS system is capable of communicating with signal control hardware as well as simulated traffic environment by sending and receiving messages through a generally designed interface. The machine-to-machine (M2M) connectivity protocol is mainly applied for the information exchange in distributed computing. Using such an approach, the system has been successfully tested with an external open source traffic simulator, SUMO. In a case study, FITS is compared with several mainstream signal control strategies, including stage-based VA control, dual-ring VA control and group-based VA control. Among these tested signal control strategies, FITS exhibits the best performance in terms of improvement on mobility efficiency.

In addition, the effects of detection malfunctions have also been investigated and evaluated for those control strategies. The results indicate that vehicle actuated controls, irrespective of phasing techniques, are highly affected by a malfunction of the long detectors. However, FITS mitigates the negative effects of detection malfunction by predicting the traffic states at the whole intersection with the aid of real-time traffic simulation.

While FITS represents a new concept for adapting current traffic signal control infrastructure to meet increased requirements on smart transport and city, the system is still evolving quickly with continuous research and development. For example, our recent research has been focused on short-term adaptive control strategies. Meanwhile, the system will be integrated with more vehicle sensing technologies in the near future.

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Appendices

I. LHOVRA

LHOVRA is vehicle actuated signal control widely applied in the Nordic countries such as Sweden. The name LHOVRA comes from the Swedish initial letters of the following functions:

- Lastbils-prioritering (Truck-priority and can be replaced by Bus-priority);
- Huvudledsprioritering (Main road priority);
- Olycksreduktion (Accident reduction);
- Variabelt gult (Variable yellow time);
- Rödkörningskontroll (Red light driving control);
- Allrödvändning (Green-yellow-red-green sequence).

These functions are implemented as modules in the controller. For different intersections, traffic planner can plan in advance and decide which functions should be applied in operation.

II. Inference rules for the fuzzy logic based control

This appendix presents a set of 24 rules used for research at the System Simulation & Control Lab, Department of Transport Science, KTH Royal Institute of Technology. The controller based on the rules approximate the performance of FITS. All fuzzy rules are based on inputs of the queue length of the activated signal groups (Q_a), the overall queue length of the inactivated signal groups (Q_{ia}) and the accumulated green extension time of the signal groups currently activated (T_{ag}). The inference output is represented by the fuzzy sets of terminating (T) and extending (E). Below is the list of fuzzy rules:

1. ($Q_{ia} = \text{ZERO}$) $\rightarrow$ E
2. ($Q_{ia} = \text{HIGH}$) $\rightarrow$ T
3. ($Q_{ia} = \text{MEDIUM}$) $\rightarrow$ T
4. ($Q_{ia} = \text{MED_HIGH}$) $\rightarrow$ T
5. ($Q_a = \text{LOW}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
6. ($Q_a = \text{LOW}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ E
7. ($Q_a = \text{MED_LOW}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
8. ($Q_a = \text{MED_LOW}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ T
9. ($Q_a = \text{MEDIUM}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
10. ($Q_a = \text{MEDIUM}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ T
11. ($Q_a = \text{MED_HIGH}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
12. ($Q_a = \text{MED_HIGH}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ T
13. ($Q_a = \text{HIGH}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
14. ($Q_a = \text{HIGH}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ T
15. ($Q_a = \text{LOW}$) $\oplus$ ($Q_{ia} = \text{LOW}$) $\rightarrow$ E
16. ($Q_a = \text{LOW}$) $\oplus$ ($Q_{ia} = \text{MED_LOW}$) $\rightarrow$ E
17. ($Q_{ia} = \text{LOW}$) $\oplus$ ($T_{ag} = \text{MEDIUM}$) $\rightarrow$ T
18. ($Q_{ia} = \text{LOW}$) $\oplus$ ($T_{ag} = \text{MED_HIGH}$) $\rightarrow$ T
19. ($Q_{ia} = \text{LOW}$) $\oplus$ ($T_{ag} = \text{HIGH}$) $\rightarrow$ T
20. ($Q_{ia} = \text{MED_LOW}$) $\oplus$ ($T_{ag} = \text{LOW}$) $\rightarrow$ E
21. ($Q_{ia} = \text{MED_LOW}$) $\oplus$ ($T_{ag} = \text{MED_LOW}$) $\rightarrow$ T
22. ($Q_{ia} = \text{MED_LOW}$) $\oplus$ ($T_{ag} = \text{MEDIUM}$) $\rightarrow$ T
23. ($Q_{ia} = \text{MED_LOW}$) $\oplus$ ($T_{ag} = \text{MED_HIGH}$) $\rightarrow$ T
24. ($Q_{ia} = \text{MED_LOW}$) $\oplus$ ($T_{ag} = \text{HIGH}$) $\rightarrow$ T

References

- Boillot, F., Midenet, S., Pierrelée, J.-C., 2006. The real-time urban traffic control system CRONOS: Algorithm and experiments. *Transportation Research Part C: Emerging Technologies* 14 (1), 18–38.
- Brilon, W., Wietholt, T., 2013. Experiences with adaptive signal control in germany. *Transportation Research Record: Journal of the Transportation Research Board* (2356), 9–16.
- Cai, C., Wong, C. K., Heydecker, B. G., 2009. Adaptive traffic signal control using approximate dynamic programming. *Transportation Research Part C: Emerging Technologies* 17 (5), 456–474.
- El-Tantawy, S., Abdulhai, B., Abdelgawad, H., 2013. Multiagent reinforcement learning for integrated network of adaptive traffic signal controllers (MARLIN-ATSC): Methodology and large-scale application on downtown toronto. *IEEE Transactions on Intelligent Transportation Systems* 14 (3), 1140–1150.
- Gartner, N. H., 1983. OPAC: A demand-responsive strategy for traffic signal control. *Transportation Research Record* (906).
- Henry, J.-J., Farges, J.-L., Tuffal, J., 1984. The PRODYN real time traffic algorithm. In: *Proceedings of the IFAC/IFIP/IFORS Conference on Control*.
- Hunt, P., Robertson, D., Bretherton, R., Royle, M. C., 1982. The SCOOT on-line traffic signal optimisation technique. *Traffic Engineering & Control* 23 (4).
- Jin, J., Ma, X., 2015. Adaptive group-based signal control by reinforcement learning. *Transportation Research Procedia* 10, 207–216.
- Jin, J., Ma, X., Kosonen, I., 2015. Stochastic optimization of group-based signal control and coordination using traffic simulation. In: *Proceedings of the 94th Transportation Research Board Annual Meeting*. pp. 389–403.
- Kosonen, I., 1999. HUTSIM-Urban Traffic Simulation and Control Model: Principles and Applications. Vol. 100.
- Kosonen, I., 2003. Multi-agent fuzzy signal control based on real-time simulation. *Transportation Research Part C: Emerging Technologies* 11 (5), 389–403.
- Krajzewicz, D., Erdmann, J., Behrisch, M., Bieker, L., 2012. Recent development and applications of SUMO—simulation of urban mobility. *International Journal On Advances in Systems and Measurements* 5 (3 and 4), 128–138.
- Luyanda, F., Gettman, D., Head, L., Shelby, S., Bullock, D., Mirchandani, P., 2003. ACS-Lite algorithmic architecture: applying adaptive control system technology to closed-loop traffic signal control systems. *Transportation Research Record: Journal of the Transportation Research Board* (1856), 175–184.
- Ma, X., Jin, J., Lei, W., 2014. Multi-criteria analysis of optimal signal plans using microscopic traffic models. *Transportation Research Part D: Transport and Environment* 32, 1–14.
- Niittymäki, J., Pursula, M., 2000. Signal control using fuzzy logic. *Fuzzy Sets and Systems* 116 (1), 11–22.
- Peterson, A., Bergh, T., Steen, K., 1986. LHOVRA, a new traffic signal control strategy for isolated junctions. In: *Proceedings of the International Conference on Road Traffic Control*.
- Sims, A. G., Dobinson, K. W., 1980. The Sydney coordinated adaptive traffic (SCAT) system philosophy and benefits. *IEEE Transactions on Vehicular Technology* 29 (2), 130–137.
- Tarnoff, P. J., Ordonez, J., 2004. Signal timing practices and procedures-state of the practice. No. FHWA-HOP-05-015.
- Vincent, R., Peirce, J., 1988. MOVA: Traffic responsive, self-optimising signal control for isolated intersections. Tech. rep.