Structure and effectiveness analysis of an integrated traffic supervisory system

Y.E. Hawas
Civil Engineering Department, UAE University, Al-Ain, UAE

Abstract

This paper addresses the problem of integrating Advanced Traveller Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS). A framework that allows the integration of existing successful control implementations is reviewed. This framework is utilized to integrate the ATIS/ATMS control decisions of two operational schemes; ATIS stand-alone system (dynamic route guidance), and ATMS stand-alone control system (responsive signal control), and to form a dual non-cooperative supervisory traffic control system. The two operational schemes are formulated as bi-level optimization problems. Approximate simulation-based optimization algorithms are devised as representations of the existing control logic operating these schemes. These operational schemes are then integrated via as fuzzy-logic supervisory control system. Neural nets are utilized to develop the knowledge base of the fuzzy system and to calibrate the fuzzy set parameters. The neuro-fuzzy algorithm is tested on a simplified urban network.

1 Introduction

This paper addresses the problem of integrating ATIS and ATMS control systems. A common practice in developing ATIS/ATMS control logics is to assume independent operation; the path proportions are determined assuming known signal settings, and the signal control is made assuming known path proportions. ATIS logic is commonly used for normative control assuming known signal settings and/or origin-destination (OD) demand patterns (Hawas and Mahmassani 1996, Papageorgiou 1990, Peeta and Mahmassani 1995). Hawas and Mahmassani (1996) developed heuristic-based decentralized local
control (DLC) algorithm for the pure assignment problem (signal control was assumed known). Hawas (2000) upgraded the pure assignment algorithm to a decentralized local integrated assignment traffic signal control (DLIC) system. The premise of this heuristic-based approach is its validity for on-line control; the processing time is rather short as compared to the optimization-based procedures. Nonetheless, the heuristic-based approach does not guarantee achieving optimal performance. On the other hand, network signal control models assume known path proportions. Link flows are predicted using detector data and the path proportions, and in turn, are used to optimize the settings through small adjustments (Lum and Lee 1992, Gartner et al. 1995, Newell 1998, Head and Mirchandani 2001).

In the last decade, several optimization procedures were developed for integrated traffic-assignment and signal control (Smith and Ghali 1991, Gartner and Al-Malik 1996, Abdelfatah and Mahmassani 1998). They mostly exhibit better performance than those of pure assignment logic (Hawas and Mahmassani 1996, Papageorgiou 1990, Peeta and Mahmassani 1995) or those of heuristic-based integrated control logic (Hawas, 2000). These models rely on the prior knowledge of the OD demand. They require excessive computational efforts, which limit their validity for real-time control (Meneguzzer 1997).

Fuzzy logic has been utilized for complex traffic systems’ control. Sayers and Anderson (1999) developed a multi-objective fuzzy logic for traffic-isolated signals. Trabia et al. (1999) developed a fuzzy logic system for an isolated intersection. The memberships (parameters) and the knowledge base (rules) of the fuzzy logic systems are set intuitively using reasoning arguments of huge data sets, and as such, optimal performance is not guaranteed.

An important observation is that previous research attempts in the area of integrating ATIS/ATMS have proceeded with their own new procedural developments neglecting how could the existing successful implementations of the individual control systems (ATMS and ATIS) be integrated. One distinctive objective of this work is the development of a supervisory control system with ability to integrate existing successful controls. Hawas (2002a) used the neuro-fuzzy logic to represent a normative ATIS stand-alone control scheme. It is assumed that the ATMS control decisions (signal settings) are unknown to the ATIS controller. However, to calculate the route proportion decisions, the most probable ATMS signal control decisions are guessed (predicted) and incorporated within the ATIS logic. To overcome the deficiencies caused by the intuitive reasoning, the so-called neuro-fuzzy logic (integrated fuzzy and neural nets) is used. The idea is to develop a fuzzy logic with ability to replicate the decisions of ATIS/ATMS by utilizing the training capabilities of the neural nets. The training algorithm is used to calibrate the fuzzy sets and knowledge base to replicate the logic of the integrated system.
This paper will briefly present the formulation of some sample of what could be regarded as really existing ATIS/ATMS control systems; other formulations might be used if available. The algorithmic procedures to solve these formulations may be characterized as approximate local optimization procedures, and are used for generating the data replicates required for the supervisory fuzzy system's training using the so-called neuro-fuzzy logic. The supervisory control system is intended to exhibit the effectiveness of the optimization procedure, and the computational superiority of the decentralized heuristic procedures. This paper will only focus on the formulation of the ATMS stand-alone algorithmic procedure. For details on the ATIS control, the reader is referred to Hawas (2002a).

2 ATMS Stand-Alone control system

The system is envisioned as a stand-alone ATMS control centre that employs some responsive signal setting logic, taking into account the path assignment decisions that may take place at the ATIS control centre (if any). It is assumed that the ATIS control decisions (path proportions) are unknown to the ATMS controller. Nonetheless, to calculate the phase split decisions, guessing the ATIS decisions is essential to minimize the overall travel time. ATMS decisions consist of several decisions (e.g. phase splits, offsets, and phase sequence). Herein, we consider only a subset of these ATMS decisions; namely, the phase splits. The ATMS control system is formulated as a bi-level optimization problem. The upper level represents the guess of the optimal path proportions. The phase splits are determined in the lower level, where the objective is to minimize the overall local network instantaneous travel time, taking into account the path proportion decisions guessed at the upper level.

Consider a simplified network where the decision node $i$ represents the signalized intersection. The upstream side of the decision node represents the links incoming to the decision node. The travel times along these upstream links are mostly affected by the signal settings at $i$. Let us assume that these links represent the various phases to be served by the signal at $i$; each phase is represented by a separate link. The outgoing paths from the decision node are assumed to lead to the same destination node. The traffic times along these paths are affected by the routing decisions. The problem is formulated using a discrete-time approach. At the decision node $i$, at any time $t$, the phase splits and/or the path proportions are to be determined so as to minimize the sum of the instantaneous travel time on all the incoming links, and the emanating paths. Let $A_i$ refers to the set of all links (phases) incident to node $i$, and $P_i$ refers to the set of all outgoing paths from node $i$. The total travel time in this network is the sum of two components; the total travel time on all the links incident to $i$, $T_{A_i}^t$, and the total travel time on all the paths emanating from $i$, $T_{P_i}^t$. 
2.1 ATMS upper-level formulation

The upper-level formulation assumes that the travel time on the links downstream of the decision node is a function of the path proportions solely. The primary objective of this formulation is to estimate the path assignment decisions probably undertaken by the ATIS system (ATIS decisions guess). To calculate the path assignment decisions, the phase splits are initially assumed. The phase splits' assumptions are then rectified at the lower level problem. Let \( \tilde{g}_a^t \) denotes the assumed phase split allocated to phase (link) \( a \) at time \( t \), where the superscript "\( \_ \)" indicates assumed values. The objective function becomes:

\[
\text{Min}_{f^t_p \in F} \left[ \sum_{p \in P_i} T_p' \left( f^t_p, \tilde{g}_a^t \right) \right]
\]

- \( F \): Refers to the set of all possible paths' proportions;
- \( T_p' \): Total travel time on path \( p \) at time \( t \). The travel time on path \( p \) is assumed to be a function of the variables; \( f^t_p \) (the path proportion of path \( p \) at time \( t \)), \( \tilde{g}_a^t \) (the phase splits of link \( a \) at time \( t \));
- \( P_i \): Set of all paths emanating from \( i \);
- \( f_{ap}^t \): Fraction of the exit vehicles from link \( a \) to allocate to path \( p \) at time \( t \).

Herein, it is assumed that \( f_{ap}^t = f_p^t \). Note that the sum of this fraction over all emanating paths must be equal to one (i.e. \( \sum_{p \in P_i} f_{ap}^t = 1 \));

The travel time of path \( p \), \( T_p' \), is the sum of the travel time on all the path links.

The travel time of link \( a \) is a function of the two variables; \( \tilde{g}_a^t \) (phase split allocated to link \( a \) at time \( t \)), and \( f_{ap}^t \) (percentage of link \( a \) flows to assign to path \( p \)). The decision variables of the upper level formulation are the optimal path proportions for all the paths emanating from the decision node \( i \), \( f^t_p, \forall p \in P_i \). Furthermore, the link-path proportions are set equal to estimated path proportions (i.e., \( f_{ap}^t = f_p^t*, \forall a \in A_i, p \in P_i \))

2.2 ATMS lower-level formulation

Given the guessed optimal path decisions \( f_p^t* \), the objective function of the ATMS control becomes as shown below:
The travel time of link \( a \) is a function of the two variables; \( g^i_a \) (the phase split allocated to link \( a \) at time \( t \)), and \( f_{ap}^i \) (the guessed percentage of link \( a \) flows to assign to path \( p \)). The \( G \) represents the set of all possible phase splits. The lower level decisions are the optimal phase splits, \( g_{a^*}^i \), \( \forall a \in A_i \). The path proportions although explicitly accounted for by the upper level formulation; they may not be actually implemented. The above formulation did not explicitly account for the effect of the phase offsets and sequence; yet the simulation process within the optimization procedure simulates the effect of the two variables (Hawas 2002a).

3 Dual ATIS/ATMS non-cooperative control system

The integration of ATIS/ATMS refers to the integration of control decisions and not the integration of logic or knowledge. This tends to be the most notable case of the current traffic control practice; the two components work independently, even if they are operated from a single control facility. The two logics are devised to operate independently (yet they may share same data source) and their decisions to be individually implemented. As shown in Fig. 1, the two control logics attempt to optimize the network performance represented by the overall travel time. Each control system is represented by a bi-level formulation as indicated in the earlier formulations. The ATIS control decisions of the dual system are the path proportions \( f_{p}^{i*} \), \( \forall p \in P_i \), and the ATMS control decisions are the phase splits \( g_{a^*}^i \), \( \forall a \in A_i \). The integration of the control decisions is carried out via a supervisory control agent.

Approximate optimization procedures are developed to estimate the system control decisions and to perform comparative effectiveness analysis. As previously indicated, these optimization procedures are utilized as examples to represent the existing control ATIS/ATMS logic. If any other logic exists, it could be easily utilized to replace these optimization procedures. Their main purpose is to generate data replicates that could be used to train the fuzzy logic systems. Due to the space restrictions, this paper will not present the optimization procedures. For details on the optimization procedures utilized to solve the above formulations, the reader is referred to (Hawas 2002a).
4 Neuro-Fuzzy control system

This paper utilizes the so-called "rule-based" fuzzy logic method; commonly used in recent fuzzy logic applications in the area of transportation engineering (Sayers and Anderson 1999, Trabia et al. 1999). The key benefit of "rule-based" fuzzy logic is that it enables describing the system with simple "if-then" relations. As such, the engineering prior knowledge could be easily incorporated to optimize the control system's performance. While this is the advantage of fuzzy logic, it is its major limitation. In many applications, the system's performance knowledge may only be gained by substantial exploration of huge data sets. To overcome this limitation, new developments combine neural net capabilities within the fuzzy logic systems. Neural nets act as the reasoning (training) mechanism to derive the if-then rules from the huge data set.

In general, fuzzy logic systems consist of three processes: fuzzification, fuzzy inference, and defuzzification (Ross 1995). Fig. 2 illustrates the schematic diagram of the fuzzy logic structures for the ATIS and the ATMS stand alone.
systems. Each system has two or more modules for the calculation of the phase and path weights (to be explained later). At each stage, the input numerical values are converted into state linguistic descriptions (e.g. high speed, medium blockage, low length, etc). This is referred to as the fuzzification process, as it uses fuzzy sets (membership functions) in the conversion process. Following the fuzzification process, the so-called fuzzy inference process scans the entire set of the if-then rules (knowledge base) and specifies the system’s decision variables. The results of this process are the linguistic terms of the output variables such as “high phase split weight”. Finally, the defuzzification process is used to convert the output linguistic terms to numerical values. For more details, on the input/output variables interpretations, the calibration of the fuzzy sets, the reader is referred to (Hawas, 2002a).

The ATIS fuzzy system (shown in Fig. 2.a) constitutes two modules as follows:

1. **ATIS-Signal Control Stage (ATIS-SCS):** This fuzzy module calculates the so-called phase weight (that can be used to calculate $g^*_a$).
2. **ATIS-Traffic Assignment Stage (ATIS-TAS):** This fuzzy module calculates the so-called path weight, which may be regarded as $f^*_p$.

The ATMS fuzzy system (shown in Fig. 2.b) constitutes three modules; the first and last are identical those explained earlier in the ATIS system:

1. **ATMS-Traffic Assignment Stage (ATMS-TAS):** This fuzzy module calculates the path weight for the paths.
2. **ATMS-Expected Outflow Stage (ATMS-EOS):** This module calculates the maximum expected outflow from the decision node.
3. **ATMS-Signal Control Stage (ATMS-SCS):** This module calculates the phase weight.

The dual control system incorporates all the above modules for the ATIS and the ATMS stand-alone systems.

5 Experimental results

This section focuses on the results of the system training and effectiveness utilizing a simplified network. The network simulation is carried out using MTSSIMA (Hawas 2000, 2002b). Fig. 3 illustrates the deviation between the fuzzy-estimated and the training data used in the calibration. The average and maximum difference between the ATIS fuzzy-estimated path proportions and the corresponding training data values are 3% and 8%, respectively. The ATMS system exhibits average and maximum deviations (between the fuzzy estimated and phase splits) of 3.8 and 9.3, respectively.

Fig. 4 shows the network average travel time under the three fuzzy logic schemes. As shown, the ATIS stand-alone system exhibits the best performance at low to medium demand level (up to 2000 vehicles/hr). The ATMS control
resulted in worst performance at the low demand levels. The delay time (at the intersection) represents a small percentage of the overall travel time at low demand levels, and a major portion of the travel time at high demand levels. On the other hand, the paths’ travel-times contribute a major portion of the vehicle’s travel time at low demand level, and a minor portion at the high demand levels. The ATMS decisions primarily affect the delay times (the smaller portion of the travel time), and as such the travel time savings due to signal settings optimization at low demand levels is lesser than that savings that could be achieved by the ATIS control system. At high demand levels, the savings achieved by the ATMS are higher than those by the ATIS.
The dual control system presented herein is non-cooperative; better performance might be accomplished by devising dual control systems with cooperative abilities that allow information, decision and knowledge sharing among the ATIS/ATMS individual control systems. The on-going research focuses on developing dual cooperative integration schemes and assesses their performance comparatively against the schemes presented in this paper.

![Graph showing average travel time of fuzzy-logic systems](image)

Fig. 4. Average travel time of fuzzy-logic systems.

6 Concluding Comments

The premise of utilizing the neuro-fuzzy approach is that it could be used to develop integrated control systems that combine successful control components. It preserves the usability of existing control logics and enables upgrading. Individual control components could have various bases (analytical, simulation-based, mathematical, etc.). This provides the flexibility of maintaining/upgrading existing codes, as well as selection/testing various control strategies. Individual components could be maintained under any operating system, platform, etc. Then, they could be integrated using the fuzzy logic, which is then calibrated to resemble the performance of such components.

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References


