An Intelligent Multi-agent Approach for Road Traffic Management Systems

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Abstract—Due to the strong interrelations between traffic situations at different locations of a road network, the traffic control actions applied for solving a local traffic problem can create another traffic congestion at a different location in the network. This can result in the average travel time on the network level being the same or worse. Therefore, coordinative control strategies are required to make sure that all available control actions serve the same objective. In this paper, an intelligent traffic control system based on multi-agent approach is proposed to assist the human operator of the road traffic centre to manage and control the current traffic state. In the proposed system, the total network is divided into sub-networks, each of which has its own evaluation agent. In the proposed system, the agent will be able to react with other (affected) agents to find the optimal global traffic control action using an intelligent traffic control. The capability of the proposed multi-agent-based system was tested for a case study of a part of the traffic network in the Riyadh city of Saudi Arabia. The obtained results show the merits and capabilities of the proposed multi-agent-based system to identify the optimal global control action.

Index Terms—Multi-agent, Road Traffic Control, Decision support system.

I. INTRODUCTION

The traffic control actions influencing a traffic state in one local area of a road network can also influence the traffic states of the neighboring areas. Therefore, the spatial interrelations between traffic situations at different locations in the network get stronger, and consequently the interrelations between the traffic control actions at different locations in the network also get stronger. These interrelations may differ per situation (and depend on, e.g. network topology, traffic demand, etc.) and the control actions may be cooperative or counteract each other. Coordinative control strategies are required in these cases, to make sure that all available control actions serve the same objective. For example, solving a local traffic congestion only, can have a consequence that the vehicles run faster into another (downstream) congestion, where still the same number of vehicles have to pass the downstream bottleneck (with a given capacity). In such a case, the average travel time on the network level will still be the same or worse.

In large metropolitan areas, several agencies share the administration of the transport infrastructure, through a distributed network of Traffic Operations Centers (TOCs) responsible for the management and control of their facilities. Even if the ultimate goal of these agencies is, in general, the efficient management of the urban network, different agencies have different policies that may generate conflicting operations. Furthermore, the spatial and administrative organization of such agencies often results in a localized distribution of data and information and on the presence of multiple decision-making entities that pursue different goals and adopt different criteria to achieve those goals. Therefore, the presence of different modes of transportation and the different demand and performance characteristics of interacting subsystems, such as freeways and surface streets, require an intelligent multi-agent control system. Several reports, for example [1,2], address the need of inter-agency cooperation for a more efficient resolution of the conflicts that may arise.

The notion of software agents has become increasingly popular over the decade. Public entities as well as private companies spend a considerable amount of time, effort and money in research development and promotion of the idea of software agents. The real potential of this technology becomes unleashed when several software agents are put to use in the same environment. In this case, the group of agents is usually conceived as a multi-agent system, as the successful completion of their tasks is subject to the decisions and actions of other agents. Multi-agent Systems (MAS) is the subfield of AI (Artificial Intelligence) that aims to provide both principles for construction of complex systems involving multiple agents and mechanisms for coordination of independent agents’ behaviors [3]. Thus, in multi-agent systems, agents are forced to coordinate their activities so as to avoid negative interactions with their acquaintances and to exploit synergic potentials.

In this paper we propose a multi-agent based traffic control decision support system for intelligent road traffic management centers. The system proposed in this paper is a major extension and improvement of the system we have presented in our previous work [4]. In [4] we have developed an intelligent traffic control decision support system (ITC-DSS) to help the operator to select the best control action. ITC-DSS has been successfully tested for a small-size network and for a limited number of traffic situations and control actions. In this work the system has been developed to obtain a scalable control system, we are using a multi-agent approach where the total network is divided in sub-networks, each of which has its own ITC-DSS and its evaluation agent.

Several authors have proposed a multi-agent system for traffic management. Cuena et al. [5] have proposed a multi-agent environment for traffic management called TRYS. TRYS is knowledge based multi-agent environment for building intelligent traffic management systems applications for urban, interurban and mixed traffic areas. The TRYS approach has been applied to develop several intelligent traffic management systems (such as InTRYS [6] and TRYS2 [7]). Another knowledge based multi-agent architecture for traffic management has been proposed by Logi and Ritchie [8].

De Schutter et al. [9] have developed a multi-agent case-based decision support system to assist traffic operators in...
evaluating or predicting the effects of control actions. In the proposed approached the traffic network was divided into tractable sub-networks, and each sub-network was also divided into several sub-sub-networks. Multi-agent system technology is also adopted in constructing simulation models for road traffic management, for example [10] and [11].

The paper is organized as follows. The next section describes the overview of the proposed multi-agent control system including an overview structure of ITC-DSS. This is followed by the application of the proposed system for a case study to demonstrate the merits and capabilities of the system. Finally, the conclusions and direction for the further research are drawn in section IV.

II. THE PROPOSED MULTI-AGENT TRAFFIC CONTROL SYSTEM

In this section we describe the proposed multi-agent architecture for traffic control system. The architecture of the proposed multi-agent system is a decentralized coordination, where the network is subdivided into regions with homogeneous flow characteristics. Coordination between regions is achieved through communication that takes place on the same hierarchical level. An example of such architecture is given in [7].

A. Structure

Consider a traffic network consisting of several motorway (highway) links. Traffic enters the network via origin links (e.g., on-ramps or motorway links coming from outside the network), and leaves the network via destination links (e.g., off-ramps or motorway links going out of the network). The given traffic network is divided into overlapping region, called sub-networks, and each sub-network is supervised and controlled by an agent. Each agent has three traffic sub-systems (see Fig.1).

![Diagram of the proposed multi-agent system](image)

1) Monitoring and detection sub-system. This subsystem is used to determine the current traffic state in the sub-network and, to detect any traffic problem present in the sub-network and provide the operator with diagnosis of that problem together with an explanation justifying such a diagnosis.

2) Traffic control sub-system. This sub-system is used to assist the operator to predict the local performance of the proposed control actions using ITC-DSS [4].

3) Traffic devices control sub-system. This sub-system is used to monitor and control the available traffic signal devices.

The overall structure of the proposed multi-agent system is depicted in Fig. 1. In this paper we focus on the traffic control sub-system (ITC-DSS) and how can this sub-system react with other agents to find the optimal global traffic condition. For each of the sub-networks a control actions data-table \( CA_{\text{table}} \) will be constructed with all possible traffic control actions that can be applied on the sub-network. A traffic control action can be one control measure such as lane closures, ramp metering, dynamic route information panels (DRIPs), variable message signs (VMS), etc, or a combination of several control actions. The control action data-table \( CA_{\text{table}} \) is generated for a given sub-network off-line using the available road control facilities, traffic operator’s experience, and historical traffic data. This also takes into consideration the interrelations between the traffic control actions at different locations in the network.

The structure of \( CA_{\text{table}} \) is illustrated in Table I. Consider sub-network \( Z \), each record in \( CA_{\text{table},Z} \) is characterized by the following:

- Traffic control action \( (ca_{\text{f}}) \): name (or description) of the traffic control action that can be applied on the sub-network \( Z \).
- Affected sub-networks \( (sn_{f,j}) \): all sub-networks (or agents) that mainly are influenced by the traffic control action \( ca_{\text{f}} \). This field is characterized by the following:
  1. Agent-ID \( (g_{f,j}) \): the identity (or name) of the agent that controls the sub-network \( sn_{f,j} \).
  2. Influence rate \( (Y_{f,j}) \): represents a percentage change (positive or negative) that may happen in the traffic demand of sub-network \( sn_{f,j} \) due to applying the traffic control action \( ca_{\text{f}} \) in sub-network \( Z \). The values of \( Y_{f,j} \) can be estimated using the historical data or alternatively using a traffic simulation program.

![Table of the proposed data-table](image)

B. Operation

Once the control actions data-table has been constructed it is used for controlling the traffic as follows. Suppose there are 4 traffic agents (A, B, C, and D), which control 4 spatial problem areas \( (sn_1, sn_2, sn_3, sn_4) \) respectively. When a traffic problem is detected by the monitoring subsystem in agent \( A \), first, agent \( A \) will runs ITC-DSS (see next section for a brief overview of ITC-DSS) to propose a ranked list of op-
timal local control actions \( S \). Let \( S = \{ca_1^A, ca_2^A, ca_3^A\} \). Next, all agents that will be affected by any control action of the proposed \( S \) are determined using \( CA_{table,A} \). Let Agent \( B \) is affected by \( ca_1^A \) and \( ca_2^A \), Agent \( D \) is affected by \( ca_3^A \) and \( ca_4^A \), and Agent \( C \) is not relevant (i.e. its traffic state will not be affected by any control action of \( S \)). In this case, Agent \( A \) will send \( ca_1^A \) and \( ca_2^A \) associated with their Influence rate \( Y_{B,1}^A \) and \( Y_{B,2}^A \) to Agent \( B \) to calculate their fitness. Similarly, \( ca_3^A \) and \( ca_4^A \) associated with their Influence rate \( Y_{D,1}^A \) and \( Y_{D,3}^A \) will be sent to Agent \( D \) to calculate their fitness.

The affected agents will calculate the fitness of the proposed control actions using Influence rate \( Y_{B,1}^A \), as we will see in Section (D) below, then will return the results to agent \( A \). The global performance of each control action of \( S \) is predicted by agent \( A \) using the fitness of the control actions received from the affected agents and the operator experience. The process of calculating the global performance of the control actions is explained in Section (E) below. Finally, the \( S \) set will be re-ranked by agent \( A \) based on the global performance of the proposed control actions. In some cases, the operator may need to use a traffic simulation program to effectively compare between the best two (or more) control actions before applying them.

![Fig. 2. The overall structure of ITC-DSS.](image)

### C. ITC-DSS

As discussed earlier an agent runs ITC-DSS to assess the performance of a control action in local area. In order to clarify this process, this section gives a brief overview ITC-DSS. The overall structure of the Framework is depicted in Fig. 2. All details about ITC-DSS including the training process have been reported in [4] and [12].

ITC-DSS is an Intelligent Traffic Control Decision Support System to assist the human operator of the traffic control centre to select the most promising traffic control action in real-time. The inputs of ITC-DSS are the current traffic state which is characterized by the average state (consisting of, e.g. day time, traffic densities, flows, speeds, inflow demands, outflow restrictions, incidents status) and all possible control actions. The output is a ranked list of the control actions. ITC-DSS receives the current values of the traffic state (e.g. from the monitoring and detecting subsystem) and all possible control actions (from the operator). It employs a pre-trained fuzzy-neural network tool to predict the performance of each control action, and finally, generates a ranked list of the best control actions.

There are a range of traffic criteria such as queue lengths, total travel times, number of vehicles enter the network, number of vehicles leave network, etc, can be considered to assess the performance of a control action. The aggregated performance of each control action \( c_i \) can be calculated by considering one or more of the performance criteria, or by using a weighted sum [9], which is defined as:

\[
P_{c_i} = \frac{\sum_{k=1}^{N} W_k E_{k,c_i}}{\sum_{k=1}^{N} W_k}
\]

where \( 0 \leq P_{c_i} \leq 1 \) represents the aggregated performance of control measure \( c_i \) for the given traffic state; \( E_{k,c_i} \) is the evaluation of control action \( c_i \) over the performance criterion \( k \) for the given traffic state \( E_{k,c_i} \) is in the range \([0,1]\), where a low value of \( E_{k,c_i} \) indicates a low performance of \( c_i \) over the performance criterion \( k \); \( w_k \) is the weight of the performance criterion \( k \); and \( N \) is the number of considered performance criteria. These weights \( (w_k) \) are usually selected by the operators based on the current traffic management policies and other considerations.

### D. Calculation of Control Action Fitness

Once the affected agents receive the proposed local control actions \( (ca_1^A) \) with their associated influence rate \( Y_{B,1}^A \), they will run its ITC-DSS subsystem to calculate the fitness of each control action. Suppose in our example, \( A \) is the agent which detected the problem, and \( B \) is the agent which is affected by the control action \( ca_1^A \). To calculate the fitness of \( ca_1^A \), agent \( B \) runs its per-trained ITC-DSS sub-system. In this case, the input of ITC-DSS will be the current traffic state of sub-network \( (s_{m_2}) \) (including any current traffic incident and the predicted traffic demand coming from agent \( A \) during the application of \( ca_1^A \) and only the internal control actions that mainly influence the traffic flows within its network (such as ramp metering or variable speed limits). The main reason behind using only the internal control actions by agent \( B \) is to ensure that the nominated control action will not have the negative knock on effect of creating a new problem for one or more of its neighbours.

The predicted traffic demand of agent \( B \) coming from agent \( A \) during the application of \( ca_1^A \) can be calculated by using the influence rate \( Y_{B,1}^A \) as follows:

\[
P_{Dem_{B}} = C_{Dem_0} + \left( C_{Dem_0} * Y_{B,1}^A / 100 \right)
\]

where, \( P_{Dem_{B}} \) and \( C_{Dem_0} \) denote the predicted and the current traffic demand of agent \( B \) coming from agent \( A \) (i.e. the sub-network \( s_{m_1} \) ) respectively.

Finally, the best control action will be selected by agent \( B \) and its aggregated performance will be used as the fitness \( F \) of \( ca_1^A \). The fitness of a control action \( F \) is in the range \([0,1]\). When \( F \) equals zero, the control action is totally unsuitable. In contrast, when \( F \) equals 1, the control action is suitable. If \( ca_1^A \) has been selected by agent \( A \) as an optimal global control action, agent \( B \) (and all affected agents) will
be informed, so agent \( B \) can apply its selected control action simultaneously.

**E. Calculation of Control Action Global Performance**

The process of calculating the global performance of a control action is performed by the agent where the traffic problem was detected (in our example agent \( A \)). All affected agents will calculate the fitness of the proposed local control actions then return the results to the agent who has the problem (agent \( A \)). The global performance \( p_g \) for each proposed local control action \( ca \) is now determined as:

\[
p_g = \frac{p_l + \sum_{j=1}^{N} (F_j \omega_j \mu_j)}{1 + \sum_{j=1}^{N} (\omega_j \mu_j)}
\]

where \( p_l \) is the local aggregated performance of the control action \( ca \) i.e. the local fitness of \( ca \); \( N \) is the number of affected agents; \( F_j \) is the fitness of \( ca \) which is provided by the affected agent \( j \); the weights \( \omega_j > 0 \) represent the relative importance of agent \( j \). The weights \( (\omega_j) \) are not necessarily fixed, but can be changed on-line by the traffic operator depending on the current traffic management policies and other considerations; and \( \mu_j \) is a measure that shows how much impact is the traffic control action \( ca \) having on agent \( j \). \( \mu_j \) is with \( 0 \leq \mu_j \leq 1 \). i.e. when \( \mu_j \) is close to 1, \( ca \) has a high impact on the traffic flow in agent \( j \), while, when \( \mu_j \) is close to 0, \( ca \) has a low impact on the traffic flow in agent \( j \). \( \mu_j \) is calculated as follows:

\[
\mu_j = \frac{P_{Dem_j}}{outf low_{max}}
\]

where \( Dem_j \) is the predicted traffic demand of agent \( j \) coming from agent \( A \), this can be calculated by using Equ. (2). \( outf low_{max} \) is the maximum possible traffic outflow from agent \( A \) coming into agent \( j \).

**III. Prototype of the Proposed Multi-agent Traffic Control System**

**A. Riyadh Traffic Case Study**

In order to test the technical feasibility of the proposed approach, a traffic case-study was created for a part of the traffic network in the Riyadh city of Saudi Arabia, see Fig 3. The selected network consists of three parallel motorways (Olaya motorway, King Fahd motorway, Takhassusi motorway) connected via several on- and off-ramps. In this case study, we only consider traffic going from the south to the north (towards the city centre). Traffic enters the network from five origins (O1, O2, O3, O4, and O5) and leaves the network through six destinations (D1, D2, D3, D4, D5, and D6). The network is divided into three sub-networks King Fahd, Olaya, and Takhassusi (see Fig 3) controlled and managed by three agents A1, A2, and A3 respectively. The sub-networks have been simulated using a traffic simulation program called METANET [13] for several traffic states and different control actions with the following parameters: 1) incidents varied in severity from 20% to 60% reduction in link capacity, and from a duration of 30 to 45 min; 2) simulated time period from 7:00 am to 12:00 am; 3) prediction horizon one hour; 4) compliance rate of traffic for Variable Direction Indication (VDSs) 75%. The traffic state has been represented by: day time, average traffic density, incident severity, and traffic demands (i.e. sub-network boundary conditions). The generated data has been used to train the ITC-DSS subsystem and to create \( CA_{a,b,c} \) for each agent.

Let us remark that, the verification results presented in the remainder of this section are not intended to verify the ability of ITC-DSS to correctly predict the performance of a control action, because this has been already done in [4]. The aim is to demonstrate the technical feasibility of the proposed multi-agent approach, and to show how the traffic agents interact effectively together to identify the optimal global control action from optimal local control actions.

![Fig. 3. The Riyadh traffic network considered in the case study.](image)

**B. Applying the Proposed Multi-agent Approach**

To apply the proposed multi-agent approach, we have considered the following usual traffic status:

- The traffic enters King Fahd sub-network is divided as:
  - 25% goes to destination D1 (90% uses King Fahd motorway, and 10% uses Olaya motorway)
  - 75% goes to destination D2 (70% uses King Fahd motorway, 10% uses Takhassusi motorway, and 20% uses Olaya motorway)
- There is a traffic incident in King Fahd sub-network causing a traffic congestion (with 45% severity) at point X (see Fig 3).
- There are three possible local traffic control actions have been selected by agent A1 based on their local performance to solve the incident problem in King Fahd sub-network:
  - \( ca^K_1 \): Using Variable Direction Indication (VDS) at point A (see Fig 3) to direct traffic goes to D2 to use Olaya motorway.
  - \( ca^K_2 \): Using Variable Direction Indication (VDS) at point A (see Fig 3) to direct traffic goes to D2 to use Takhassusi motorway.
  - \( ca^K_3 \): On the ramp metering at point B, C and D (see Fig. 3)
Table II shows the local performance of $ca^k$, $ca^l$, and $ca^s$ predicted by ITC-DSS of agent $A1$ represented by some traffic criteria (TTT: Total Travel Time, TDT: Total Delay, VDI: Vehicles Driven In, and TQL: Total Queue Length at origins). The last column shows the aggregated performance of each control action. It is in the range of (0-1) and represents the fitness of the control action. The aggregated performance is calculated by considering one criterion, or using a weighted sum of a set of criteria. In this experiment we have consider only the TQL to calculate the aggregated performance.

<table>
<thead>
<tr>
<th>Control Action</th>
<th>TTT</th>
<th>TDT</th>
<th>TD</th>
<th>VDI</th>
<th>TQL</th>
<th>Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ca^k$</td>
<td>12109.57</td>
<td>325981.4</td>
<td>4873</td>
<td>19343</td>
<td>353.23</td>
<td>0.90</td>
</tr>
<tr>
<td>$ca^l$</td>
<td>11334.7</td>
<td>322348.3</td>
<td>5002</td>
<td>19227</td>
<td>521.79</td>
<td>0.79</td>
</tr>
<tr>
<td>$ca^s$</td>
<td>11842.68</td>
<td>317359.3</td>
<td>5100</td>
<td>19056</td>
<td>666.07</td>
<td>0.69</td>
</tr>
</tbody>
</table>

It can be observed from Table II that $ca^k$ is the optimal local control action which can solve the local traffic congestion in King Fahd sub-network optimally. However, solving a local traffic congestion only can have a consequence that the vehicles run faster into another (downstream) congestion, whereas still the same amount of vehicles have to pass the downstream bottleneck (with a given capacity). In such a case, the average travel time on the network level will still be the same or worst. In the following paragraphs we will see how the proposed multi-agent approach can be applied to identify the optimal global control action from those three control actions.

<table>
<thead>
<tr>
<th>Control Action</th>
<th>Olaya Sub-network</th>
<th>Takhassusi Sub-network</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ca^k$</td>
<td>A2 82.4%</td>
<td>A3 -5.9%</td>
</tr>
<tr>
<td>$ca^l$</td>
<td>A2 -5.9%</td>
<td>A3 66.7%</td>
</tr>
<tr>
<td>$ca^s$</td>
<td>A2 +23.5%</td>
<td>A3 +22.2%</td>
</tr>
</tbody>
</table>

Creating $CA_{table}$ table for King Fahd sub-network:

As we motioned before the $CA_{table}$ table can be created using historical traffic data or a traffic simulation model. In this experiment we have used METANET program to create $CA_{table}$. Table III shows $CA_{table}$ for King Fahd sub-network with the three control actions ($ca^k$, $ca^l$, and $ca^s$). For example, as can be seen from the table, the traffic control $ca^k$ affects the traffic demand on Olaya Sub-network negatively by 82.4% and the traffic demand on Takhassusi Sub-network positively by 5.9%. That is, $ca^k$ increases the traffic inflow into Olaya Sub-network from King Fahd sub-network by 82.4% and decreases the traffic inflow into Takhassusi Sub-network from King Fahd sub-network by 5.9%. This is because that 75% of traffic enters King Fahd sub-network and needs to go to D2 (i.e. 70% uses King Fahd motorway, 20% uses Takhassusi motorway, and 10% uses Olaya motorway) as directed by $ca^k$ to use only Olaya Sub-network.

Calculation of Control Action Fitness:

Agents A2 and A3 (the affected agents) have calculated the fitness of $ca^k$, $ca^l$, and $ca^s$ using their ITC-DSS, as explained before. Table IV and Table V show the best performance of the three control actions $ca^k$, $ca^l$, and $ca^s$ predicted by agents A2 and A3 after considering the traffic demands predicted by agent A1 and only the local control actions. The fitness of the control actions, which will be returned to agent A1, are listed in column 5 of each table. In this experiment, we have only considered the Total Queue Length (TQL) values to calculate the aggregated performance (the fitness) of each control action.

<table>
<thead>
<tr>
<th>Control Action</th>
<th>TTT</th>
<th>TDT</th>
<th>TD</th>
<th>VDI</th>
<th>TQL</th>
<th>Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>$ca^k$</td>
<td>10307.66</td>
<td>91095.3</td>
<td>7578</td>
<td>10575</td>
<td>1721.73</td>
<td>0.11</td>
</tr>
<tr>
<td>$ca^l$</td>
<td>8919.19</td>
<td>88286.3</td>
<td>6705</td>
<td>9554</td>
<td>900</td>
<td>1</td>
</tr>
<tr>
<td>$ca^s$</td>
<td>9660.31</td>
<td>10562.6</td>
<td>7302</td>
<td>10130</td>
<td>1391.96</td>
<td>0.58</td>
</tr>
</tbody>
</table>

It is observed from Table IV that, $ca^k$ is recommended by agent A2 (with fitness 1) because $ca^k$ has a positive impact on its sub-network (Olaya sub-network), while $ca^l$ is the least recommended (with fitness 0.11) because it affects the sub-network traffic state very negatively. On the other hand, Table V shows that A3 strongly recommends $ca^l$ (with fitness 1) because $ca^l$ has a positive impact on its sub-network (Takhassusi sub-network), while, it does not recommend $ca^k$ (with fitness 0.69) because $ca^k$ has a slight negative impact on the sub-network traffic state.

Calculation of Control Action Global Performance:

The last step was calculating the global performance for the three control actions. Table VI summarizes the final results of the proposed multi-agent approach. The table shows how Olaya sub-network is assigned a large weight $\omega = 0.8$ than Takhassusi sub-network $\omega = 0.2$, indicating the high importance of that network part at that time. The $\mu$ value of each sub-network, which indicate how the sub-network was affected by the control action, computed for each control action using equation 3 and summarized in columns 4 and 6. In the second and the last columns of the table, the local and the global performance (fitness) of the control actions are summarized.
It is observed from Table VI that, the optimal global control action is $ca_2^T$ which can solve the congestion problem in King Fahd sub-network and also improve the overall traffic state in the network. Although, $ca_3^T$ has the best performance (fitness) to solve the local traffic congestion in King Fahd sub-network, it is not the optimal global control action. That is simply because that $ca_3^T$ passes a large number of vehicles from King Fahd sub-network to Olaya Sub-network at a time when Olaya Sub-network suffers from a bad traffic state, which will not improve the overall traffic state in the network.

This example demonstrates that the proposed multi-agent based approach can recommend an effective global control action to the traffic control decision makers.

### IV. CONCLUSIONS AND FUTURE WORKS

We have presented an intelligent decision support system based on the multi-agent approach to assist the human operator of the road traffic control centre to manage the current traffic state. In this paper, we have extended the intelligent traffic control decision support system (ITC-DSS) from being used only for controlling a small-sized network to be used to control a large-sized network. We have opted for a multi-agent approach where the total network is divided in sub-networks, each of which has its own evaluation agent. In order to test the technical feasibility of the proposed multi-agent decision support system, a case study of a large section of the ring-roads around Riyadh is presented and discussed. The obtained results demonstrate merits and capabilities of the proposed system in order to help the operator in the traffic centres to identify the optimal global control action.

This research investigation has demonstrated the technical feasibility of the proposed multi-agent approach with limited number of traffic control actions. In the next stage, we will test the proposed system with a large number of traffic control action and assess its performance by comparing the obtained results with traffic simulation model results.

### References


