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Decision Support System for Network Traffic Control Risk Management

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Abstract— Risk management is a constant and necessary practice in the daily operation of traffic systems, especially since they are vulnerable to everyday risks that can cause failures in their performance. The concept of risk analysis and management is therefore necessary in traffic management and it is important to develop strategies, methods and tools for risk management to aid decision makers through a systematic process based on Decision Support Systems (DSS). In this paper, we present a framework for a DSS to help Traffic Control Centers on the analysis of the performance risk of a transport system and the development of traffic control methods in an urban area. In this context we have developed a planning tool as part of the DSS for formulating, testing and selecting the near optimal traffic control strategy. The approach followed the concept of Conditional Value-at-Risk (CVaR) for the assessment of the network performance and the optimization of traffic control parameters for a signalized network. The benefits of the proposed approach were demonstrated through an implementation in a reference network and compared with the network performance with traffic signal settings obtained using TRANSYT-7F. The basic hypothesis of our proposed methodology is that traffic plans designed and optimized by minimizing the CVaR will offer users a lower risk of experiencing higher values of delays. This hypothesis was validated through a sensitivity analysis of 46 tests with different demand levels and incidents occurring at the network using the AIMSUN mesoscopic dynamic model.

Index Terms— Conditional Value-at-Risk, Decision Support System, Dynamic Traffic Assignment, Mesoscopic Assignment, Multi-objective Genetic Algorithm, Risk Assessment, Traffic control optimization.

1 Introduction

RISK management is a constant and necessary practice in the daily operation of traffic systems. Traffic management centers set strategic goals, such as the reliable and efficient movement of people and goods, and develop and implement strategies and measures to achieve them. Internal and external factors and events may, however, affect the achievement of these objectives and cause failures in the systems' performance. In that respect, traffic management centers set specific indicators to measure traffic performance and develop decision-making systems to optimize the operation of their systems. The concept of risk analysis and management is therefore necessary in traffic management and it is important to develop strategies, methods and tools for risk management to aid decision makers through a systematic process based on Decision Support Systems (DSS). DSS for traffic management have been considered for helping Traffic Control Centers to address congestion problems since 1980s. FRED (Freeway Real-Time Expert System Demonstration) [1] and the Santa Monica Smart Corridor Demonstration Project [2] were the first attempts reported in this field. Since then many DSS frameworks for traffic management have been proposed and investigated incorporating multiagent techniques, simulation based techniques, fuzzy logic, neural networks, heuristic approaches, case-base logic, etc. (e.g.[3],[4],[5],[6],[7],[8]).

The congestion effects at signalized networks has been the focus of research for many decades aiming to its mitigation by developing and optimizing traffic control strategies based on the estimation of time-dependent traffic states depicting the network performance though time evolution. Traffic control strategies can be classified, according to [9], depending on (a) the period which they have been designed and/ or implemented: i.e. fixed-time and traffic responsive (real-time) strategies; (b) the area of their implementation and the level of incorporation of other traffic control locations, i.e. isolated and coordinated strategies; (c) the queue accumulation procedure which is used, and therefore strategies can be applicable to undersaturated and/ or oversaturated conditions. The strategies which do not take into consideration the queue build-up effects and the dissemination of the queue, cannot describe the oversaturated traffic conditions accurately especially for an extended period of time. The optimization of traffic control strategies and the traffic assignment are highly interdependent especially in congested networks, therefore their combination is necessary in order to eliminate inconsistencies and to provide solutions that enhance the performance of the network. The combined user equilibrium traffic assignment and signal optimization problem is defined as the optimization of traffic signals while users choose their routes according to the equilibrium principles [10]. The combined problem has been investigated by many researchers over the past years in its static formulation (e.g. [11],[12],[13]) and in its dynamic extension (e.g. [14],[15],[16]).

DSS focusing on developing a suitable traffic signal control strategy for a network have been proposed over the years. Choy et al. [17] presented a cooperative, hierarchical, multiagent system for real-time traffic signal control of a complex traffic network divided into subproblems, each of them handled by an intelligent agent with a fuzzy neural decision making-module. Chen et al. [18] developed a systematic framework for implementing and evaluating traffic signal operations under severe weather conditions by evaluating the

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most suitable plans based on a set of pre-defined timing plans. Hashemi and Abdelghany [19] presented a real-time traffic network state estimation and prediction system with built-in decision support capabilities for selecting efficient traffic management schemes for recurrent and non-recurrent congestion based on a meta-heuristic search mechanism for constructing the schemes by integrating a wide variety of control strategies which are pre-approved, such as set of pre-approved timing plans for all intersections, diversion messages along dynamic signs, ramp metering rates for the different freeway ramps, pricing scenarios of toll facilities, etc. Their work was extended in [20] where the objective was to develop robust traffic management schemes such that the network overall performance remains close to optimality under all possible future operational conditions (e.g. demand level, road closures, weather, etc.). Their decision support module adopted a meta-heuristic search algorithm for determining the most robust traffic network management scheme considering the uncertainty in the network operational scenarios expressed by the mean value and variance of the network performance (i.e. the total travel time) estimated through a dynamic traffic assignment (DTA) simulation-based model.

In this paper, we present a framework for a Decision Support System to help Traffic Control Centers on the analysis of the risk of a transport system performance and the development of traffic control methods in an urban area, by taking into account methods and strategies for analyzing and limiting the system performance risk. In this context it is necessary to use tools simulating the traffic conditions under dynamic loading so that the analysis takes into account the important evolution of dynamic conditions prevailing in the network and the available routes that the users of the network choose accordingly. In addition, a dynamic mesoscopic approach provides a platform for the implementation of online and offline traffic control strategies and is used by many traffic control systems in the industry as well as in research applications. The approach followed the concept of Conditional Value-at-Risk (CVaR) for the analysis of both the network performance and the optimization of traffic control. CVaR is a widely used risk quantification and prediction measure developed in the context of financial activities with applications to other research fields. Our research contributions are in the following subjects:

- The proposed DSS evaluates the system performance based on a risk analysis of excess travel times using a dynamic mesoscopic traffic assignment simulation model and generates proactive traffic control plans that are consistent with both the anticipated network conditions and drivers' route choice behavior.
- The optimization of the traffic signal plans in the network is performed using a multi-objective genetic algorithm which minimizes the risk of delays in the signalized intersections and the risk of non-coordinated predefined routes of the network, analyzing the traffic dynamics in the context of risk.
- Both the optimization algorithm and the mesoscopic model include detailed description of the geometric and operational characteristics of the signalized intersections.
- The optimization of the traffic signal plans is based on the procedure of multiple period analysis of the Highway Capacity Manual 2010 [21].

To our knowledge, there is only one paper [20] which deals with the risk minimization in a DSS framework evaluating traffic plans. In that case, the risk is defined using the mean value and the variation of the performance measure estimated from different operational cases in order to evaluate predefined timing plans. In our case, both the optimization of traffic plans and the evaluation of the system is based on a risk analysis of a coherent risk measure (CVaR), which is defined as a metric for the performance for the delays experiencing by users within the analysis period.

The paper is organized as follows: the next section provides information about the risk analysis adopted in the context of this work, the third section describes the proposed DSS and the optimization methodology for finding the optimal traffic signal settings in an urban network. The application of the proposed methodology in a referenced network and the sensitivity analysis performed to the alternative solutions compared to the results obtained through the benchmark tool TRANSYT-7F (a genetic algorithm optimization of cycle length, phasing sequence, splits, and offsets) are presented in the sections 4 and 5. Finally, the main conclusions are summarized in the last section with some remarks on future research.

2 Risk Analysis

The international standard [22] defines risk as 'the effects of uncertainty on objectives' and therefore in its broadest terms risk is defined as the combination of the probability of a situation and the extent of its consequences. Risk management is the process of analyzing and identifying uncertainties that are important risk factors as well as designing and implementing measures and strategies to limit these factors. In each system there are events that may have a positive or a negative effect on their consequences. The usual practice in risk analysis is to take into account the negative consequences that a system may have and attempt to prevent, as well as to reduce these negative consequences.

In the late 1980s, major financial institutions, regulatory authorities and the academic community were interested in developing a Market Risk model, driven by major financial crises, largely due to the lack of risk analysis and risk management methods. Risk measures, according to [23], are classified into two categories: the dispersion and the downside risk measures. Dispersion measures quantify the dispersion of the estimated value around the expected value. Such measures are the variance and standard deviation, the absolute deviation and the absolute moment. Since most important in the portfolio optimization is the results that are short of expectations, researchers have proposed the downside risk measures. Such measures are the lower-partial moment measure, the semi-variance and quantile-based measures, like Value-at-Risk (*VaR*) and Conditional Value-at-Risk (*CVaR*) models, which are widely used in financial applications. *VaR* is a quantile-based risk measure which was developed and adopted in response to financial disasters. VaR determines the level of exposure of a position (portfolio or investment) which will not be exceeded over a specific period of time and can be interpreted as the maximum level of loss that is expected and accepted at financial activities. Thus, *VaR* of a portfolio for a given confidence level, α, is the smallest number r such that the probability of the portfolio loss R to exceed r is at most (1 - α). *VaR* is not considered as a coherent risk measure [25], because it is not affected by the tail of the distribution. So, *CVaR*, was introduced by [26] and [27], which approximates the average of the worst-case loss scenarios, in order to cover the shortcomings of *VaR*. Hence, *VaR* answers the question 'how bad the conditions are?', while *CVaR* answers the question 'if the conditions are bad, how much is the expected loss?'. The following figure demonstrates the relationship between these two measures.

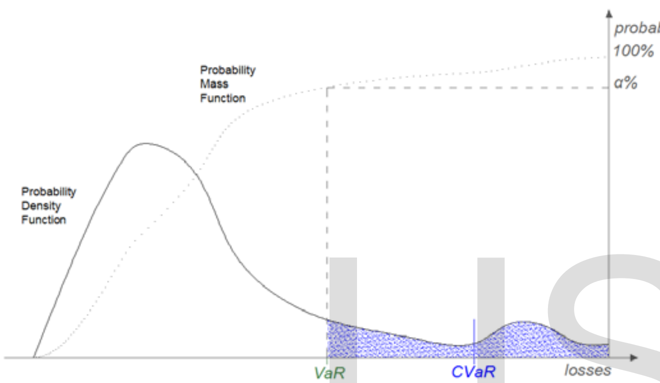

Fig. 1. Graphical representation of *VaR* and *CVaR*

According to [26], *CVaR* is better than *VaR* in optimization applications, because it provides convexity and therefore it can be solved as a linear programming problem for continuous or discrete samples. Also, the estimation of *CVaR* incorporates the potential losses in the tail and not only the probability of the tail. So, if higher values are observed in the tail beyond the level of confidence, *CVaR* is affected by those values, whereas *VaR* isn't.

In the proposed risk analysis of the traffic network performance, we define as losses the loss of travel time corresponding to the delay that a user is experiencing over a certain period of time. Thus, in the case of the signalized network, the *VaR* for a confidence level a is the value r that the travel time losses (due to delays), *TTL*, will not exceed this value with a probability less than or equal to $(1-a)$. Correspondingly in our case, *CVaR* for a confidence level a is the expected loss in travel time due to delays throughout the analysis period when *VaR* is exceeded.

Rockafellar and Uryasev provide the following definition of *CVaR* and proof that *CVaR* is a coherent measure in [26]. Let $f(\boldsymbol{x},\boldsymbol{y})$ be the loss of capital value or time (i.e. delay) associated with the decision vector $\boldsymbol{x}$, which is selected from a subset $\boldsymbol{X} \in R^n$, and the random variables vector $\boldsymbol{y} \in R^m$. The portfolio combination or the traffic signal settings is represented by $\boldsymbol{x}$, with $\boldsymbol{X}$ representing all available portfolios combinations or all available traffic signal settings subject to certain constraints. Vector $\boldsymbol{y}$ is representing the uncertainties that can affect the loss, such as market parameters or demand flow in our case. For each $\boldsymbol{x}$, the loss $f(\boldsymbol{x},\boldsymbol{y})$ is a random variable with a distribution in $\mathbb{R}$, affected by $\boldsymbol{y}$. The underlying probability distribution of $\boldsymbol{y}$ is considered to have density $p(\boldsymbol{y})$, which is not required to be analytically estimated as proved by [26]. The probability that $f(\boldsymbol{x},\boldsymbol{y})$ will not exceed the lower bound r is given by:

$$\Psi(\boldsymbol{x},r)=\int_{f(\boldsymbol{x},\boldsymbol{y})\le r} p(\boldsymbol{y})\,dy \quad (1)$$

which is a cumulative distribution function of the loss with respect to $\boldsymbol{x}$. Generally, $\Psi(\boldsymbol{x},r)$ is a non-decreasing function with respect to r and it is considered to be continuous. The VaR_a and $CVaR_a$ for the random variable of the loss associated with $\boldsymbol{x}$ at the confidence level a is given by

$$VaR_a=min\{\, r\in R : \Psi(\boldsymbol{x},r) \ge a \,\} \quad (2)$$

$$CVaR_a=\frac{1}{(1-a)}\int_{f(\boldsymbol{x},\boldsymbol{y})\ge VaR_a} f(\boldsymbol{x},\boldsymbol{y})p(\boldsymbol{y})dy \quad (3)$$

Rockafellar and Uryasev [27] formed the following expression for $CVaR_a$ in terms of function F_a on $X\times R$ and proved that it is superior because it provides convexity and it can be solved as a linear programming problem for discrete samples, as well, by sampling the probability distribution of $\boldsymbol{y}$ according to its density $p(\boldsymbol{y})$ and generating a collection of $[y_1,\dots,y_q]$ vectors with probabilities p_k and including in the decision variables the $VaR_a = \xi$:

$$\bar{F}_a(\boldsymbol{x},\xi)=\xi+\frac{1}{(1-a)}\sum_{m=1}^{q} p_k \max\{f(\boldsymbol{x},\boldsymbol{y}_m)-\xi,0\} \quad (4)$$

CVaR has been used in traffic control optimization by other researchers, in order to capture the day-to-day variations in traffic demand ([28],[29],[30],[31],[32]) and to provide a robust traffic signal plan taking account the uncertainty of demand estimation in the optimization. In this paper, the *CVaR* is used in a different context, capturing the uncertainty in delays experiencing by the users in a planning horizon, extending the work presented in [33] for an isolated intersection to a coordinated network in the framework of DSS.

3 Decision Support System Framework

In general, a DSS for traffic management consists of the following tasks (Fig.2):

- Monitoring the state of the network, i.e. collecting and storing data reflecting the state and performance of the network. The data are processed and used for the detection and recognition of traffic flow patterns. Raw and processed data, traffic flow patterns and Origin-Destination matrices are stored in the DSS database.
- Predicting the state and performance of the network using analytical or/and simulation models based on real-time data and/or historical data. The demand and the network is calibrated and validated employing a simulation based model for mesoscopic dynamic traffic assignment.
- Formulating, testing and selecting strategy for mitigating traffic congestion.
- Implementing and evaluating the selected strategy. A risk analysis of the system performance with the implemented strategy is performed in order to improve and correct the activities involved in the demand pre-

diction and the planning tools.

Our research is focused on the activities involved with the traffic control strategy formulation, testing and selection within the framework of a DSS for traffic management, which can be used for optimizing the traffic control parameters and assessing the performance of the network in order to provide to the operators a planning tool for the risk management of the users' delay. Our proposed Planning Tool contains five tasks (Fig.2):

- The transport system representation components, where all the attributes of the network are coded for importing in the mesoscopic Dynamic Traffic Assignment (mDTA) and in the optimization algorithm. The attributes include the temporal Origin-Destination (O-D) demand, the physical characteristics of the network (i.e. intersections, links, lanes, etc.) and the operational characteristics (i.e. signal plans, parking restrictions, traffic management schemes, etc.).
- The system performance evaluation, where the actions for performing a mDTA is included based on the system's characteristics for an extended peak period (i.e. three hours). The mDTA is performed using the AIMSUN microsimulation model in order to assign the users to the network based on dynamic user equilibrium.
- The risk analysis of the performance of the system, where the CVaR of the travel time losses by users due to delays during the extended peak period is estimated and compared to previous solutions. Based on "(2)"-"(3)", we have formed an equivalent definition of the CVaR of the average delay of users:

$$VaR_a = min\{\, r \in R : Pr(\,TTL > r) \geq a \,\} \quad (5)$$

$$CVaR_a = \frac{1}{(1\text{-}a)} \sum_{i:TTL_i \geq VaR_a} p_i \, TTL_i \quad (6)$$

where VaR_a at confidence level a is the value r (i.e. users' delay) such that the probability that the travel time losses by users (TTL) will exceed r is not more than $(1\text{-}a)$; $CVaR_a$ is the expected delay which exceeds the respective VaR_a at the same confidence interval; TTL_i is the average travel time losses by users due to delays, which are estimated for every interval i of the analysis period; and p_i is the probability of each average TTL_i to be experienced by the users which is taken as the ratio of the demand experiencing this TTL_i over the total demand of the entire analysis period.

- The traffic control strategy is selected based on the minimum value of *CVaR* of travel time losses accrued to network users due to delays during the extended peak period, as estimated by "(5)" and "(6)".
- The traffic control optimization algorithm (mGA-CVaR) solving an anticipatory signal control optimization problem for an extended peak period, where its ultimate objective is to find the optimal network signal parameters which minimize the risk of delays of the users based on the dynamically assigned traffic flows. The network signal parameters refer to the green times of the phases of the signalized intersections' plans and the offsets for their efficient coordination. The problem is solved using a multiobjective optimization by minimizing the *CVaR* of average delays at intersections and the *CVaR* of average losses due to non-coordination of predefined routes.

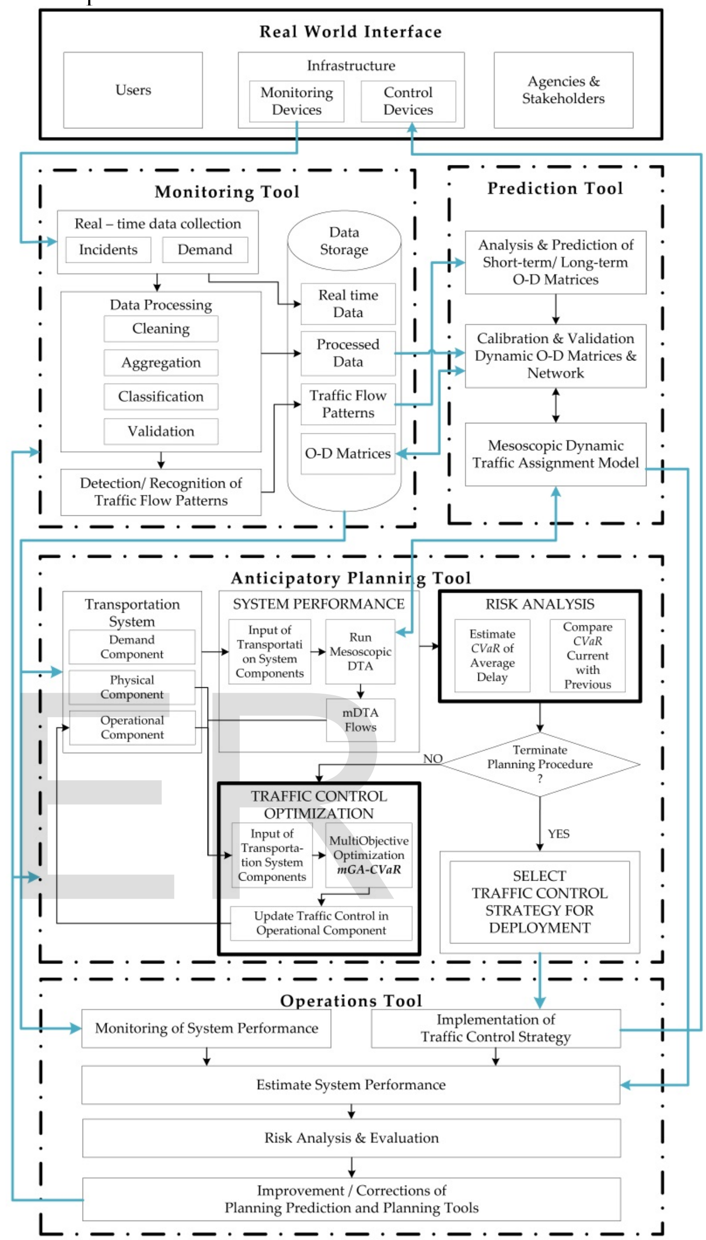

Fig. 2. Proposed Decision Support System

The proposed optimization method (mGA-CVaR) uses as solution algorithm the multiobjective genetic algorithm function gamultiobj in Matlab R2014a. The objectives have as decision variables the green times of all signal phases and the offsets of the signal plans of network intersections and they are described in the following.

The first objective function refers to the mesoscopic delay experienced by users from all signalized intersections. The algorithm minimizes the *CVaR* of average delay though the entire simulation horizon, which is estimated for all intersections at each interval based on the U.S. Highway Capacity Manual HCM2010 [21] formula for multiple period analysis. The estimation of delay for the multiple-period analysis is ex-

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pressed by the following formula:

$$d_{i,lg,n}=d1_{i,lg,n}+900\,T\left[(X_{i,lg,n}-1)+\sqrt{(X_{i,lg,n}-1)^2+\frac{8\,k\,l\,X_{i,lg,n}}{c_{i,lg,n}\,T}}\right]+$$

$$+\frac{3600}{u_{i,lg,n}\,T}\left(t_{A,i,lg,n}\frac{Q_{b,i,lg,n}+Q_{e,i,lg,n}-Q_{eo,i,lg,n}}{2}+\frac{Q^2_{e,i,lg,n}+Q^2_{oe,i,lg,n}}{2c_{A,i,lg,n}}-\frac{Q^2_{b,i,lg,n}}{2c_{A,i,lg,n}}\right) \quad (7)$$

where T is the duration of interval i, k is the incremental delay factor, l is the upstream filtering/metering adjustment factor and for each lane group, lg, and for all intersections n, at each period i: $d_{i,lg,n}$ is the average vehicle delay, $d1_{i,lg,n}$ is the uniform delay, $g_{i,lg,n}$ is the effective green time, $X_{i,lg,n}$ is the ratio of traffic flow over capacity, $c_{i,lg,n}$ is the capacity, $u_{i,lg,n}$ is the traffic flow, $t_{A,i,lg,n}$ is the adjusted duration of unmet demand in the i-th period, $Q_{b,i,lg,n}$ is the initial queue at the beginning of the i-th period, $Q_{e,i,lg,n}$ is the initial queue at the end of the i-th period, $Q_{eo,i,lg,n}$ is the initial queue at the end of the i-th period when $u_{i,lg,n} > c_{A,i,lg,n}$ and $Q_{b,i,lg,n}=0$, $c_{A,i,lg,n}$ is the average capacity during the i-th period.

The above mentioned variables of each lane group is estimated according to the same methodology [21], depending on the type of movement (e.g. protected or permitted, shared or exclusive, etc.) and the geometric and traffic characteristics (e.g. lane width, HGV percentage, parking maneuvers, etc.). Especially in the case of permitted movements, the variables have an additional dynamic complexity due to the different demand levels occuring each period.

The network average vehicle delay (s/veh) at the *i-th* period is:

$$d_i = \sum_{lg,n} u_{i,lg,n}\, d_{i,lg,n} \Big/ \sum_{lg,n} u_{i,lg,n} \quad (8)$$

Therefore the first objective function is:

$$CVaR\text{-}d_a=\xi_d+\frac{1}{(1-a)}\sum_{i=1}^{I} p_{d,i}\max\left\{d_i-\xi_d,0\right\} \quad (9)$$

where ξ_d is an additional variable corresponding to the VaR of the average delay and $p_{d,i}$ is the probability of each delay level, which is taken as the ratio of the demand during the period i over the demand of the entire analysis horizon, I.

The second objective function is constructed for finding the optimal offsets and is the minimum $CVaR$ of the number of vehicles travelling through the predefined routes without stopping (SV). This is based on the primary principles of the bandwidth optimization developed by [34], where the bandwidth B^r for the route r of the network is estimated through the lower, I^r_{L,n_r}, and upper, I^r_{U,n_r}, interferences of the coordinated phases of nodes, n_r, in the r-th route and the minimum green time, G^r_{min}, of the coordinated phases in the r-th route:

$$B^r=G^r_{min}-\left\{\max_{\forall r} I^r_{U,n_\delta}+\max_{\forall n_r} I^r_{L,n_r}\right\} \quad (10)$$

The loss from not having coordinated routes at period i along all routes of the network is given by:

$$SV_i=\sum_r u^r_i\left(1-B^r/C\right)\Big/\sum_r u^r_i \quad (11)$$

where C is the cycle length and u^r_i is the demand along route r during period i.

Therefore the second objective function is:

$$CVaR\text{-}SV_a=\xi_{SV}+\frac{1}{(1-a)}\sum_{i=1}^{I} p_{SV,i}\max\left\{SV_i-\xi_{SV},0\right\} \quad (12)$$

where ξ_{SV} is an additional variable corresponding to the VaR of the SV and $p_{SV,i}$ is the probability of each loss to happen, which is taken as the ratio of the routes' demand during the interval i over the routes' demand for the entire horizon, I.

The general formulation of the optimization problem is as follows:

$$\min_{\boldsymbol{x},\xi_d,\xi_{SV}}\left\{CVaR\text{-}d_a(\boldsymbol{x},\xi_d);CVaR\text{-}SV_a(\boldsymbol{x},\xi_{SV})\right\} \quad (14)$$

subject to the following constraints:

$$\left\{\begin{matrix} C_{min} \le \sum_{N^n_\varphi} L^n_\varphi + \sum_{N^n_\varphi} g^n_\varphi \le C_{max} \\ L_b \le g^n_\varphi \le U_b \\ 0 \le o^n \le C \\ -G^r_{min} < I^r_{L,n_r} < G^r_{min} \\ -G^r_{min} < I^r_{U,n_r} < G^r_{min} \\ 0 \le B^r \le G^r_{min} \end{matrix}\right\} \quad (15)$$

where $\boldsymbol{x}=[\boldsymbol{g},\boldsymbol{o}]$ is the vector containing the decision variables of the problem; $\boldsymbol{g}$ is the vector containing the duration of green time, g^n_φ, of the N^n_φ phases of all nodes n; $\boldsymbol{o}$ is the vector containg the offsets of all nodes n; C_{min} and C_{max} are the minimum and maximum cycle length; L^n_φ is the lost time of each phase φ $(\varphi \in N^n_\varphi)$ for each node n; L_b, U_b are the lower and upper bounds of green time duration.

4 Application of Methodology

The proposed methodology (mGA-CVaR) of traffic signal optimization by minimizing the risk of delay at a mesoscopic level was implemented for a reference network. The mGA-CVaR approach was compared with the traffic signal settings obtained using the TRANSYT-7F as the Traffic Control Optimization task in Fig.2. Also, the Risk Analysis task (Fig.2) of the proposed approach was replaced by the comparison of the network's mean delay throughout the simulation horizon as simulated in mDTA with the TRANSYT-7F settings, in order to compare the proposed risk approach to a classic approach.

4.1 Test Network

The test network has 13 nodes, 28 links (one-way), 22 Origin-Destination (O-D) pairs and 18 signal groups at 6 signalized intersections, as described by Allsop & Charlesworth [35]. The mirrored layout of the network and the traffic signals plans of each intersection are depicted in Figure 3. The network was analyzed into four routes, which were included in the optimization process for finding the best offsets. The selected routes connect all network centroids in a way that all intersections are included at least on two routes. The route selection was also based on the most critical O-D pairs. Route 1 has two directions connecting the intersections: {1-2-3-4}. Route 2 has two directions connecting the intersections: {1-6-5-4}. Route 3 has one direction connecting the intersections: {6-2}. Route 4 has one direction connecting the intersections: {3-5}.

4.2 Demand Distribution

In this paper the analysis period of the network traffic conditions is performed for an extended peak period of three hours, which is a typical period for implementing a fixed time signal plan at urban areas. The referenced demand is representing the peak hour as reported in [35]. The temporal distribution of the demand for the extended peak period was derived by assuming a log-normal distribution for the morning period and using appropriate factors in order the total number of trips for the peak hour to be 5000 vehicles, as in [35]. Thus, the total number of trips for the extended peak period was 10880 vehicles.

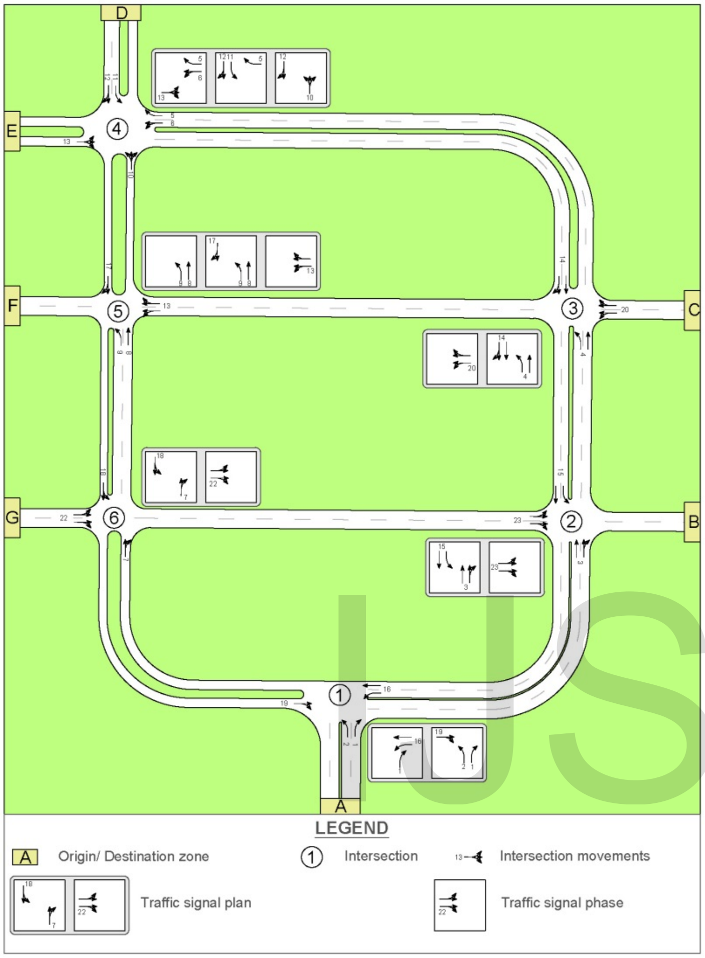

Fig. 3. Mirrored layout of Allsop and Charlesworth's network [35]

4.3 Model Setup

The dynamic mesoscopic assignment was performed in AIMSUN 8.2.1, calculating the costs every 5min and used for the Dynamic User Equilibrium the Gradient-Based model. The optimization algorithm for finding the best signal timings and the associated offsets was implemented in Matlab R2014a for the proposed method and in TRANSYT-7F for comparison. The duration of the interval in the proposed optimization procedure is 5min, in order to provide fine resolution to the traffic performance of the network without creating instability issues resulting from the variations of the cycle length. The optimization in TRANSYT-7F followed the multiple period approach by analyzing the entire period into 20min intervals, due to software limitations. The parameters and constraints of the optimization procedure are set to the following values:

- Lower cycle time: 50s,
- Upper cycle length: 150s,
- Minimum phase green time: 7s,
- Intergreen time: 5s,
- Coordination speed: 50km/h
- Confidence level for *CVaR*: 0.9

The initial traffic signal plans for the intersections were obtained by [12], which having 70s cycle length and equally distributed green times to phases.

4.4 Results

The comparative results between the alternative approaches were analyzed based on the data obtained from the mDTA, analyzing the overall average network delay, the total travel time and the *CVaR* of the average network delay (Table 1). The mGA-CVaR solution provides 33.9s/km overall average network delay, 291.5h total travel time and 38.3s/km *CVaR*. The TRANSYT-7F solution increases the average network delay by 4.2% (35.4s/km), the total travel time by 3.7% (302.8h) and the CVaR of average network delay by 6.6% (38.3s/km) compared to mGA-CVaR. Figure 4 presents the time variation of the average network delay at each interval through the simulation horizon from the implementation of the solution of the two approaches, where it can be seen that there is a decrease in the maximum values of the average delay per interval with the mGA-CVaR solution. This reduction in the maximum average delay values observed, when the highest number of vehicles is loaded in the network, is the most important advantage of the proposed method. This reduction is important not only because it is experienced by a high percentage of vehicles, but mainly because it prevents the occurrence of high values of delays in the system, which are not easily manageable and reversible during an unexpected event that may cause increased demand or reduced network capacity.

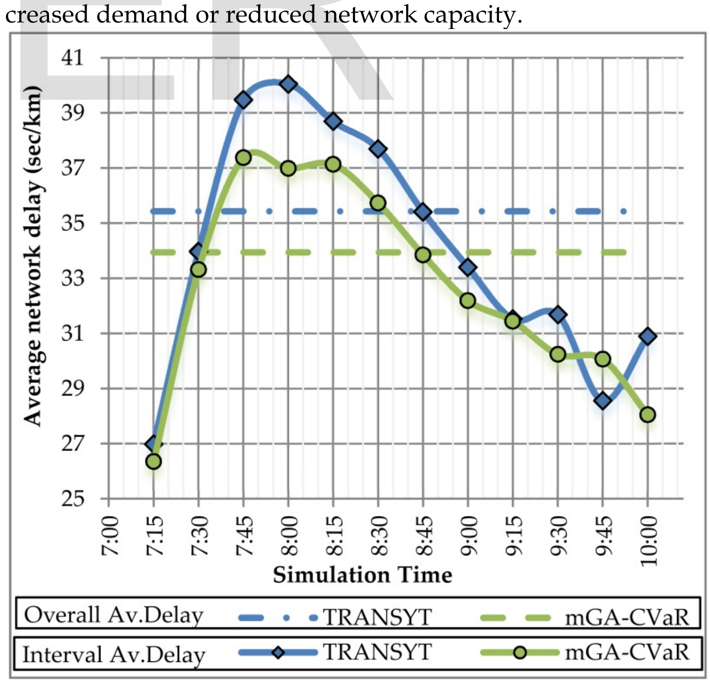

Fig. 4. Average network delay per interval for basic demand scenario

We have, also, performed the same comparison between the solutions provided by mGA-CVaR and TRANSYT-7F for an increased demand of 20%, in order to capture the benefits of our approach in a more congested network. The indices of the resulting performance with the two solutions were com-

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pared between the two methods and between the basic scenario. The results are presented in Table 1, where it can be seen that in the higher demand scenario the benefit of optimizing traffic signals with the proposed methodology of risk minimization is higher comparing to the TRANSYT-7F solution. Another interesting finding is that the increase in the values of indices at the higher demand scenario is greater with the TRANSYT-7F solution compared to our methodology, satisfying thus our hypothesis that the risk minimization approach provides lower risk of experiencing high levels of demand especially when the network is oversaturated.

TABLE 1
RESULTS OF BASIC AND HIGHER DEMAND SCENARIOS

Scenario	Optimization approach	Overall Av. Network Delay (s/km)	Total travel time (h)	CVaR Av. Network Delay (s/km)
Basic Demand	mGA-CVaR	33.94	291.52	38.34
	TRANSYT	35.43	302.81	38.34
	Comparison	-4.2%	-3.7%	-6.6%
Higher Demand	mGA-CVaR	39.60	374.87	48.15
	TRANSYT	45.15	394.80	68.91
	Comparison	-12.3%	-5.0%	-30.1%
Comparison between demand scenarios				
mGA-CVaR		16.68%	28.59%	25.59%
TRANSYT-7F		27.43%	30.38%	79.73%

The benefit in the time variation of the average network delays (Fig.5) experienced by users during the peak hour is even more obvious in the case of a more congested network as in the case of the higher demand scenario, where it can be observed that the peak of average delay experienced with the TRANSYT-7F solution presents a higher peak whereas the mGA-CVaR solution has a lower steady curve during peak hour.

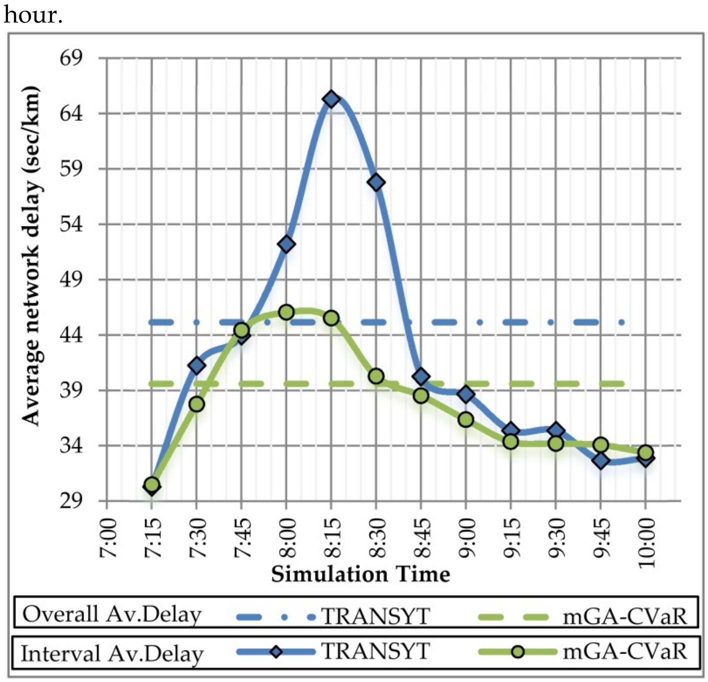

Fig. 5. Average network delay per interval for higher demand scenario

5 Sensitivity Analysis

The basic hypothesis of our proposed methodology is that traffic plans designed and optimized by minimizing the *CVaR* will offer users a lower risk of experiencing higher values of delays. This hypothesis was be tested through a sensitivity analysis of different demand levels and incidents occurring at the network. The scenarios developed and processed in the sensitivity analysis are 46 and are summarized in the following:

1-3. Increase in total demand by 15%, 20%, 25%
4-6. Increase during peak hour (07:30-08:30) by 15%, 20%, 25%
7-9. Increase in total demand by 20% for the O-D pairs with the highest volume {C,F},{A,D},{G,A}
10. Increase in total demand by 20% for the O-D pairs with the highest volume simultaneously.
11-14. Extension of peak hour demand by 15, 30, 45, 60min
15-23. Lane closure for 30min during peak hour along the sections with two lanes
24-28. Speed reduction to 30km/h for 30min during peak hour along the sections with one lane
29-33. Speed reduction to 20km/h for 30min during peak hour along the sections with one lane
34-35. Speed reduction for the entire period for the entire network to 30km/h and 20km/h
36-37. Speed reduction during the peak hour for the entire network to 30km/h and 20km/h
38-46. Different seed numbers

Therefore, using the solutions from the risk minimization proposed algorithm, mGA-CVaR, and TRANSYT-7F, we have run these 46 scenarios and compared the network performance for both levels of demand (with basic and higher demand). In the basic demand level the proposed approach was superior compared to the TRANSYT-7F solution, since only two tests had higher overall and *CVaR* average network delay and one test had higher total travel time compared to the performance of the network with the TRANSYT-7F solution. In the higher demand scenario, the proposed method was superior compared to TRANSYT-7F in all 46 tests. The performance indices for both demand levels for all scenarios are depicted in Figure 6 and 7.

Basic statistics from the application of mGA-CVaR and TRANSYT-7F solutions to the 46 scenarios at both demand levels are presented in Table 2, where it can be seen that the mean value, the standard deviation, the range and the coefficient of variation of all indices are higher with the TRANSYT-7F solution compared to the proposed method. This can be seen as an important element of uncertainty in the operation of the network in cases of diversification of demand or supply conditions. So, in both demand levels the main hypothesis is satisfied, i.e. the signal plan risk optimization ensures better and more stable network performance not only in the baseline scenarios, but also when conditions are altered either due to increased demand or due to incidents that affect the network capacity.

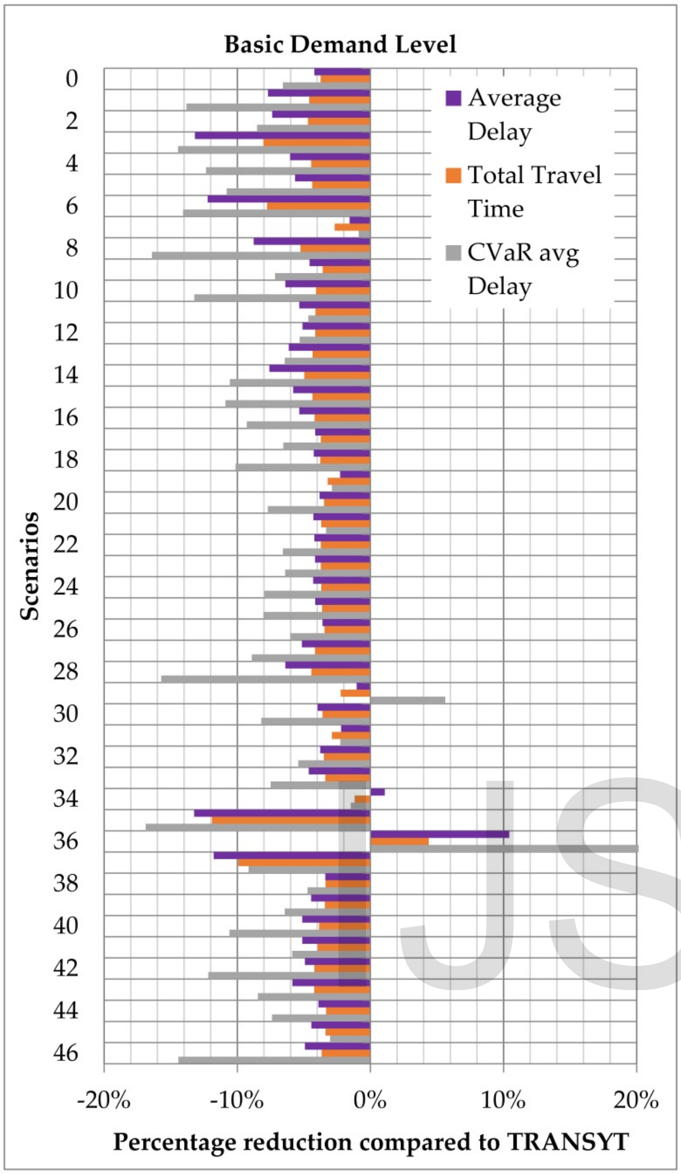

Fig. 6. Sensitivity analysis test comparison between mGA-CVaR to TRANSYT-7F – Basic Demand Scenario

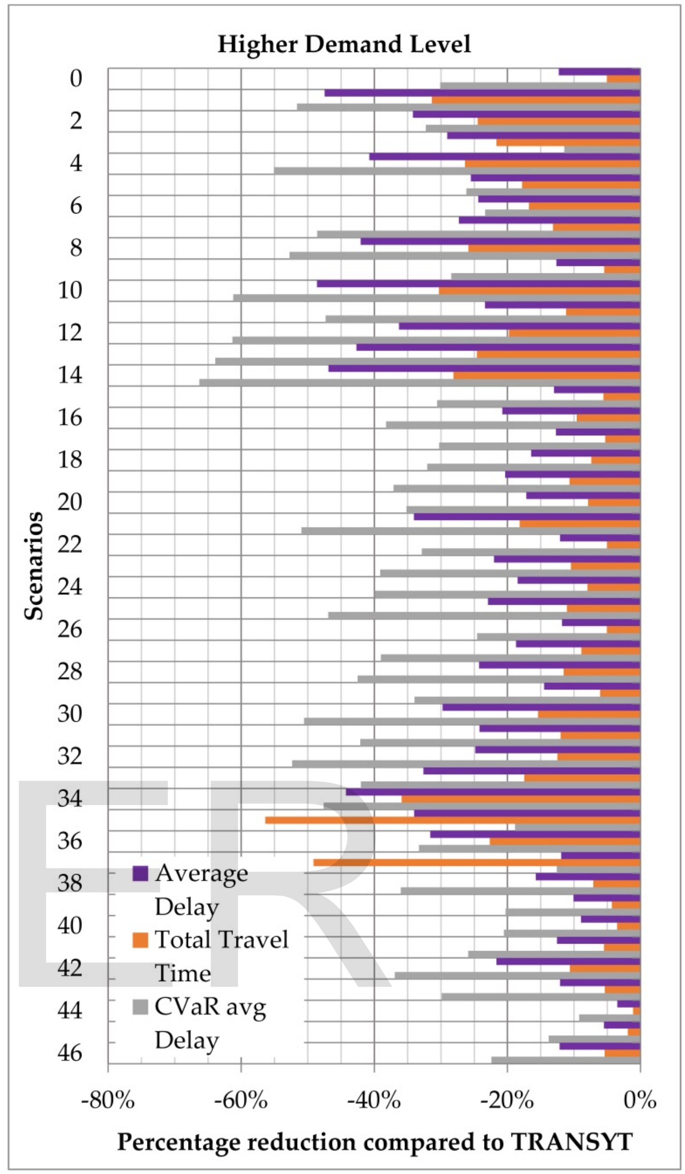

Fig. 7. Sensitivity analysis test comparison between mGA-CVaR to TRANSYT-7F – Higher Demand Scenario

TABLE 2
SENSITIVITY ANALYSIS RESULTS

De-mand Level	Indices	TRANSYT-7F			mGA-CVaR-NSV		
		Overall Av. Network Delay (s/km)	Total travel time (h)	CVaR Av. Network Delay (s/km)	Overall Av. Network Delay (s/km)	Total travel time (h)	CVaR Av. Network Delay (s/km)
Basic Demand Level	Average	45.8	346.2	59.2	43.1	330.7	54.5
	St. deviation	32.9	101.5	51.8	28.8	87.4	45.9
	Range	192.3	578.9	257.5	163.8	485.4	214.9
	Coefficient of variation	72.0%	29.3%	87.5%	66.9%	26.4%	84.3%
Higher Demand Level	Average	81.3	552.2	135,0	59.1	442.9	87.1
	St.deviation	70.9	257.8	110.8	48.6	111.4	91.7
	Range	396.7	1,250.1	571.1	249.7	400.8	462.1
	Coefficient of variation	87.2%	46.7%	82.0%	82.1%	25.1%	105.3%

6 Conclusions

This paper presents a framework for a DSS to aid Traffic Control Centers in the analysis of the risk of a transport system performance and the development of traffic control methods in a signalized network. In this context we present a planning tool as part of the DSS for formulating, testing and selecting the near optimal traffic control strategy using the concept of Conditional Value-at-Risk (*CVaR*) for the assessment of the network performance and the optimization of traffic control parameters for a signalized network. The main contributions of our research are:

- The proposed tool evaluates the system performance based on a risk analysis of excess travel times using a dynamic mesoscopic traffic assignment simulation model and generates proactive traffic control plans that are consistent with both the anticipated network conditions and drivers' route choice decisions.
- The optimization of the traffic signal plans in the network is performed using a multi-objective genetic algorithm which minimizes the risk of delays in the signalized intersections and the risk of non-coordinated predefined routes of the network, analyzing the traffic dynamics in the context of risk.
- Both the optimization algorithm and the mesoscopic model include detailed description of the geometric and operational characteristics of the signalized intersections.
- The optimization of the traffic signal plans is based on the procedure of multiple period analysis of the Highway Capacity Manual 2010.

The benefits of the proposed approach were demonstrated through an implementation in a referenced network and their comparison to a benchmark tool (TRANSYT-7F). The analysis of the performance of the network in the mesoscopic DTA model AIMSUN showed that the proposed approach presented lower values of total delays over the entire simulation period for both demand scenarios (basic and high level). The temporal analysis of the average delay showed that the proposed approach resulted in a decrease in the maximum values of the average delay per interval, which is important not only because it is experienced by a high percentage of vehicles, but mainly because it prevents the occurrence of high values of delays in the system, which are not easily manageable and reversible during an unexpected event that may cause a demand spike or reduced network capacity.

The basic hypothesis of our proposed methodology, which is that traffic plans designed and optimized by minimizing the *CVaR* will offer users a lower risk of experiencing higher values of delays, was validated through a sensitivity analysis of 46 tests with different demand levels and incidents occurring at the network.

Future research will be aimed at enhancing the performance of the optimization algorithm in order to reach optimal solution faster and thus incorporating this approach in an online environment. An extension of our work for solving larger scale problems will be also investigated using clustering techniques for analyzing and optimizing subnetworks.

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