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INTELLIGENT TRAFFIC CONTROL IN ITS SYSTEMS

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ABSTRACT

The progress in communication, computer and information sources technologies supplemented by new DSS (Decision Support Systems) tools giving new until now inaccessible information / knowledge about real traffic situations [4-6,19]. It opened up new horizons and opportunities for development of professional ITS (Intelligent Integrated Transportation Systems) systems offering much more advanced intelligent management, supervision and control system-wide actions. Such systems offer great deal of real-time responsiveness, high operational flexibility/ intelligence that may eliminate the weak points of the classical transportation systems and the need for human operator's interventions. It is obvious that the efficiency of advanced control logic (in intelligent control in particular) depends on the quality of real-time information and knowledge feedback used to recognize the multi-criteria dedicated control problem specifications and adequate solutions. In this context the intelligent recognition, analysis, diagnosis and prediction of traffic situations appears to be the most important prerequisite in implementing the sophisticated control concepts removing the existing weak points of classical transportation systems. [1-5, 11-12, 18-22].

INTRODUCTION

The present weak points to be generators of high costs in transportation systems are as follows:

- Lack of system reactions on unpredictable traffic incidents generating very high various costs.
- Lack of adequate signal timings reactions for heterogeneous traffic conditions on intersection approaches, arteries links/segments and network sub-areas.[7-10]
- Lack of multi-modal control actions dedicated to different traffic modes (e.g. public transport, individual traffic, logistics vehicles) in urban areas.[15-17,23].
- Lack of recognition and exploration of favorable traffic situations of "synergic and opportunity" types for get high operational profits under low costs [18-21].
- Implementation of historical off-line single criteria control methods of fixed –time/ vehicle actuated type which are not based on the exploration of fundamental feedback mechanism to be a crucial in the control area.

The suggested remedies for significant improvement of ITS systems efficiency are as follows:

- Proposals of dedicated ITS systems generated by professional system platform HITS [18,20].
- Exploration of new possibilities offered by new enabling technologies (communication, information, sensors, computing etc.).[19]
- Proposals of new intelligent, integrated ITS systems services based on exploration of intelligent technologies and modern tools [8, 10-13].
- Proposals of multi-criteria intelligent control methods based on intelligent recognition, analysis, diagnosis and prediction of traffic situations (e.g. traffic incidents) by intelligent supervision and monitoring ITS system layer [1-5, 14, 17, 21].
- High flexibility preferences of individual ITS system layers activities and ITS structure-related inter-layers cooperative activities in generation of system-wide multi-time horizon, multi-criteria compatible management, adaptation, optimization, supervision/monitoring and control actions.

In the paper the ITS system option dedicated to intelligent supervision and system monitoring layer is proposed which conditioning the intelligent flexible system functionalities. In particular the adequate traffic situations recognition and diagnosis to be the most important prerequisite of implementing dedicated control actions by bottom direct control layer is proposed. In the case of multi-criteria real-time traffic control it is realized by dedicated structure of control preferences. Therefore the crucial problem for the intelligent supervision and control layers concerns the recognition of adequate to observed and predicted traffic situations, structure of preferences for control actions. The above adequacy is conditioning by the traffic situations related quality / representatives

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of the selected traffic information and implementation of dedicated intelligent tools. These requirements are realized respectively by multi-criteria traffic situations related selection of representative data sources and communications media and traffic situations markers based dedicated recognition, analysis and diagnosis tools.

RANDOM FIELD MODELS OF THE TRAFFIC FLOW

The road traffic is a good example of the 2-D (space x time) phenomena therefore the random fields (RF) as traffic control models were first proposed in [14, 16-17, 21]. The basic intelligent activities of the bottom supervision and control layers first of all deals with the estimation for the proposed classes of Vector Random Field (VRF) e.g. traffic volumes, speeds, headways, trip times) of theirs parameters relations like correlation function, entropy or traffic situations markers on the available data basis (e.g. data taken at scattered locations in the detection zones). In particular to illustrate the importance of the spatial information the optimal control problem with the RF of entropy real-time estimated parameter used as a measure of smoothness of the vehicle flow was presented in [7-10] for normal traffic situations. In the case of traffic incidents the entropy parameter can be used to detect and integrate the compatible episodes in the traffic incident and after incident diagnosis to propose the adequate structure of preferences for multi-criteria control of a mix of normal/ abnormal traffic situations.

The attractiveness of entropy parameter as an traffic situations marker in normal situations is related to the fact that the entropy control with more sophisticated entropy definitions provides a means trading off some performance and robustness features like in H_2 and H_∞ optimal control problems. Additionally, the time-domain entropy notion for LTI systems is equivalent to the usual frequency domain criterion, therefore some practical references to the expected power (energy) spectral density of stochastic representations are possible [10]. In general many of traffic features make sense only when one sees the traffic processes as spatio-temporal interactions i.e. represented by spatio-temporal model in the form:

$$\{\xi(s,t) : s \in D(t), t \in T\} \qquad (1)$$

Where *s* and *t* denote location in detection zone $D(t)$ and time indexes of the random observation $\xi(s,t)$. The particular cases of (1) i.e. purely spatial/temporal models representations are as follows: $\{\xi(s) : s \in D(t) \subset E^n\}$; $\{\xi(t) : t \in T \subset R^1\}$. The detection zone D(t) may vary with time and take different forms; e.g. it may be continuous region, finite/countable set of sites (lattice models), random set of random events. The space and time coordinates can be on a par, in that they take values in sets of comparable cardinality, and the process may show stochastic invariance under transformations of space as well as time. On the other hand, it is along the time axis that one has "causal flow". A spatial process (i.e. a random function of *s* or of *s* and *t*) is often referred to as a Random Field (RF). In Fig.1 different degree (p) neighbors $NH^{(p)}(N)$ of vehicles on two lanes are presented. Neighborhood (nearest) of $N \subseteq X$ denoted by ***N*H**(N) is the set consisting of N itself and all neighbors of members of N. The boundary ∂N is the complement N in ***N*H**(**N**) (i.e. ∂N=***N*H**(N)\N), (see Fig.1.). To introduce the probabilistic formalism note that when the field variable can only take a discrete set of values at each site, than probabilities $P[\xi_N]$ and conditional probabilities $P[\xi_{N1} \mid \xi_{N2}]$ have their definitions, at least for finite N. Then, at least for finite N the quantity $P(\xi)$ is well-defined.

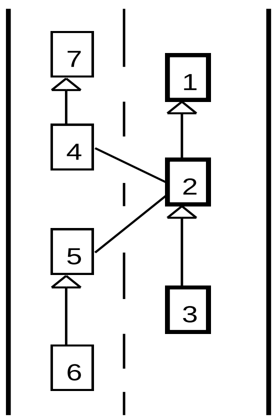

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Fig. 1. Vehicles sites on 2 lanes

Example: (see Fig. 1.) N = {1,2,3}= $\mathcal{N}\mathbf{H}^{(0)}$(N);
$\mathcal{N}\mathbf{H}^{(1)}$(N) = {1,2,3,4,5}; ∂N ={4,5};
$\mathcal{N}\mathbf{H}^{(2)}$(N)=$\mathcal{N}\mathbf{H}${$\mathcal{N}\mathbf{H}^{(1)}$(N)}={$\mathcal{N}\mathbf{H}^{(1)}$,6,7} and
$\mathcal{N}\mathbf{H}^{(2)}$(N)-$\mathcal{N}\mathbf{H}^{(1)}$(N)={6,7} is the set of sites which are neighbours of N at exactly 2 steps. In general we can write: $\mathcal{N}\mathbf{H}^{(\mathbf{p})}$(N) = $\mathcal{N}\mathbf{H}${$\mathcal{N}\mathbf{H}^{(\mathbf{p-1})}$(N)}

Remarks:

1. The extremal cases will correspond to cliques i.e. set of nodes any pair of which are neighbours) and single node which is regarded as self-neighbour.
2. One can have neighbours of various degrees, therefore we can represent the neighbourhood on a different levels of aggregation.

In the case of infinite N and continuously varying ξ i.e. continuous representation of the traffic field, we will define densities relative to an appropriate measure. This can be done in natural way by adopting at each site *s* some "ground (reference)" state ξ (*s*)=0 (i.e. null field) corresponding to absence of the traffic (vehicles) at the sites. Then the field ξ is regarded as being built up from the null-field by modification at successive sites and $P(\xi)/P(0)$ has a clear evaluation if ξ is non-null at only finitely many sites (i.e. finitely many vehicles can appear in these sites). Denoting by $T_S(\xi)$ the point operator which modifies the value of field at site *s* to a prescribed value ξ (*s*), we may used it for modification of the functions of the field e.g. for the field function of *V*(.) the modification of $T_S(\xi)$ $V(\eta)$ = $V[\xi(y)]$ if y=s or $V[\eta(y)]$ when y≠s.

Remarks:

R1. In situation of a dynamic traffic model we regard the random field as an equilibrium distribution of this dynamic stochastic model. That is, one embeds the spatial process in a spatio-temporal process ξ (*s*,*t*). We shall use the $T_S(\xi)$ operator to describe the field transition e.g. one-point transition of type $\eta \rightarrow T_S(\eta')\ \eta$ to describe after transition the field which is equal to η except at a single site *s*, where it takes the value $\eta'(s)$.
Assuming that the spatial-temporal process ξ (*s*,*t*) have the following features:

- It is homogeneous Markov in time and time-reversible
- The only possible translations are the one-point type.
- These transitions are locally conditioned, in thus the intensity for transition is a function only of $\eta'(s)$ and of η (*y*) for $y \in \mathbf{NH}(s)$ (i.e. "local interaction in space) and that the ξ (*s*,*t*) reaches equilibrium, then the equilibrium field is spatially Markov.

R2. The field {ξ (*s*)} on N is Markov (MRF) if for any set of sites N: $P[\xi_N | \xi_{X-N}]$=$P[\xi_N | \xi_{\partial N}]$ i.e. if the expressions of the G_N in the representation of $P(\xi)=\exp(-\sum_N G_N(\xi_N))$ are zero whenever N is not a clique. Replacing the boundary ∂N by the boundary of thickness *p*, ∂^p N=$\mathbf{NH}^{(p)}$(N)\N one can define a p^{th} order Markov property.

R3.Random Field with Second -Order Increments (RF-SOI)
The traffic random fields (RF) in practice exhibit no homogeneous (i.e. non stationary in location) nature and their means and covariance functions are not known a'priori. The convenient description of such type RF may be introduced by means of RF with second-order increments. This field is defined by the mean and variogram

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functions i.e. the RF of $\{\xi(s): s\in D\}$ is assumed to have the finite mean and spatial variogram: $m(s)=E\{\xi(s)\}$ and $V(s,y)=E\{|\Delta\xi - E(\Delta\xi)|^2\}/2$ where the increment is defined as $\Delta_\xi = \xi(s) - \xi(y)$ for $s, y\in D$.

Estimation of the area based traffic flow parameters

The problem concerns the estimation of the Vector Random Field **(VRF)** (e.g. volume, density, velocity) from the noisy observation data taken at scattered locations e.g. from video-detector along the approach to the intersection. We deals with a homogeneous/ non-homogeneous random fields (RF) possibly with unknown statistics. The class of non-homogeneous RF may be for example modelled by RF-SOI (i.e. Random Field with Second Order Increments), that are described by mean $m(s)$ and finite variogram $V(s, y)$. Minimum variance estimator should be determined for $\xi(s_0)$ at any arbitrary location s_0 on $D\subset R^2$ basing on N noisy observations $y_N=[y(s_1),\ldots,y(s_N)]$ or in vector-matrix notation $y_N = H\xi_N + Rz_N$ where $H=diag\{0,h(s_i)\}$, $R=diag\{r(s_i)\}$, $i=1,\ldots,N$ and $h(\cdot)$, $r(\cdot)$ are known functions, $\xi_N=[\xi(s_0),\xi(s_1),\ldots,\xi(s_N)]$ but $z_N=[z(s_1),\ldots,z(s_N)]$ is an observation noise modelled by a zero-mean Gaussian random field, independent of $\xi(\cdot)$ and having a covariance function of $C[z(s_i)z(s_j)]=V(z)\delta_{ij}$, where δ_{ij} denote the Kronecker delta. Two cases of the random fields are considered which depend on availability of a'priori information about the mean values $m(s)$ of these random fields.

Case 1: *m*(*s*) is non-available: The WLS estimator of the $\hat\xi(N)=\lfloor\hat\xi_0(N),\hat\xi_1(N),\ldots,\hat\xi_N(N)\rfloor$ is given by: $\hat\xi(N)=PH'R^{-2}y_N/V(z)$ where $P=[Q^{-1}+H'R^{-2}H/V(z)]^{-1}$ is the error covariance and $Q=E[\xi\xi']=Q_{ij}$; $Q_{ij}=[Q_{ji}+Q_{jj}-2V(s_i,s_j)]$ is the correlation function.

Case 2: *m*(*s*) is available: The $\hat\xi(N)=PH'R^{-2}y_N/V(z)+PS^{-1}m$, is the minimum variance estimator where $S=E[(\xi-m)(\xi-m)']=\{s_{ij}\}$ with $s_{ij}=(Q_{ji}+Q_{jj})/2-m^2-V(s_i,s_j)$, $(i,j=0,1.2,\ldots,N)$ whereas the error covariance matrix $P=S-SH'(HSH'+R^2V(z))^{-1}HS$.

Remarks:

1. For m=0 both cases are equivalent. The estimator in case 2 is unbiased but in case 1 is biased. In both cases the information about variogram $V(.,.)$ and correlation function $Q(.)$ is required. The estimates for these functions can be obtained from observations e.g. for homogeneous field and constant $h(\cdot)=h_0$ and $r(\cdot)=r_0$ functions $Q_{ii}=Q_0=const$ and LS estimate is given by:
$$Q_0=\frac{\sum_{i=1}^{N}y^2(s_i)/N-V(z)r_0^{\,2}}{h_0}$$
2. Area-based traffic flow parameters can be defined as follows $\xi(s)=\{\xi_j(s): j=1,2,3\}$ to be VRF of 1.traffic volume, 2.density and 3.vehicle speeds. We modelled each of $\xi_j(s)$ by RF-SOI. Observations are taken for the VRF at N observation sites $\{s_i: i=1,\ldots,N\}$ and may be represented in the form of $y_j(s_i)=h_0\xi_j(s_i)+r_0z_j(s_i)$ or in the matrix notation as $Y=h_0\xi+r_oZ$; where Y, ξ, Z are matrices; h_0 and r_0 constants.

The estimation problem may be formulated as follows: Find the best estimate $\xi(s_0)$ of the VRF, at arbitrary $s_0\in D$ basing on Y data and available information on $V_j(s_i)$ i.e. variances at each site s_i. The estimates of area-based moments are given by:

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A. $m(s) = W\Phi(s)$ i.e. linear combination of some known functions, where W and $\Phi(.)$ are matrices. MLE estimates for w^j and the modelling error variance $V(\varepsilon)$ are:

$$\hat{W} = [\Phi\Phi']^{-1}\Phi y^j / h_0; \qquad V(\varepsilon) = \sum_{j=1}^{M} \left[y^j - h_0\Phi'\hat{w}^j\right] \cdot \left[y^j - h_0\Phi'\hat{w}^j\right]$$

B. Variogram and Variance.

$$\hat{V}_k(s_i, s_j) = \left[(1/2N)\sum_{i=1}^{N}(1/N_c)\sum_{j-1}^{N_c}\left[y_k(s_j) - y_k(s_i)\right]^2 - r_0^2 V(0)\right] - \left[m_k(s_i) - m_k(s_j)\right]^2 / 2$$

Where N_c is the number of couples of observation locations whose distance from $s + i$ belongs to the strip $[d - \Delta d/2, d + \Delta d/2]$

$$\hat{V}_k(s_0) = (1/h_0^2)\left[(1/N)\sum_{i=1}^{N} y_k^2(s_i) - r_0^2 V(0)\right] - m_k^2(s_0)$$

Traffic smoothness measures and prediction problems

The variogram is a second order measure of spatial dependence exhibited by spatial data. the other possible measures include the entropy, power spectrum and the mathematically equivalent auto covariance function. It may be demonstrated that the class of processes with variogram contains the class with an auto covariance function and that the linear prediction can be carried out on a wider than traditionally used statistics, class of processes. For a real-valued process $\{\xi(s) : s \in D \subset E^n\}$ the variogram is defined as $\mathrm{var}[\xi(s+h) - \xi(s)] = V(h)$ for all $s, s+h \in D$ i.e. variogram is a function of only the difference between the spatial locations. To guarantee that all variogram-based variances are nonnegative; the variogram must satisfy the natural conditional-negative-semi definiteness condition $\alpha^T V(s_i - s_j)\alpha \le 0$ for any finite number of spatial locations s_i I=1,…,k and real numbers $\alpha_i \;\; i = 1,\dots,k;\; \sum_i \alpha_i = 0$. If condition $V\|h\|$ with $\|\cdot\|$ denoting Euclidean norm and $V\|h\| / \|h\|^2 \xrightarrow[\|h\|\to\infty]{} 0$ is fulfilled, the variogram is said to be isotropic (otherwise it is said to be anisotropic). In this case variogram models that depend on only a few parameters e.g. linear (power in general), exponential or wave types can be used as summaries of the traffic spatial dependence. The existence of the auto covariance function $\mathrm{cov}[\xi(s+h), \xi(s)] = C(h)$ for all $s, s+h \in D$ is the stronger assumption than the existence of variogram, therefore for mean function to be constant $E[\xi(s)] = m$, for all $s \in D$ the variogram defines the class of intrinsically stationary processes that strictly contains the class of second order stationary processes defined by auto covariance function. Of course, from the spatial data e.g. spacings $\{s_i\}_1^n$ between the vehicles observed at one or several frames, we can in a typical way estimate robust variogram or auto covariance function parameters and use of these traffic smoothness measures for traffic volume or traffic density prediction purposes. In particular, due to real-time control requirements the simple "tuning" variogram or auto-correlation dependent coefficient derived on the one frame basis are proposed to predict traffic volume on a short prediction horizon or SAR (i.e. spatial autoregressive) models prediction approach is suggested with coefficients derived on the frame by frame basis. The proposed approach is especially attractive for lattice models. In the case when the detection zone *D* of the traffic spatial process is a finite collection of spatial sites at which vehicles are observed, we have lattice model. The set of vehicle sites is supplemented with neighborhood information that define (conditional) dependencies between sites. Because of lattice is irregular; the neighbors are defined by Euclidean distances to nearby sites i.e. s_i and s_j are neighbors if $\| s_i - s_j \| \le r$. The spatial analogue of the temporal Markov property says that the i-th site, conditioned on all other sites, in fact depends on its neighboring values { $\xi(s_j) : j \in \mathrm{NH}(s_j)$ };

$P[\xi(s_i) \,|\, \{\xi(s_j) : j \neq i\} = P[\xi(s_i) \,|\, \{\xi(s_j) : j \in N\mathrm{H}(s_i)\}]$. Of course, when right hand sites of above expression define joint distribution; the ξ is called a Markov random field. A very attractive feature of working with a Markov random field is that modelling can be carried out at the local level by specifying the neighbors and conditional probabilities site by site.

The entropy is a very attractive traffic smoothness measure and can be used on the one frame basis (e.g. the entropy normalized parameter derived from vehicle spacings) or on the frame by frame dynamic basis. In the last case the vehicle spacings are treated also as realizations of the temporal process with the relative entropy rate $H_s = \lim_{n\to\infty} \frac{1}{n} E\left\{ \ln\left[\frac{1}{f_{S_n}(s_n)} \right] \right\}$ where $f_{s_n}(s_n)$ is the n-th order joint probability density for the vector of vehicle spacings, to be a relative measure of the average traffic smoothness per time sample (frame). The particularly intriguing entropy features are concerned with the facts:

1. Among all possible processes that have the same n+1 autocorrelation values (e.g. used for AR Youle-Walker prediction purposes) the smaller *n*-th order AR process fitting is the most random in the sense of having maximum entropy rate.
2. For the spacings input process LTI transformations, represented by transfer function G(f), the gain in entropy rate (i.e. difference between output and input entropy rate) is given by $\Delta\overline{H} = \frac{1}{2} \int_{-1/2}^{1/2} \ln |G(f)|^2 \, df$ i.e. the gain of spectral density of mean squared spacings fluctuations.

INTELLIGENT SUPERVISION, MONITORING AND CONTROL ITS SYSTEMS LAYERS

The representative evaluation of the ITS systems operational conditions is realized by the intelligent supervision and monitoring layer and is conditioned by fulfillment of several essential requirements e.g. adequate recognition and diagnosis traffic modes and theirs 2-D dynamics of robust types. The traffic modes are represented by adequate traffic situations markers to be aggregated transformations of the representative traffic processes quantities in different operational quality measures of transportation network elements (e.g. for artery delays, number of stops, travel times, queue lengths etc.). The reaction of the ITS systems for uncertainty, heterogeneous traffic phenomena dynamics, users behavioral aspects are compatible system-wide decisions of robust type , multi-time horizons system activities and intelligent recognition and diagnosis of behavioral patterns and traffic incidents. These system activities are supported by modern information, communication, computing enabling technologies [18, 19]. The 2-D dynamic operational environment of traffic processes require the similar reactions from ITS systems and stimulating the demand for recognition and diagnosis of traffic situations basing on representative data, traffic situations markers, expert knowledge and intelligent tools to generate adequate system-wide management and control actions. The functionalities of the bottom intelligent supervision, monitoring (ISM) and direct multi-criteria control layers in the context of traffic incidents are presented in Fig. 2. The ISM layer supported by data/knowledge basis, DSS tools/ methods recognize dedicated for traffic incidents 2-D traffic situations markers MR(t) (e.g. based on travel times T_p, vehicle speeds v_p, inter-vehicles headways H_p, traffic volumes q_p, traffic densities k_p, number of lanes changes n_p). On the basis of representative markers the reference quantities/ markers are created enabling the detection with the high confidence of the traffic episodes / incidents. After verification of recognized episodes the intelligent 2-D aggregation in traffic incidents and theirs diagnosis is realized with proposals of structure of preferences for direct multi-criteria control layer basing on importance level of recognized incident. The control layer generate the final structure of preferences basing on markers concerning the normal and detected incidents. The solution of adequate multi-criteria real-time control (e.g. by PIACON method) is professional system reaction on intelligent recognized traffic situation for a given transportation network element.[5,16,21].

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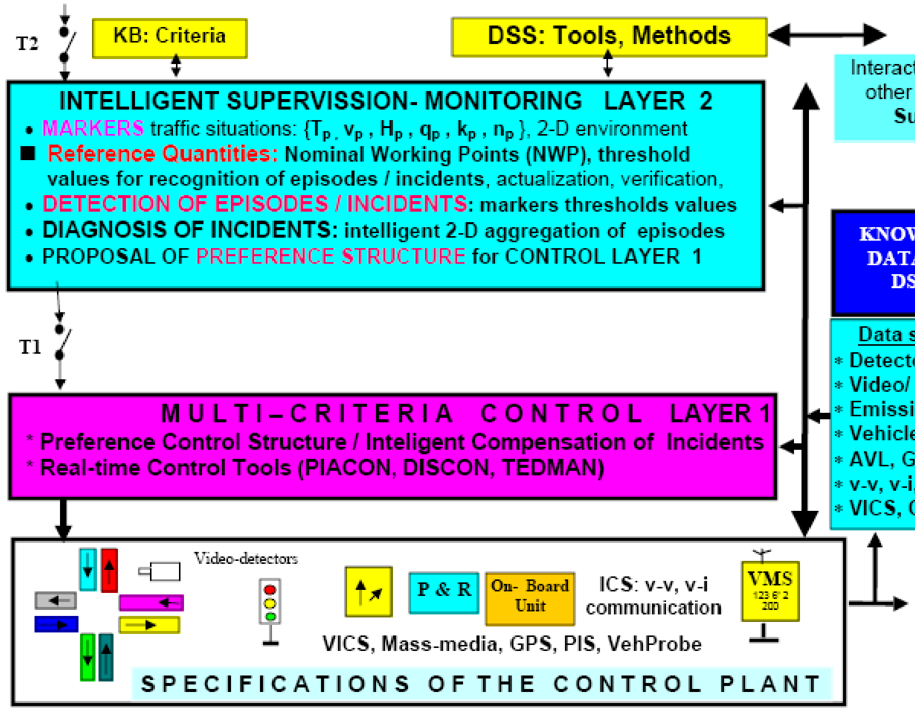


Fig. 2. Intelligent supervision, monitoring and multi-criteria control ITS system layers

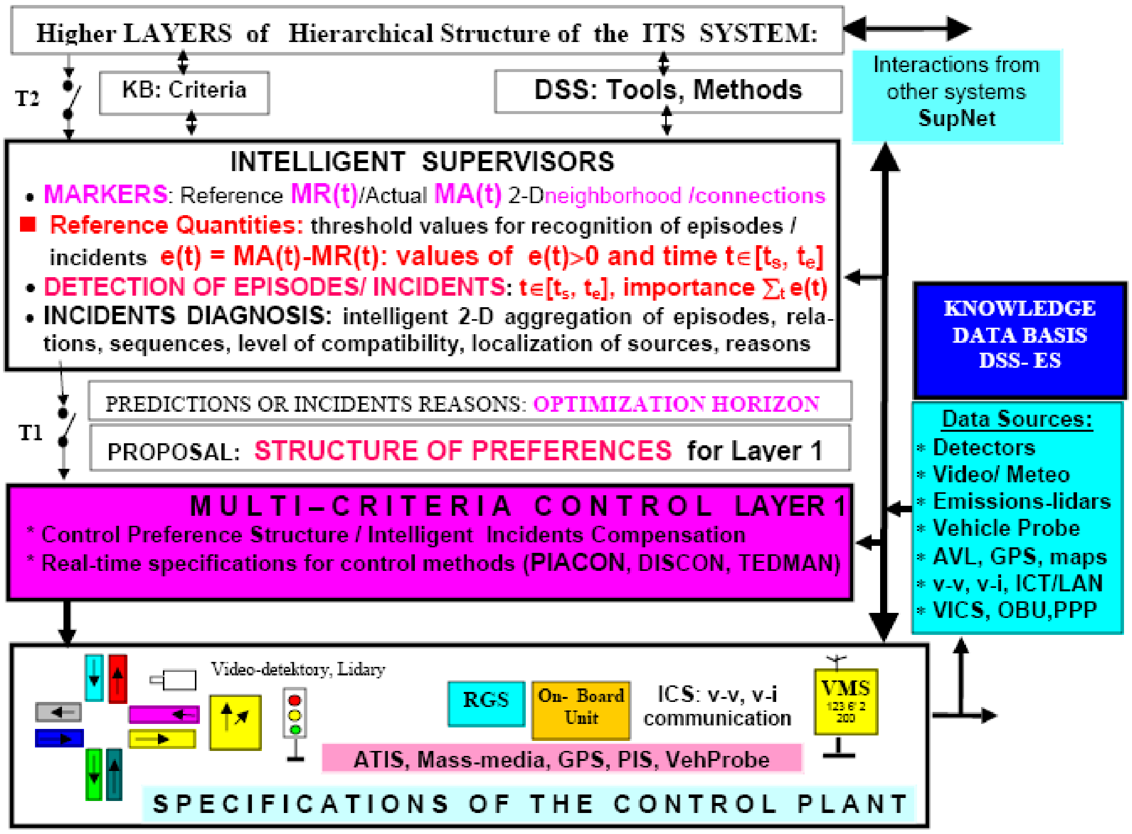


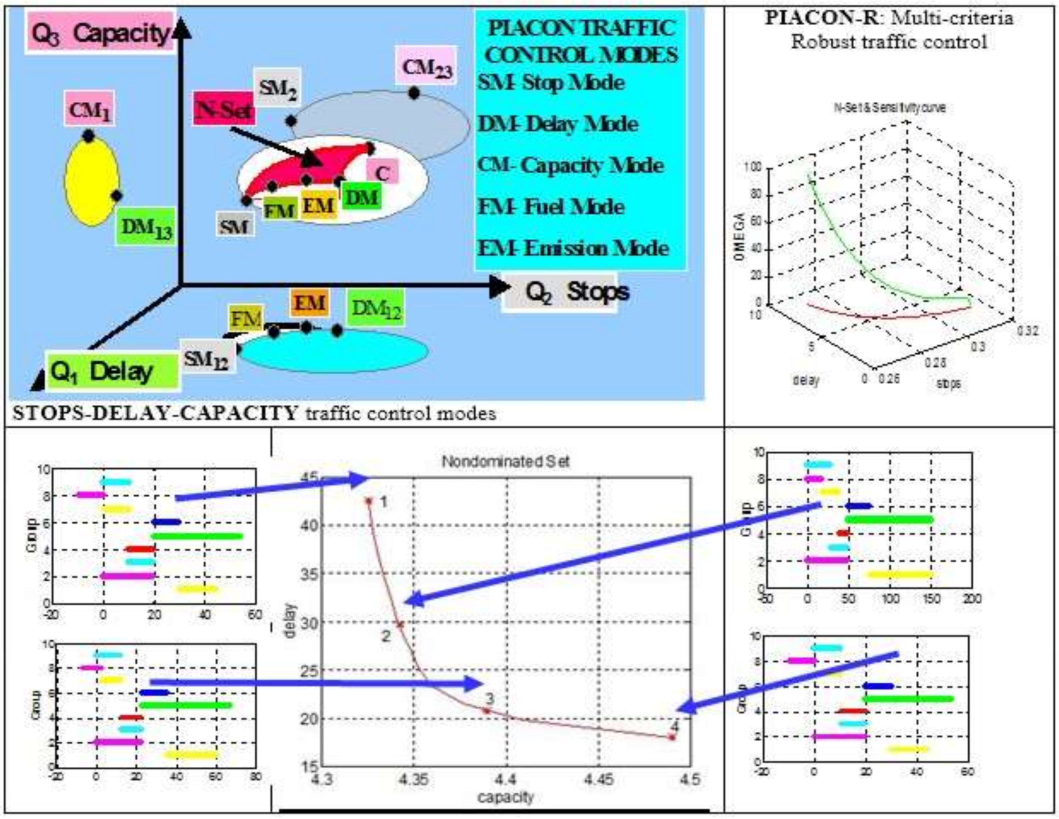
Fig. 3 Intelligent Supervisor functionalities in traffic incidents context

Traffic incidents related functionalities of the Intelligent Supervisor

To illustrate the IS functionalities the simple method of detection of traffic episodes is proposed. The basic detection tool concerns the difference between actual MA(t) and reference MR(t) markers: $e(t)=MA(t)-MR(t)>0$ with existence time $t\in[t_s,t_e]$ and significance level $pw(t)= \sum_t e(t)$. The aggregation of essential episodes in traffic incidents can be realized by cause and effect 2-D neighborhood relation related from vehicle trajectories [16-17]. The simplified approach may used the matrix of links incidence and 1-D time conformity of episodes (e.g. common existence time and proper time sequence of episodes). The 2-D incidents diagnosis make use intelligent DSS tools and localize the incident sources, recognize the reasons and predicts the incidents effects propagation along the given time horizon (to be the time horizon for the optimal control problem). The advantage of this approach is proposal of dynamic structure of preferences for dynamic multi-criteria control problem in direct control layer. The analysis of traffic incidents by IS is realized in the cyclic way.

PIACON: structure preferences impacts on the control problem

The Fig. 4 illustrates the impacts of suggested structure of preferences on the selection of adequate control criteria (e.g. stops, delay, capacity, queue lengths). Moreover the original mechanism of selection of dedicated parts of compromise set by preference cones was illustrated [12].



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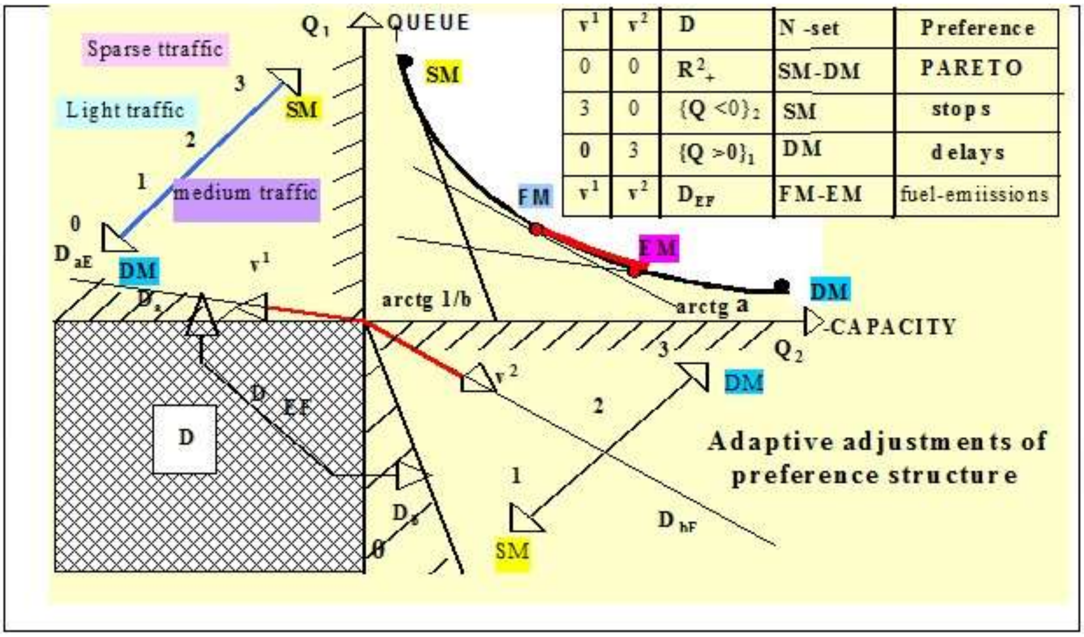

Fig.4. Structure preferences impact on the multi-criteria traffic control problem

APPLICATION OF INTELLIGENT CONTROL METHOD

To illustrate the efficiency of the proposed control method a one of the most congested in Krakow junction: Czarnowiejska Street and Mickiewicza Avenue has been selected (Fig.5).The signal plan includes i=1,.., 6 traffic groups ($x_i(k)$ state variables) controlled by 3 phases ($u_i(k)$ green times control variables) (Fig.6.) The information from video-detectors about the traffic flow composition, with different types of vehicles classified mainly according to their length, is used for control feedback purposes. Table 1 shows the high fraction of long and very long vehicles in traffic flows at this junction. The vehicle queue evolution for traffic groups is modelled by $Q_i(k+1)=Q_i(k)=q_i(k) - s_i^l u_i(k)$ where $q_i(k)/ s_i^l$ - are arrival/saturated (for traffic mode TM(l)) traffic volumes [12]. The traffic modes TM(l) l=1,..,5 classify the traffic situations in the detection zones into thin(l=1), small (l=2), medium (l=3), long vehicle queues (l=4), over saturated / incident (l=5) classes. The recognition of TM(l) can be realized by traffic situations

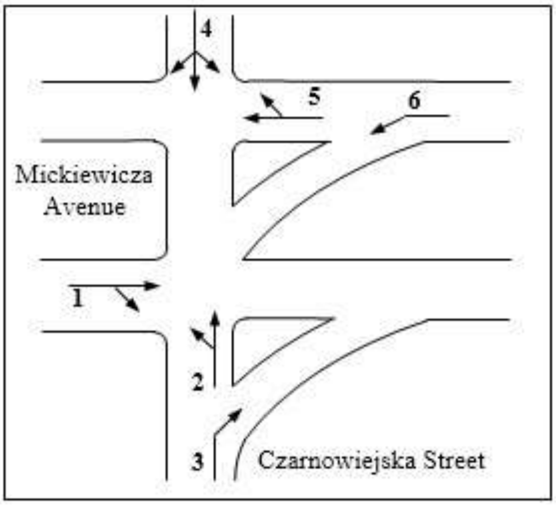

Fig. 5 Intersection plan.

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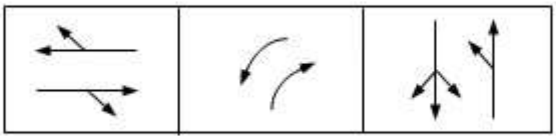

Fig. 6. Phasing diagram

Table 1.Composition of traffic flows at intersection.

Flow	Cars	Vans	Trucks	Buses
1	72%	9%	10%	9%
2	66%	12%	12%	10%
3	74%	10%	1%	15%
4	82%	14%	4%	0%
5	79%	10%	2%	9%
6	68%	12%	9%	11%

Markers M(k) (e.g. $\bar{y}$= max{ $\bar{y}_i = \bar{q}_i / s_i^l$ $\forall$i} average samples over last several periods).

Table 2. Preference control structure based on M(k) traffic situations markers

TM(l)	M(k)	Traffic control modes i=1,..,6 (structure of control preferences)
l=1	$\bar{y}\in[0.1\div0.2)$	$u_i(k)$= K C where $K = s_i^l / \sum_i s_i^l$ is proportional controller
l=2	$\bar{y}\in[0.2\div0.4)$	$J_1(u) = \sum_i Q_i^2(k+1)$
l=3	$\bar{y}\in[0.4\div0.6)$	$J_2(u) = \sum_i [s_i^l - s_i^l u_i(k)/C]^2$
l=4	$\bar{y}\in[0.6\div0.8)$	$J_3(u) = \sum_i Q_i^2(k+1)[C- u_i(k)]$ discomfort measure of drivers
l=5	$\bar{y}\in[0.8\div1.2)$	Bang-Bang control strategy for over saturated congestion

In the case of artery synchronization (including this intersection) the 2-D different traffic situations markers can be used (e.g. RF spatial measures deviations from reference values). The prediction f traffic flows in this example was realized by detection zone occupancy level o_i and theirs increments $\nabla\bar{o}_i$. The simple recurrent MLE estimator in the form of $\lambda=\sigma^2_{o,i} /(\sigma^2_{o,i} -\sigma^2_{\nabla o,i})$; $o_i^*=\lambda(\nabla \bar{o}_i + o_{i-1}) + (1-\lambda)\,\alpha\,\bar{o}_i$ for I=1,..,6 and α=0.8÷1. Was used to forecast TM(l) and selection of adequate control actions [12].

ECM: Entropy Control Mode: The spatial distribution of n-detected vehicles in detection zone L is represented by a set of spatial headways $\{s_i\}_1^n$ to be realisation of spatial discrete random variable with $p_i=s_i/L$ i=1,..,n. probabilities. The corresponding entropy $H = -\sum_i p_i \log(p_i)$; $H\in[H_{min}, H_{max}]$ or in normalized form $HP= (H_{max} - H)/(H_{max} - H_{min}) \in[0, 1]$ with max/min values corresponding to uniform/ platoon spacing distributions [9]. For the stationary traffic conditions, the entropy may be treated as a measure of smoothness of traffic flow that is increasing/decreasing with the spacing uniformity /bunching over a road section. After estimation of HP the predicted traffic volume $q_{pr} = KV_f\left(1-K/K_j\right)HP$ where: V_f – is free speed, K, K_j – are density and jam density, respectively [6] and corresponding (after g_{min}) green time g admissible (i.e. $g\in[g_{min},g_{max}]$) readjustments to the expected traffic volume $q = q_{pr} - w/(g_{max} - g)^2$ with real-time selected w –weighting coefficient can be implemented [9]. As presented in [9] the entropy control model significantly reduce average delays and queue lengths therefore can be used as an alternative for bi-criteria delay-queue control modes. (see Table 3)

Table 3. Comparison of different single criteria control modes solutions: SM (number of stops/vehicle); DM (average delay/vehicle [sec]); QM (queue length/stream [m])

SINGLE CONTROL MODES:		A; f-t; C=90 s	B:HP; C=90 s	C:DM; C=var	D: HP; C=var
SM: STOP MODE:		0.73	0.67	0.78	0.70
DM: DELAY MODE		21.82	15.16	12.12	10.53
QM: QUEUE MODE:	1	15.68	11.39	8.85	6.48
- average queue length	2	13.52	6.36	7.35	6.25
for streams {m]	3	6.15	4.21	3.62	3.20
	4	8.10	5.44	4.17	4.14

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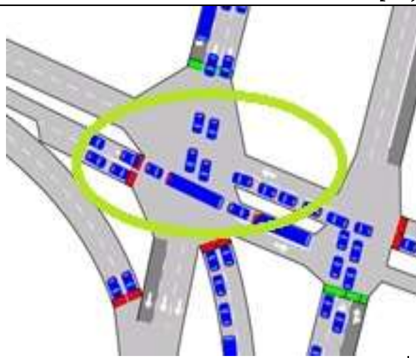
	5	5.95	2.46	3.41	3.20
	6	7.45	3.73	3.66	3.51

A – *Fixed-time, C= 90 s.;* **B/D** – *Entropy control C= 90 s/ C=var ;* **C** – *Delays mode C=var;*

Table 3 shows that the maximum efficiency of the control method corresponds to the situations of the cycle time and green split readjustments to the volume of traffic arrivals. Nevertheless, even in the case of fixed cycle time, entropy control can reduce the average delay per vehicle by about 25%, average queue length by 20 to 60% depending on the traffic flow and insignificantly reduce the average number of stops.

In Tab. 4 the intersection blocking traffic incident is recognized and diagnosed (i.e. signal group with assigned green time cannot driving due to blocking). The results from simulation model in Aimsun and control recurrent adjustments to new traffic parameters were illustrated in [22]. In this paper the PIACON multi-criteria control reactions for recognized structure of preferences by IS supervisor using the robust entropy based traffic situations markers offered good results in the DM-Delay Mode; QM; Queue Mode, SM: Stops Mode and Travel Times context.

Table 4 Traffic incidents detection and Aimsun model [20, 22]

		Aimsun	PIACON	%
		**DM:** 103.58 **QM**: 189.62 **SM**: 2.32 Travel Time: 221.9	52.97 65.72 1.47 124.3	51% 35% 63% 56%

CONCLUSIONS

This paper emphasize and illustrate, by a simple practical example, the importance and potential of the new real-time intelligent control feedback offered by professional exploration of available traffic real-time information sources, communication systems and vehicle platforms.

The importance of the original 2-D traffic model RF based traffic situation markers characteristics for detection, analysis and diagnosis in real-time traffic situations with proposal related preference structures for the adequate control actions was practically illustrated.

In the presented example the simple form of entropy parameter as a measure of traffic smoothness is selected from several potential candidates (e.g. spatial variogram or correlation functions). The practical entropy advantages result from the simple analytical form preserved by one-one bijection mappings e.g. for Green shields linear speed-density model, the entropy of the traffic speed, density and volume may be easily formulated. The proposal of the natural stochastic approach (i.e. description of the vehicles interactions by appropriate random fields on the basis of 2-D data) seems to be very useful especially in the context of traffic intelligent microscopic control. Implementation of intelligent 2-D supervision and traffic control actions can provide new spatial traffic detection capabilities (e.g. wide-area flexible modified traffic parameters dedicated detection zones) and possibilities to define high quality of area based traffic flow parameters estimators and predictors. The proposed intelligent traffic control method that is based on real-time estimated traffic situations markers (e.g. entropy parameter) seems to be presently one of the most attractive control tools. This approach can be easily extended to pro-ecological intelligent control [5] and public transport intelligent priority control [1, 5, and 16]

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