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# DIGITAL ECOSYSTEM FOR MONITORING AND FORECASTING TRAFFIC FLOWS: A COMPOSITIONAL FUZZY MODELING APPROACH

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**Abstract.** The paper proposes a compositional approach to monitoring and forecasting traffic flows in urban agglomerations, based on the integration of socio-economic factors, structural analysis of road scenes, and fuzzy time series models. Transport demand is estimated using an expert-based fuzzy model that aggregates socio-economic indicators. Traffic density is derived from structural image analysis through the identification of an optimal spatial scale, as well as a spatial heterogeneity index characterizing the internal organization of the flow. The state of the transport system is represented by a linguistic variable obtained via fuzzy inference. This variable is further incorporated into a forecasting model formulated as a fuzzy time series, taking into account both historical dynamics and the current state of the traffic flow. Experimental validation based on video monitoring and sensor data demonstrates that the proposed approach provides more accurate forecasting compared to classical fuzzy time series models, particularly in transitional traffic regimes.

**Keywords:** Traffic flows; structural image analysis; traffic density; spatial heterogeneity; fuzzy systems; fuzzy time series; forecasting.

**AMS Subject Classification:** 03E72.

## 1. Introduction

The rapid development of urban agglomerations is accompanied by increasing traffic demand and growing complexity of traffic flow structures, which necessitates the development of adequate models for monitoring, interpretation, and forecasting. Modern intelligent transportation systems generate large volumes of heterogeneous data obtained from sensors, computer vision systems, and statistical observations of socio-economic indicators. However, such data are typically weakly structured, contain uncertainty, and cannot be fully described within the framework of classical deterministic models.

Existing studies in this domain are usually focused on individual aspects of traffic analysis [2, 14]. In particular, transport demand models are constructed based on socio-economic factors, traffic density is estimated from traffic monitoring data, and dynamic characteristics such as travel time are analyzed using time series methods. Despite significant progress in each of these areas, they are often considered in isolation, without explicitly establishing relationships between demand formation, traffic state, and its temporal dynamics. This leads to fragmented models and limits the ability to perform comprehensive analysis of transportation systems.

Another important challenge lies in the interpretation of quantitative indicators in terms of qualitative traffic states. Characteristics such as road load or congestion levels are naturally described using linguistic categories and require appropriate mathematical tools. In this context, fuzzy logic provides a suitable framework, as it enables the formalization of expert knowledge, accounts for uncertainty, and ensures interpretability of results.

In this paper, we propose an approach based on the integration of three interrelated components: a transport demand model driven by socio-economic factors, a fuzzy linguistic model for traffic state interpretation based on structural indicators, and a mobility modeling and forecasting framework using fuzzy time series. Unlike existing approaches, these components are treated as elements of a unified compositional structure, where the output of one model serves as the input to the next, forming a consistent "demand–state–dynamics" chain [10, 11, 12].

The proposed structure is interpreted as a digital ecosystem for monitoring and forecasting traffic flows, enabling the integration of heterogeneous data sources, handling uncertainty, and providing both quantitative and qualitative descriptions of traffic system states. The compositional nature of the model allows different levels of representation to be coherently combined, resulting in a unified view of traffic formation and evolution processes. The main contribution of this work is the development of a compositional fuzzy modeling framework that integrates demand, density, and mobility models into a single formalized structure.

## 2. Problem formulation

A transportation system of an urban agglomeration is considered, evolving in discrete time instants ($t$=1, 2, …). The system is assumed to be characterized by a set of interrelated parameters reflecting the processes of transport demand formation, the current state of traffic flow, and its temporal dynamics.

Let $X(t)=(x_1(t), x_2(t), \dots, x_n(t))$ denote the vector of socio-economic factors. The transport demand is defined as

$$D(t) = f(X(t)). \tag{1}$$

The traffic density on the considered segment of the transportation network is defined as

$$\rho(t) = g(D(t), \Theta), \tag{2}$$

where $\Theta$ denotes the parameters of the transportation infrastructure.

The speed $v(t)$ is obtained from sensor-based monitoring data. The average travel time for a road segment of length $S$ at time $t$ is estimated as

$$\tau(t) = S / v(t), v(t)>0. \tag{3}$$

To interpret the state of the traffic flow, a linguistic variable $L(t)$ is introduced [4, 15], defined via a fuzzy mapping as

$$L(t) = \Phi(\rho(t), v(t), \delta(t)), \tag{4}$$

where $\delta(t)$ denotes a spatial heterogeneity index of the traffic flow, characterizing the degree of non-uniform distribution of vehicles within the considered road segment.

The system dynamics are described by the time series $\tau(t)$, for which a forecasting model is introduced:

$$\tau(t+1) = F(\tau(t), L(t)). \tag{5}$$

Thus, the transportation system is represented by a chain of interrelated mappings

$$X(t) \to D(t) \to \rho(t) \to v(t) \to \tau(t), \tag{6}$$

supplemented by a fuzzy interpretation of the system state through the variable $L(t)$.

The objective of the study is to develop an integrated compositional model that ensures a consistent transformation of socio-economic factors into traffic flow parameters, their linguistic interpretation, and the forecasting of system dynamics under uncertainty [1, 3, 4, 13, 15].

## 3. Integrated modeling framework

An integrated model of the transportation system is proposed, combining the processes of transport demand formation, traffic state estimation, and mobility forecasting. The model has a compositional structure, in which the output of one component serves as the input to the next. It consists of three interrelated modules: a transport demand model, a model for traffic density estimation and state interpretation based on structural features, and a mobility forecasting model.

### 3.1. Transport Demand Model

Within the proposed compositional framework, the transport demand $D(t)$, defined by (1), is derived from a set of socio-economic factors using an expert-based fuzzy approach. The choice of this approach is motivated by the fact that the influence of macroeconomic and demographic parameters on traffic flows is complex, nonlinear, and inherently uncertain, making purely deterministic models insufficiently adequate.

The input data consist of a set of factors $x_k(t)$ characterizing the state of the urban agglomeration. These include indicators of economic activity, demographic characteristics, and transport availability, among other variables affecting mobility intensity. While these factors define the input space of the model, their impact on transport demand is heterogeneous and requires a formalized evaluation procedure.

The construction of the transport demand model is carried out through a sequence of stages.

At the first stage, expert-based ranking of factors is performed. Each expert provides an ordered list of factors according to their influence on transport demand. The ranks $r_{k,i}$, assigned to the $k$-th factor by the $i$-th expert, are converted into quantitative scores and subsequently normalized to obtain $e_{k,i}$, ensuring the comparability of results: $\sum_{k=1}^{n} e_{ki} = 1$, where $n$ is the number of socio-economic factors and $m$ is the number of experts.

Since expert judgments may be inconsistent, the next stage involves assessing their agreement using Kendall's coefficient of concordance. This coefficient is computed according to the standard formulation and provides a quantitative measure of agreement among experts. If the coefficient exceeds a predefined threshold (e.g., 0.6), the set of evaluations is considered consistent and used for further analysis. Otherwise, the expert assessments are revised or the composition of the expert group is reconsidered.

The aggregation of expert evaluations is performed by accounting for different levels of expert competence. For this purpose, competence coefficients $w_i$ are introduced to represent the contribution of each expert to the overall assessment, subject to the normalization condition $\sum_{i=1}^{m} w_i = 1$. Based on these coefficients, the aggregated weights of the factors are computed as [8]: $\omega_k = \sum_{i=1}^{m} w_i e_{k,i}$ .

The expert competence coefficients are refined through an iterative procedure. At each iteration, the deviation of individual expert evaluations from the aggregated result is assessed, and the values of $w_i$ are accordingly updated. The iterative process continues until convergence of the weight vector $\omega_k$ is achieved, ensuring the stability and consistency of the resulting factor weights.

As a result of the described procedure, a weight vector $\omega_k$ is obtained, reflecting the relative importance of the factors. Based on this vector, an integral indicator of the socio-economic state is computed as

$$R(t) = \sum_{k=1}^{n} \omega_k x_k(t) ,$$

which represents an aggregated characterization of the external environment of the transportation system.

The resulting indicator $R(t)$ is used as an aggregated input to the fuzzy inference system that determines the transport demand $D(t)$. At the same time, individual factors $x_k(t)$ may also be included as additional input variables, allowing both aggregated and differentiated effects of the factors to be taken into account.

The mapping (1) is implemented using a fuzzy inference system in which the input variables are represented as linguistic variables. For each factor, a set of linguistic terms (e.g., "LOW", "MEDIUM", "HIGH") is defined along with corresponding membership functions that quantify the degree to which a given value belongs to these terms. The membership functions are specified in parametric form and can be adjusted based on expert knowledge or empirical data.

The output variable associated with transport demand is also expressed in linguistic terms. The rule base of the fuzzy system is constructed using expert knowledge and captures the influence of different combinations of factors on the demand level. Each rule follows an “If <…>, then <…>” structure and represents typical interaction patterns among the factors, accounting for both their individual and combined effects.

The fuzzy inference procedure consists of the standard stages of fuzzification, rule evaluation, and defuzzification [3, 15]. As a result, a quantitative estimate of transport demand is obtained that is consistent with expert knowledge and accounts for uncertainty in the input data.

It should be emphasized that the integral indicator $R(t)$ is used as an aggregated input to the fuzzy inference system determining the value of $D(t)$ In this way, linear aggregation of factors and fuzzy inference jointly form a compositional mapping that links socio-economic characteristics to transport demand estimation.

As a result, the transport demand $D(t)$ can be interpreted as an integral indicator of traffic activity, reflecting the potential load on the transportation system. The obtained estimate is further used as an input for traffic state analysis, establishing a connection between the macro-level socio-economic conditions and the characteristics of the road situation within a unified compositional framework.

Thus, transport demand formation is realized as a sequence of interrelated transformations, including expert-based evaluation of factor significance, consistency assessment, aggregation with respect to expert competence, and subsequent fuzzy inference. This procedure enables the transition from the initial vector of socio-economic characteristics to an integral estimate of demand, taking into account uncertainty and nonlinear relationships.

For clarity, the described sequence of transformations is illustrated in Fig. 1, which presents the structural scheme of the transport demand model.

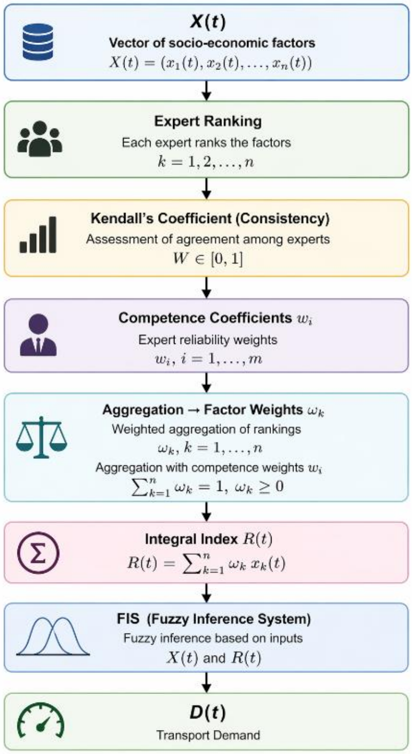


**Fig. 1.** Structure of the transport demand model based on expert ranking, consistency assessment, weighted aggregation, and fuzzy inference.

As shown in Fig. 1, the input factor vector $X(t)$ undergoes expert-based ranking and consistency assessment, after which the weighting coefficients are determined and the integral indicator $R(t)$ is computed. The values of $R(t)$ together with $X(t)$ are then used as inputs to the fuzzy inference system, yielding an estimate of the transport demand $D(t)$.

### 3.2. Traffic Density and State Interpretation Model

Within the proposed framework, the estimation of traffic density and state is based on the analysis of structural characteristics of the road scene extracted from visual monitoring data. Unlike conventional approaches relying on direct vehicle counting or trajectory analysis, the proposed method employs integral features of the spatial organization of the scene and does not require prior geometric calibration.

Let $I(t)$ denote an image of a road segment at time $t$. To analyze the structure of the traffic flow, a family of derived images is constructed by partitioning the observation area into windows of varying spatial scales. For each scale, the structural properties of the scene are analyzed in the feature space.

Each scale $w$ corresponds to a set of local image patches for which feature vectors are computed, capturing the textural and structural characteristics of the road scene. In particular, transformations sensitive to local structural variations (e.g., wavelet transforms) are employed to obtain a robust representation of the scene in the feature space.

To evaluate the adequacy of the representation at each scale, a set of formalized criteria is employed, characterizing: (i) the uniformity of feature variation ($C_1$); (ii) the symmetry of the feature distribution ($C_2$); (iii) robustness to structural changes ($C_3$); and (iv) sensitivity to partitioning parameters ($C_4$). The overall measure of structural consistency is defined as an aggregated function of these criteria:

$$Q(w) = \sum_{k=1}^{4} \alpha_k C_k(w),$$

where $C_k(w)$ are the criterion values and $\alpha_k$ are their corresponding weights.

The function $Q(w)$ is interpreted as a structural inconsistency measure, and the optimal scale is determined by minimizing this value:

$$w^*(t) = \arg\min Q(w).$$

The parameter $w^*(t)$ is interpreted as an integral structural indicator of traffic density, reflecting the spatial organization of the road scene. Empirical observations indicate that as traffic density increases, the optimal partitioning scale decreases, which is associated with growing structural complexity of the scene.

A stable monotonic relationship exists between traffic density and the optimal scale, which can be approximated analytically. In the simplest case, this relationship can be expressed as an inverse proportionality:

$$\rho(t) \sim \frac{r}{w^*(t)}$$

where $r$ is a scaling coefficient.

Thus, the traffic density $\rho(t)$, introduced in (2), is determined through structural image analysis as $\rho(t) = g(w^*(t))$.

It should be noted that identical density values may correspond to different traffic regimes, depending on the degree of spatial organization of the flow. To account for this, a spatial heterogeneity index $\delta(t)$ is introduced, capturing the variability of structural properties of the scene.

The index $\delta(t)$ is defined based on the dispersion of features computed at the optimal scale, in the form of the standard deviation: $\delta(t)=\mathrm{std}(\{\varphi_j(w^*(t)\})$, where $\varphi_j$ denotes the feature vectors of local image patches. Low values of $\varphi_j$ correspond to a uniform distribution of vehicles, whereas higher values indicate clustering effects, local congestion, and transitional traffic regimes.

The combined use of $\rho(t)$, $v(t)$ and $\delta(t)$ provides a comprehensive description of the traffic flow, capturing both its intensity and internal structure. The interpretation of the traffic state is performed using a fuzzy inference system defined by (4). The input variables ($\rho(t)$, $v(t)$ and $\delta(t)$) are each represented as linguistic variables.

The described procedure of structural analysis and state interpretation can be viewed as a sequence of interrelated stages that transform the observed image into a linguistic assessment of the system state. This sequence is illustrated in Fig. 2.

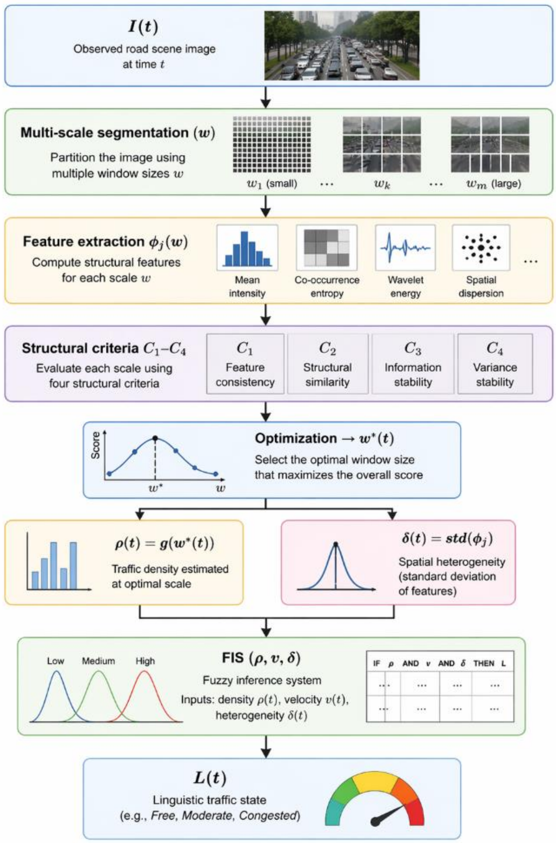


Fig. 2. Structural scheme of traffic density estimation and state interpretation based on multi-scale image analysis and fuzzy inference.

As shown in Fig. 2, the analysis begins with processing the image $I(t)$ at multiple spatial scales, after which the optimal scale $w^*(t)$ is determined based on structural criteria. The parameters $\rho(t)$ and $\delta(t)$, are then computed and, together with the speed $v(t)$, used as inputs to a fuzzy inference system to obtain a linguistic assessment of the traffic state $L(t)$.

For density and speed, the linguistic terms "LOW", "MEDIUM", and "HIGH" are used, while for the heterogeneity parameter $\delta(t)$ the terms "HOMOGENEOUS", "MEDIUM HETEROGENEOUS", and "HIGHLY HETEROGENEOUS" are defined. The membership functions are specified in parametric form and reflect expert knowledge regarding the boundaries of these states.

The rule base is constructed based on typical traffic scenarios. For example:

- "If density is HIGH, speed is LOW, and heterogeneity is HIGH, then the traffic state is CRITICAL";
- "If density is MEDIUM, speed is HIGH, and heterogeneity is LOW, then the traffic state corresponds to STABLE FLOW".

The fuzzy inference procedure is implemented using the Mamdani scheme and consists of the standard stages of fuzzification, rule evaluation, and defuzzification.

At the fuzzification stage, the numerical values of the input variables $\rho(t)$, $v(t)$, and $\delta(t)$ are transformed into degrees of membership with respect to the corresponding linguistic terms. This is achieved using membership functions $\mu(\cdot)$, which map the input values onto the interval [0, 1] and reflect expert knowledge about the boundaries of traffic states.

Further, for each rule in the rule base, the degree of its activation is computed. For implicative rules of the form

"If $\rho=A_i$ and $v=B_j$ and $\delta=C_k$, then $L=D_m$"

the activation degree is defined as

$$\beta_{ijk}(t)=\min\{\mu_{Ai}(\rho(t)), \mu_{Bj}(v(t)), \mu_{Ck}(\delta(t)\}.$$

The obtained values $\beta_{ijk}(t)$ are used to construct the output fuzzy sets corresponding to the rule consequents [2, 14]. These sets are then aggregated using the maximum operator, resulting in the overall membership function $\mu_L(y, t)$, which reflects the combined effect of all rules.

At the defuzzification stage, the fuzzy representation is transformed into a numerical estimate of the traffic state. In this study, the centroid method of defuzzification is employed:

$$L(t)=\frac{\int y\cdot\mu_L(y,t)dy}{\int \mu_L(y,t)dy}$$

The resulting value $L(t)$ provides an integral and interpretable assessment of the traffic state, taking into account the combined influence of density, speed, and spatial heterogeneity. Unlike individual indicators such as $\rho(t)$ or $v(t)$, the variable $L(t)$ enables the discrimination between traffic regimes with similar quantitative characteristics but different structural organization.

### 3.3. Mobility Modeling and Forecasting Based on Fuzzy Time Series

The final stage of the proposed compositional model is the forecasting of temporal characteristics of the traffic flow based on the current system state and its short-term dynamics [1, 13]. The primary variable considered is the average travel time $\tau(t)$ for a road segment, defined by (3).

Unlike static approaches, where the forecast relies solely on the current value of $\tau(t)$, the proposed model takes into account both the previous value of the time series and the current traffic state represented by the linguistic variable $L(t)$, obtained in Section 3.2.

The forecasting model is defined by the mapping

$$\tau(t+1) = F(\tau(t), \tau(t-1), L(t)),$$

where $F(\cdot)$ is the forecasting operator implemented as a fuzzy inference system.

The variables $\tau(t)$ and $\tau(t-1)$ are treated as fuzzy quantities and represented as linguistic variables with the terms "LOW", "MEDIUM", and "HIGH", reflecting different levels of travel time. The variable $L(t)$, characterizing the traffic state, is described by the terms "FREE FLOW", "STABLE FLOW", "HEAVY TRAFFIC", and "CONGESTED".

The membership functions are specified in parametric form and map numerical values of the variables to degrees of membership in the corresponding linguistic terms. The rule base is constructed to capture typical temporal patterns of traffic evolution. In particular, it accounts for: (i) process inertia (persistence of travel time $\tau$ under unchanged conditions); (ii) tendencies toward improvement or deterioration of traffic conditions; and (iii) the influence of the structural state of the flow on its dynamics.

Examples of such rules include the following:

- "If $\tau(t)$ is HIGH and $\tau(t-1)$ is HIGH and $L(t)$ is CONGESTED, then $\tau(t+1)$ REMAINS HIGH";
- "If $\tau(t)$ is MEDIUM and $\tau(t-1)$ is HIGH and $L(t)$ is STABLE FLOW, then $\tau(t+1)$ DECREASES";
- "If $\tau(t)$ LOW and $\tau(t-1)$ MEDIUM and $L(t)$ is HEAVY TRAFFIC, $\tau(t+1)$ INCREASES".

Thus, the model captures not only the current level of travel time but also the direction of its change.

The fuzzy inference procedure is implemented using the Mamdani scheme and includes the stages of input fuzzification, computation of rule activation degrees, aggregation of output fuzzy sets, and defuzzification. As a result, a numerical value of $\tau(t+1)$ is obtained, representing the predicted travel time. It should be noted that the proposed model is consistent with established approaches to fuzzy time series forecasting. In particular, in Chen's model, a time series is represented as a sequence of linguistic states, and forecasting is performed based on first-order fuzzy logical relationships: $\tau(t+1)=F_1(\tau(t))$. Higher-order models (Chen-2 and Chen-3) incorporate multiple previous values of the time series: $\tau(t+1)=F_k(\tau(t), \tau(t-1), \ldots)$. In the Song–Chissom model, the dynamics of the time series are described using fuzzy transition relations between states.

The proposed model extends the aforementioned approaches by incorporating an additional state parameter

$$L(t){:}\ \tau(t+1)=F(\tau(t), \tau(t-1), L(t)),$$

which enables the influence of the structural organization of the traffic flow on its dynamics to be explicitly taken into account. Thus, the operator $F$ defines a nonlinear mapping that captures both short-term temporal dynamics and the current system state. This leads to more adequate forecasting compared to classical fuzzy time series models, which rely solely on historical data.

The structural realization of the operator $F$, including the stages of input formation, fuzzy inference, and prediction generation, is illustrated in Fig. 3.

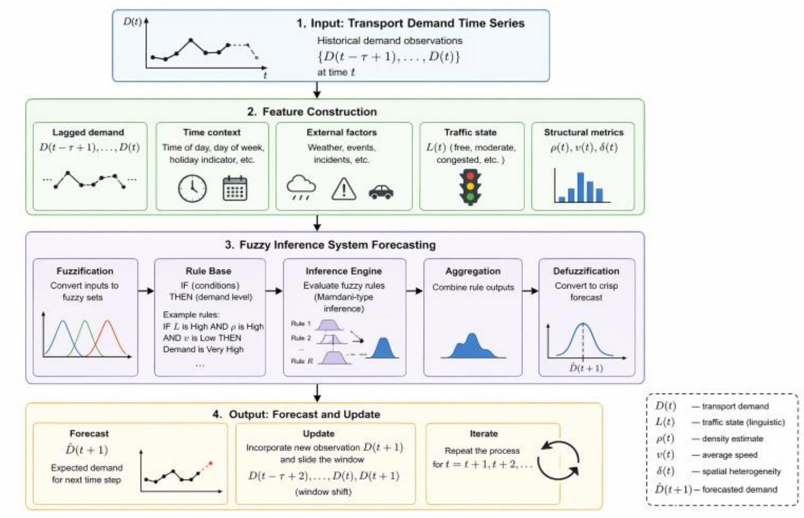


**Fig. 3.** Structural scheme of forecasting traffic flow temporal characteristics based on fuzzy time series and a state variable.

As shown in Fig. 3, the forecast is generated based on a sequence of previous values of the time series and the current traffic state $L(t)$. These inputs are fed into a fuzzy inference system comprising fuzzification, rule evaluation, aggregation, and defuzzification stages, resulting in the estimation of $\tau(t+1)$.

Unlike classical fuzzy time series models, the proposed approach introduces a state-dependent forecasting mechanism, in which the evolution of the time series is conditioned not only on its historical values but also on the current structural state of the system derived from image analysis. This enables the model to capture transitional traffic regimes that are not adequately represented in conventional time series frameworks.

## 4. Experimental Validation

Experimental validation of the proposed digital ecosystem was carried out using real-world data from the transportation network of Baku (Azerbaijan), socio-economic statistical indicators, and expert assessments.

### 4.1. Analysis and Validation of the Transport Demand Model

To assess the adequacy of the expert-based fuzzy transport demand model, a survey involving 15 qualified specialists in logistics was conducted.

*Factor ranking.* The experts evaluated five key factors: GDP level ($x_1$), industrial production volume ($x_2$), per capita income ($x_3$), population size ($x_4$), and motorization level ($x_5$). The consistency check using Kendall's coefficient of concordance yielded $W$=0.6613, indicating that the data were sufficiently consistent for further analysis.

*Weight coefficients*. As a result of the iterative procedure for refining expert competence (converging at the third iteration), the following factor weights were obtained: $\omega_1$=0.10459; $\omega_2$=0.10346; $\omega_3$=0.29643; $\omega_4$=0.19869; $\omega_5$=0.29683.

*Comparative index evaluation.* Using the weighted summation method, the average socio-economic index was calculated as 83.08. The application of the Fuzzy Inference System produced a normalized index value of 0.5918. These results were further used to compute the transport demand growth coefficient, which reached $C$=1.1548 in one of the test scenarios.

### 4.2. Density Calibration Based on Structural Indicators

To estimate traffic density without explicit object detection, an approach based on structural consistency analysis of road scene images was employed.

*Relationship between $w^*$ and $\rho$.* A stable inverse relationship between the optimal discretization scale $w^*$ and the physical traffic density $\rho$ was established experimentally:

- at a density of 5 veh/km, $w^*$=200 pixels;
- at 20 veh/km, $w^*$=50 pixels;
- at 40 veh/km, $w^*$=25 pixels;
- at 60 veh/km, $w^*$=15 pixels.

**Mathematical model.** This relationship was approximated by a hyperbolic function of the form

$$w^* = \frac{\alpha}{\rho + \beta},$$

which confirms the increase in structural complexity of the image as traffic density grows. The model demonstrated relatively smooth behavior under small variations of the optimal scale parameter: small variations in $w^*$ resulted in limited and smooth changes in the estimated density.

### 4.3. Fuzzy Interpretation of Traffic States

To evaluate the linguistic assessment module, a Mamdani-type fuzzy inference system with 12 base rules was implemented.

**Test scenario 1.** For input values $\rho$=20 veh/km, $v$=35 km/h, and $\delta$=0.5 (medium heterogeneity), the degree of membership to the term "MEDIUM" was $\mu$≈0.67. Defuzzification using the centroid method yielded $L$≈0.45, corresponding to a "**STABLE FLOW**" state (stable flow with early signs of densification).

**Test scenario 2.** Under conditions of HIGH density ($\rho$=45), LOW speed ($v$=25), and INCREASED HETEROGENEITY ($\delta$=0.4), the model produced $L$=0.65, classifying the situation as "CRITICAL" (a near-congested state).

### 4.4. Mobility Forecasting Based on Time Series

The forecasting capabilities of the proposed ecosystem were evaluated on a segment of Heydar Aliyev Avenue in Baku (segment length $S$=1063.68 m). The dataset consisted of 144 measurements of average speed collected at 10-second intervals.

*Fuzzification.* The time series was transformed into a fuzzy representation using 51 symmetric trapezoidal membership functions, allowing the weakly structured nature of visual data to be effectively captured. The number of membership functions was selected empirically to ensure sufficient resolution of the fuzzy representation while preserving model stability.

*Forecasting accuracy.* A comparison between first-order and second-order fuzzy time series models demonstrated a clear advantage of the latter:

- MSE (mean squared error) decreased from 0.7635 to 0.0934;
- MAPE (mean absolute percentage error) decreased from 1.1609% to 0.2316%;
- MPE (mean percentage error) was –0.0048%, which is significantly below the commonly accepted threshold of 5%.

Thus, the experimental results indicate that integrating socio-economic analysis, structural image-based features, and fuzzy time series within a unified ecosystem provides:

1. consistently high forecasting accuracy under the considered experimental conditions (with MAPE below 0.3%);
2. relative stability of the obtained estimates under moderate variations of observation conditions;
3. interpretability, enabling traffic management operators to obtain not only numerical predictions but also qualitative assessments of traffic conditions (e.g., “FREE FLOW”, “CONGESTED”, “CRITICAL”).

## 5. Analytical Core of the Digital Ecosystem

The models developed in Sections 3.1–3.3 form a unified compositional structure that constitutes the analytical core of the proposed digital ecosystem for monitoring and forecasting traffic flows.

Within this core, three functionally interconnected components are integrated, enabling the transformation of heterogeneous data sources into a consistent representation of the transport system state and its dynamics [10, 11, 12]. As a result, a joint mapping of different data types is achieved:

$$(X(t), I(t), v(t)) \rightarrow (D(t), L(t), \tau(\mathrm{t}+1)),$$

which links socio-economic factors [6, 7, 8, 9], the observed state of the road scene, and temporal characteristics of the traffic flow.

A key feature of the proposed architecture is the integration of structural and temporal information. Unlike conventional approaches based solely on time series analysis, the model incorporates the current traffic state derived from image analysis, improving sensitivity to transitional regimes and changing traffic conditions [10, 11, 12]. The analytical core provides a foundation for monitoring, forecasting, and decision support tasks, providing a coherent framework for data processing and the formation of integrated transport system indicators.

The conceptual structure of the analytical core is illustrated in Fig. 4.

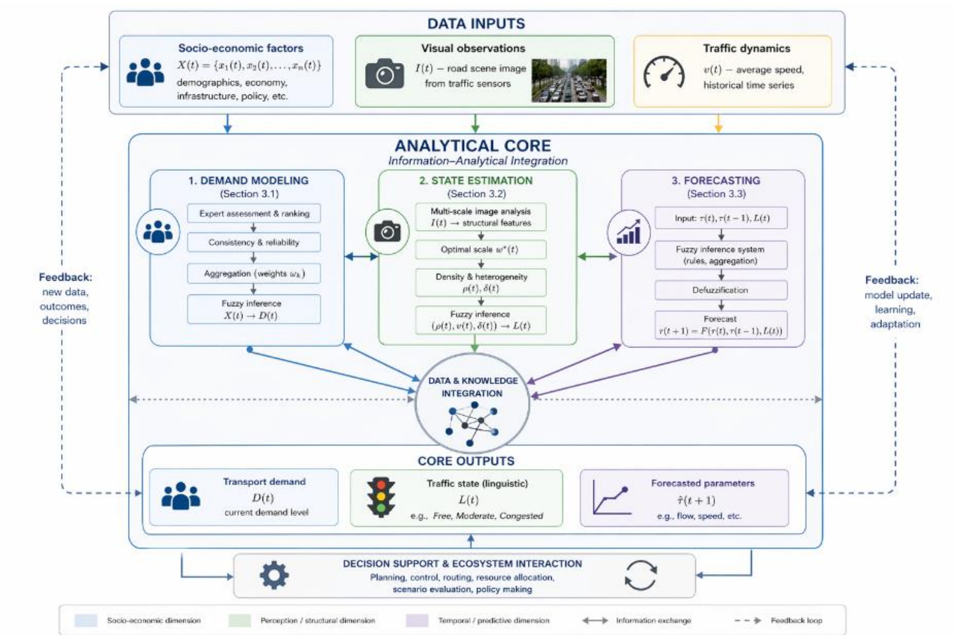


**Fig. 4.** Conceptual structure of the analytical core of the digital ecosystem for monitoring and forecasting traffic flows.

As shown in Fig. 4, the analytical core integrates the demand formation, state interpretation, and forecasting modules, ensuring a coherent transformation of input data into integrated characteristics of the transport system.

## 6. Conclusion

The paper presents a compositional approach to monitoring and forecasting traffic flows in urban agglomerations, based on the integration of socio-economic factors, structural analysis of road scenes, and fuzzy time series models. The proposed framework unifies transport demand modeling, traffic state interpretation, and temporal forecasting within a single coherent structure.

A key feature of the approach is the incorporation of the current structural state of the traffic flow, extracted from image analysis, into the forecasting process. This allows transitional regimes to be captured and improves the representation of system dynamics compared to conventional methods relying solely on temporal dependencies.

Experimental results indicate that the integration of structural, temporal, and expert-based information leads to more stable and accurate forecasting under the considered experimental conditions.

Unlike deep learning approaches such as LSTM networks, the proposed compositional fuzzy framework does not require large-scale training datasets and provides interpretable forecasting rules that can be directly analyzed by traffic management operators. At the same time, neural network models may provide advantages in large-scale adaptive learning tasks and can be considered as a possible direction for further comparative studies.

The proposed approach can be applied in intelligent transportation systems for monitoring, forecasting, and decision support under uncertainty. Future work will focus on extending the range of data sources, adapting the model to different types of transportation networks, and developing methods for automated tuning of fuzzy system parameters. Future research will also consider automated tuning of membership functions using neuro-fuzzy approaches and evolutionary optimization methods in order to reduce dependence on expert-defined parameters. This approach has several limitations, including sensitivity to the choice of membership functions and the need for sufficient data for calibration.

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