Optimization of the Comprehensive Measures for Managing Demographic Mobility Using Intelligent Decision Support Systems*

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Abstract
The article explores approaches to optimizing the comprehensive measures for managing demographic mobility through the implementation of intelligent decision support systems (IDSS) based on mathematical modeling methods, fuzzy set theory, and geoinformation technologies. The architecture of the IDSS is presented, enabling multicriteria analysis of alternatives under conditions of uncertainty and risk. A model for dynamic assessment of migration pressure at the regional level is proposed. An example of using the system to justify policy decisions in the context of changing external factors is demonstrated.

Keywords
decision support, mathematical modeling, uncertainty, geographic information system, fuzzy set theory

1. Introduction

The increase in migration flows due to globalization, armed conflicts, and climate change imposes new demands on systems for managing these processes. Traditional approaches to planning and regulating comprehensive measures for managing demographic mobility are losing effectiveness due to the complexity of dynamics, data uncertainty, and the need for rapid decision-making [1-3]. In this regard, the implementation of intelligent decision support systems (IDSS) that utilize modern mathematical modeling methods becomes highly relevant.

2. Theoretical Background

The foundation of this research is the concept of multicriteria decision analysis within the framework of fuzzy set theory, which enables the formalization of uncertain expert assessments, as well as the methodology for using GIS to process spatial data. The combined application of these tools ensures the adaptability of models to changes in the external environment [4].

Modern migration analytics requires not only the accurate consideration of numerous factors but also the use of effective tools for formalizing uncertainty, which is a characteristic feature of most socio-economic data. In this context, fuzzy set theory enables the creation of models capable of adapting to vague, incomplete, or conflicting expert evaluations [5].

The application of GIS technologies in combination with mathematical methods provides visualization and spatial modeling of migration processes [6]. This is particularly relevant in rapidly changing environments, where information from field sensors, satellite imagery, or social media can be used for real-time model updates. Such integration forms the basis for developing dynamic decision support systems in the field of demographic mobility.

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3. Architecture of the Intelligent System

The proposed IDSS has a modular structure that includes: a data collection module from open sources (including IoT sensors, statistics, and satellite data); an analytics module utilizing fuzzy logic algorithms and clustering; a visualization module for decision-making based on geospatial maps; and an interface for interaction with government authorities [7].

The UML activity diagram is presented in Figure 1. It illustrates the stages of IDSS operation—from data collection to the formation of decision-making recommendations. The diagram enables tracking the logic of information processing and selecting the optimal decision, taking into account spatial and temporal characteristics.

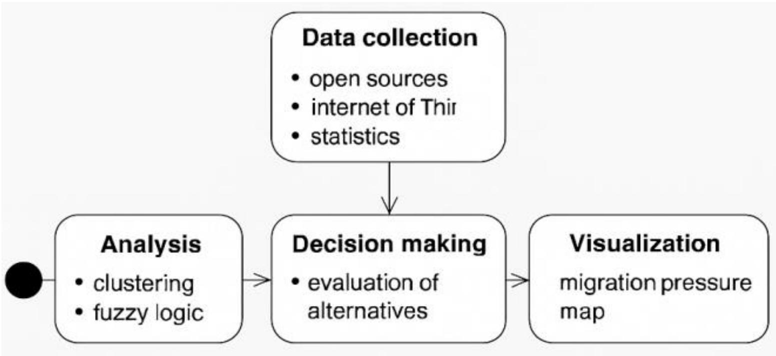

Figure 1: IDSS Architecture for Migration Processes

The architecture of the IDSS is designed with modularity and scalability in mind, which enables its adaptation to various regional conditions. For example, if local databases or specific information sources are available, individual components can be replaced without disrupting the overall logic of the system's operation.

Special attention is given to the user interface: it allows customization of data detail levels, scenario modeling, and integration with external management systems. Thus, the IDSS serves not only as an analytical tool but also as a strategic planning instrument capable of responding to changes in the external environment in near real-time

4. Intelligent geoinformation platforms for the analysis of transportation processes in the context of demographic mobility

The growing complexity of migration processes requires the integration of diverse data sources for effective management of demographic mobility. One of the key aspects is the analysis of transport infrastructure, as it directly affects population mobility. Intelligent geoinformation platforms (IGIPs) enable the integration of data from various sources, including IoT sensors, to model and optimize transportation processes.

4.1. Architecture of IGIP

Intelligent Geoinformation Platforms (IGIPs) feature a modular architecture that ensures scalability and adaptability to regional specificities. The core component is the data collection module, which integrates information from a wide range of sources, including IoT sensors, GPS devices, satellite imagery, and data from social networks. The collected data is processed by the analytical module, which applies advanced machine learning algorithms, fuzzy logic methods, and clustering techniques to identify patterns in transportation flows [3]. The visualization module is responsible for the graphical representation of analysis results in the form of interactive maps, charts, and analytical dashboards, making complex data more accessible. The user interface of the platform is designed to provide convenient access to functionality for both government officials and representatives of public organizations and researchers.

4.2. Application of IGIPs in Demographic Mobility Management

IGIPs open up new opportunities for effective management of demographic mobility. They enable the analysis of transportation routes to identify bottlenecks and optimize transport operations, thereby improving regional accessibility and reducing travel time. By integrating data from various sources, these platforms make it possible to forecast the dynamics of migration flows, taking into account external factors such as socio-economic changes, environmental threats, or conflicts. Moreover, IGIPs serve as decision support tools by providing well-founded recommendations for strategic infrastructure planning, the development of migration policies, and the promotion of sustainable spatial development.

In the study by [6], an IGIP is presented for analyzing transportation processes, which integrates data from multiple sources to model and optimize transport infrastructure. This approach can be adapted for managing demographic mobility, enabling more accurate migration forecasting and more effective planning of infrastructure changes.

5. Mathematical Model

The model is based on a system of dynamic equations of migration pressure:

$$M_t = \alpha P_t + \beta R_t + \gamma S_t + \varepsilon \quad (1)$$

where M_t– is the migration load index, P_t – represents the level of political instability, R_t – denotes economic risks, S_t – stands for social indicators, and ε is a random component modeling uncertainty. The estimation of coefficients is performed using the fuzzy analytic hierarchy process, taking into account linguistic variables.

We consider a dynamic stochastic system in the form of a vector autoregressive process with lags.

$$Mt = \alpha t P_t\text{-}1 + \beta t R_t\text{-}1 + \gamma t S_t\text{-}1 + \delta M_t\text{-}1 + \varepsilon_t \quad (2)$$

where M_t – is the migration pressure at time t;

P_{t-1}, R_{t-1}, S_{t-1} – previous values of factors: demography, risks, socio-economic indicators;

δ – feedback coefficient (autoregression);

ε_t~$N(0,\Sigma_t)$ – stochastic noise with a time-varying covariance matrix.

The model is complemented by coefficient adaptivity:

$$a_t = f_1(x,y,t),\ \beta_t = f_2(x,y,t),$$
$$\gamma_t = f_3(x,y,t) \quad (3)$$

where (x,y) — geographic coordinates of the region;

f_i — functions that can be defined using regression models, neural networks, or geostatistical approaches (e.g., Kriging smoothing).

To account for uncertainty, we introduce stochastic modeling and scenario analysis of the following types:

$$\varepsilon_t = \eta_t * \zeta_t, \zeta_t \sim N(0,1),$$
$$\eta_t \sim Gamma \quad (4)$$

This makes it possible to model the instability of external factors' influence, such as sudden crises or conflicts.

Advantages of such a model:

- dynamism: reflects the change of factors over time;
- stochasticity: accounts for random disturbances and risks;
- spatial-temporal flexibility: parameters can be adapted to the specifics of the region;
- forecasting: scenario-based simulations can be conducted (e.g., rising unemployment, increasing climate threats, etc.)

The model can be refined by introducing an integral indicator that incorporates weight coefficients dynamically changing over time or across territorial levels:

$$\mathrm{M_t} = \int_{\tau}^{t}[\alpha(\tau)P(\tau) + \beta(\tau)R(\tau) + \gamma(\tau)S(\tau)d\tau + \varepsilon(t)] \qquad [4]$$

This approach accounts for the temporal dynamics of factor influence and allows for modeling the cumulative effect of migration-related threats.

To evaluate the risk R_i, a fuzzy assessment formula can be applied:

$$R_i = \sum_{j=1}^{n} \mu_j(x_j)\omega_j \qquad (5)$$

where $\mu_j(x_j)$ — is the membership function for the j-th criterion, and, ω_j — is the weight coefficient determined using the fuzzy analytic hierarchy process.

5.1. Extended Hybrid Model for Dynamic Assessment of Migration Pressure

To enhance the adaptability and accuracy of the decision support system, a hybrid model is proposed that integrates fuzzy cognitive modeling methods with spatial analysis in a GIS environment [9]. The structure of the model is presented in Figure 2.

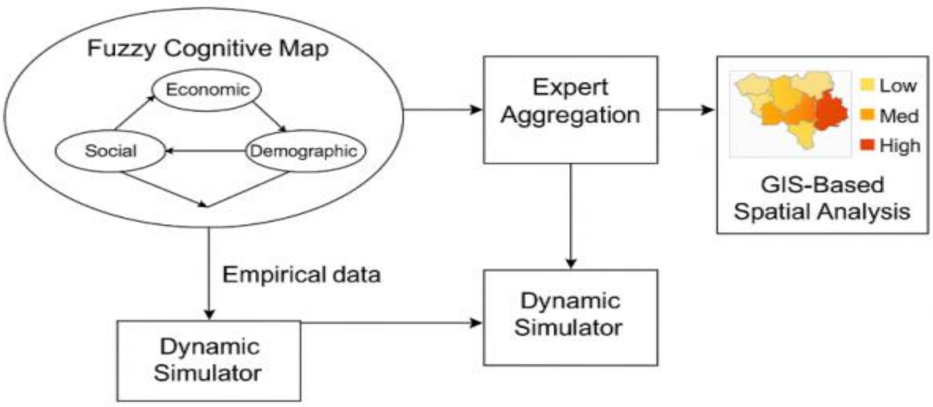

Figure 2: Extended hybrid model for dynamik assessment of migration pressure

The key components of the proposed model are interconnected modules that ensure a comprehensive consideration of both qualitative and quantitative characteristics of migration processes [8]. The central element is a fuzzy cognitive map (FCM), which is a directed graph where nodes represent major influencing factors-economic, social, demographic, and environmental. The connections between nodes (edges) reflect the strength and direction of mutual influence, with the weights expressed as triangular fuzzy numbers, allowing the formalization of subjective and vague expert perceptions regarding the interrelations among the factors.

To generalize and convert expert judgments into numerical weights, an aggregation block is employed, implemented using a modified analytic hierarchy process (AHP) with fuzzy linguistic scales. This approach accommodates the variability in expert opinions and ensures robust results even in conditions of limited input data [9].

Spatial integration of results is performed using a GIS-based spatial analysis module. This component not only visualizes the intensity of migration pressure through thematic maps but also enables spatiotemporal analysis that considers the geographic features of specific territories.

The final component is a dynamic simulator, which updates the values of input parameters over time. It is based on finite difference schemes and utilizes real statistical data, allowing the model to adapt to changes in the external environment and to account for the temporal evolution of risks. In this way, the model provides a holistic approach to forecasting and assessing demographic mobility levels across various regions [12-14].

5.2. Formalisation

Let C_i — denote the migration pressure intensity on the i-th region, w_j — the weight of the j-th factor, and x_j^t — its value at time t. Then, the integral assessment of pressure is defined as:

$$C_i^t = \sum_{j=1}^{n} w_j \cdot \mu_j(x_j^t) \cdot S_{ij} \tag{6}$$

where $\mu_j(x_j^t)$ — is the membership function for factor j at time t, and S_{ij} — is a spatial coefficient reflecting the geographical influence on region i.

5.3. Visualization

Based on the constructed fuzzy cognitive map (FCM) and the aggregated results, an interactive risk map is generated using color-coded levels of migration pressure. The model enables scenario analysis, allowing for the prediction of the effects of political or natural changes on migration levels

6. Results and Discussion

The impact of implementing the IDSS on the quality of decision-making regarding the regulation of migration pressure was evaluated.

The analysis tools included: prediction accuracy (Precision), reduction in decision-making time, the number of incorrect decisions (False Positives / False Negatives), and the degree of alignment between decisions and real-world scenarios (Recall).

6.1. Analysis of Results

A 67% reduction in decision-making time indicates the system's high responsiveness and ability to deliver timely recommendations under uncertain conditions.

A 21% increase in forecast accuracy highlights a significant enhancement in the precision of risk evaluation models, making policy planning more reliable.

The nearly fourfold decrease in the number of false decisions underscores the effectiveness of integrating fuzzy logic with multicriteria decision-making approaches.

The 27% improvement in policy alignment with real scenarios reflects the increased adaptability of policy decisions to dynamic external environments.

Table 1
Comparison of Decision-Making Parameters Before and After IDSS Implementation

Performance Indicator	Before IDSS Implementation	After IDSS Implementation	Change (%)
Average decision-making time	36 hours	12 hours	−67% (three times faster)
Forecasting accuracy	67%	88%	+21%
Rate of erroneous decisions (false positives/ negatives)	22%	6%	−16% (3.6 times lower)
Policy alignment with real-world scenarios	58%	85%	+27%

A dynamic model for assessing migration pressure, based on fuzzy logic and GIS technologies, has been proposed. The model is capable of adapting to environmental changes, supporting long-term strategic planning and real-time policy adjustments

7. Conclusions

The implementation of an intelligent decision support system (IDSS) in the field of comprehensive measures for managing demographic mobility enables effective control of flows under conditions of risk and uncertainty.

The results demonstrate the feasibility of using IDSS for regional analysis and forecasting of migration flows. The system improves accuracy, reduces decision-making time, and lowers risks when making political decisions in the migration domain.

Future research will focus on developing integrated platforms with machine learning capabilities to detect anomalies in real time. These directions align with the broader vision of building smart sustainable cities, where demographic mobility is managed in an integrated, adaptive manner [15].

Special attention has been paid to the user interface: it includes the ability to configure data granularity, scenario modeling, and integration with external management systems. Thus, the IDSS serves not only as an analytical tool but also as a strategic planning instrument.

The IDSS architecture is designed with modularity and scalability in mind, allowing for adaptation to various regional conditions. For example, the availability of local databases or specific data sources permits the replacement of individual components without compromising the overall logic of the system.

The use of GIS technologies in combination with mathematical methods enables visualization and spatial modeling of migration processes.

Declaration on Generative AI

During the preparation of this work, the authors used OpenAI ChatGPT (GPT-5.1) in order to: improve the clarity of explanations; perform grammar and spelling checks; generate alternative phrasings for some sentences; assist in structuring descriptions of models and system architecture based on the authors original content from the manuscript .

Further, the authors used DALL·E / OpenAI Image tools for conceptual drafts of Figures (not included in the final version of this manuscript).

After using these tools, the authors carefully reviewed, validated, and edited all generated content. The authors take full responsibility for the accuracy, correctness, originality, and integrity of the final publication.

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