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Serny Klaus * [1,2]
1. Venezuelan Institute of Scientific Research
11, Carr. Panamericana, Caracas, 1204, Venezuela

2. Experimental National University of Transportation
8, Carr. Panamericana, Caracas, 1204, Venezuela

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JUSTIFICATION OF ARCHITECTURE FOR INTELLIGENT AGNOSTIC MULTIMODAL TRANSPORTATION

Summary. *Urban population growth is estimated to exceed 50 % by 2050 in today's urban spaces. Therefore, the mobility patterns of people and objects become a fundamental element for planning, control, and decision-making in multimodal transportation. The use of an agnostic system that allows us to obtain the best combination of technologies and cognitive predictive inference models covering all areas of transportation (road, maritime, and air) without programming language limitations, supported by probability distribution functions on the entropic maximization theory of complex stochastic systems as the core model that could be incorporated into a machine learning logical architecture. It allows for selecting the most efficient, harmonious, and sustainable transportation trajectory. The methodology employed is exploratory-descriptive and theoretical, based on experiences implemented in other countries, and the incorporation from the coupling of Shannon theory with Gamma distribution functions in multivariate stochastic systems for the transportation sector as an innovative contribution of this work. A representative model of an intelligent agnostic logical architecture is presented, where the integration of the multivariate system is shown, nourishing the argument in the justification of the use, and could be taken as a proposal to be developed and implemented to reduce road congestion, reduce environmental pollution, and provide a sustainable alternative. The challenge is the understanding of this intelligent agnostic system by legislators in the transport area for the implementation of "IoT" devices in each transport unit and routes for connectivity to a "brain" that receives information from other areas of transport and walkers from their devices with high-speed technology in data navigation.*

Key words: *multimodal transportation, intelligent architecture, agnostic system, entropic maximization, Gamma function.*

1. INTRODUCTION

Developing countries have the opportunity to generate significant and relevant structural changes that will improve the quality of life and well-being of their populations and generate new, more efficient exchange systems that strengthen their local economies. It has been estimated that by 2050, the urban population will grow by more than 55 %. For cities [1], understanding urban mobility patterns is fundamental for effective and efficient decision-making to achieve sustainable cities [2].

Considering that people and products are moved using some type of transportation service, whether massive or not, within a given location, intra- and extra-urban transportation flows should be predictable and optimizable by establishing smart transportation through a multimodal transportation model, improving logistics efficiency by integrating different modes of transportation, reducing operational costs by optimizing routes and minimizing cargo handling, as well as promoting sustainable development by reducing traffic congestion and pollutant emissions (CO_2, NO_x, SO_x). Transportation is responsible for

** Corresponding author. E-mail: kserny@gmail.com*

more than 1/5 of global anthropogenic carbon and greenhouse gas emissions [3–5]. Scientists and government policymakers have focused on goals to reduce these emissions by between 50 % and 80 % in the coming years. Smart transportation based on efficient transportation use, parking, safety, comfort, convenience, environmental emissions, public regulations, costs, and time has focused on considering the implementation of deep neural networks [6, 7], integrating technological advances that enhance road safety, reduce road congestion, improve personal mobility, reduce environmental pollution, use energy more efficiently, satisfy end-user travel time, and represent a sustainable alternative for all [4, 8].

Transportation planning for decision-making should be supported by two fundamental pillars: prediction based on prior data knowledge, where inferential statistical models play an important role, and optimization as a key tool for finding an optimal solution from a mathematical model, abstracting a real-life problem by providing minimum and maximum bounds for an objective function to satisfy a set of conditions [9].

These cognitive predictive inference models are complex because they handle many variables in different conditions with a large or limited amount of data, achieving a robust model that can absorb variations and discrepancies in the system under study within an architecture defined as efficient modality agnostic [10–14].

2. STATEMENT OF THE PROBLEM AND RELEVANCE OF THE STUDY

Population growth in urban areas is imminent, and with multiple options for routes and transportation, intelligent planning for multimodal transportation is relevant and necessary for a sustainable system.

The objective of this work is to present a theoretical perspective that justifies the use of agnostic architecture for developing efficient, harmonious, and sustainable multimodal transportation. It reduces congestion and transit time while minimizing atmospheric emissions through the use of density distribution models supported by the entropy maximization theory of complex stochastic systems, covering all areas of transportation, as the smart agnostic systems developed in the last decade have focused on road transportation with computational applications coded in a programming language. This work seeks to justify the importance of generating an agnostic system that integrates the road, maritime, and air transportation sectors without programming language limitations.

This work is based on an exploratory, descriptive, and theoretical methodology. It allows for a deep dive and critical analysis of existing information on intelligent multimodal transportation. It focuses on bibliographical review, selection, analysis, and interpretation of existing documentation to build a robust conceptual framework that contributes to a theoretical perspective for using an agnostic intelligent multimodal transportation system with an unconventional comprehensive predictive model.

3. ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

Based on the variables aforementioned for multimodal transportation, it is presented as a multivariant stochastic system which must be continuous, positive, flexible in its asymmetric form with systemic mobility, and easy to estimate in the involved parameters [15]. One of the functions that fits these requirements is the probability distribution function [15–17] for which the Gamma-type function could be an adequate option to model the variables in a multimodal agnostic system in the transportation sector [2, 15, 18–24] and where there is an extensive explanation of its definition and mathematical development in the literature.

One of the focal points in the inference model development for multimodal transportation applications is to minimize traffic congestion, resulting in fewer emissions and shorter transit times. Two levels of application are proposed to achieve this goal [4]. The first level, categorized as high, is suggested for the development of state policies with direct responsibility for legislators. The second level, categorized as low, focuses on adaptation and planning to address traffic flow on various routes (intra-urban and extra-urban) and in locations such as rural, industrial, residential, commercial, agricultural, and other [28], where determining the energy balance in a stochastic multivariate system is essential. Therefore, the incorporation of the entropic maximization model is truly relevant from the thermodynamic conceptualization of this system under study.

The entropic maximization model, since its theorization by [29], has been used to predict situations with a high probability of occurrence under a scenario of high uncertainty. Its mathematical model is presented in equation (1):

$$H(x_i) = -\sum_{i=1}^{n} p_i \ln(p_i) / \ln(n), \tag{1}$$

where n is the study population; p – the probability of occurrence on the study variable x.

If each variable involved in the transportation system is represented by its density function, then the equation (1) could be rewritten as:

$$H(f(x,\alpha,\beta) = -\sum_{i=1}^{n} p_i \ln(p_i) / \ln(n), \tag{2}$$

where α and β are parameters of the Gamma function distribution.

This model will be adjusted, depending on its variability, for non-linear regressions by [22] and linear regression by [30, 31].

The mathematical model of predictive inference in this work focuses on a robust model that attempts to capture data uncertainty. Therefore, to improve the model of effectiveness, precision, and accuracy, a multidimensional stochastic optimization was made by incorporating decision vectors into a more comprehensive continuous uniform probability distribution model [32–34], integrating with the entropic maximization of the density distribution function of each variable of the system as presented in equation (3).

$$\mathrm{P}[\sum_{ij}\sum_{k=1}^{n} C_{ij} H(f(x_k,\alpha,\beta)) < C_{obj}] \le s, \tag{3}$$

where C_{ij} is the decision-making vector, C_{obj} is the objective vector, s the level of significance or risk (0.05 as the accepted normal value), subscript i is for the points of origin and j is for the destination points.

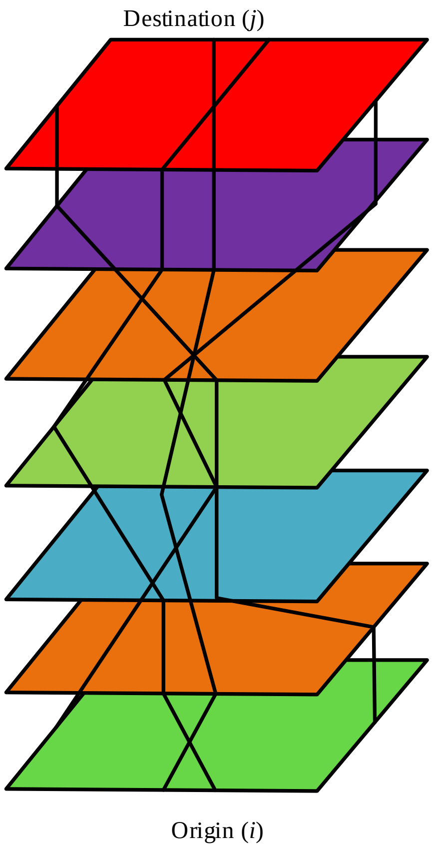
In this way, the behavior and interaction of the variables are intended to be evaluated, seeking the minimum energy of the system to predict the most probable events that satisfy the requirements of sustainable multimodal transportation.

Considering that a multimodal system represents a multivariate stochastic system, it is necessary to construct an architecture that represents the logical flow of information to be processed and analyzed to generate feasible options for decision-making. The following section provides a theoretical perspective for this architecture.

4. ARCHITECTURE OF AN AGNOSTIC MULTIMODAL SYSTEM

The diversity of routes and locations plays a fundamental role, the connections between each event and space must be considered as a multi-layered model [14, 35] that can orchestrate and harmonize all the variables involved to truly meet all requirements (road safety, route decongestion, improved mobility of people or goods, reduction of environmental pollution, more efficient use of energy, reduced travel time, and a sustainable alternative for all) from the point of origin (i) to the point of destination (j) using any mode of transportation and a combination of available IT technological advances. This last aspect underlies the agnosticism of the work, which will allow for general and specific interpretations of the “black box” models, providing inferences about the system's behavior and supporting decision-making [12].

A scheme of this interconnection is presented in Fig. 1. There, each layer, identified by a color, represents a location with multiple route and means of transportation options (walking, manual or electric bicycle, gasoline or electric motorcycle, gasoline, gas, diesel, electric, or hydroelectric vehicle, electric rail or mineral fuel, river, lake, or sea vessels, airplanes, among others) to be selected to cover mobility from an origin to a destination, ensuring less congestion, lower atmospheric emissions, greater traffic safety, and shorter travel time.



Variables:

- Multiple modes of transportation
- Costs
- Safety
- Time
- Health
- Congestion
- Regulations
- Routes
- Emissions
- Mode of transportation
- Weather conditions

Core model:

$$P[\sum_{ij}\sum_{k=1}^{n} C_{ij} H(f(x_k,\alpha,\beta)) < C_{obj}] \le s$$

Artificial Intelligence Algorithms:

- Supervised
- Unsupervised
- Reinforcement

Fig. 1. Interconnection scheme for multimodal transportation

To achieve the connections in each layer with all the variables involved, the coupling between the layers to transit from point (*i*) to point (*j*) and establish an effective intelligent agnostic system within a logical architecture that considers the mathematical model presented in equation (3) as core model, and algorithms already used in artificial intelligence, such as supervised, unsupervised, and reinforcement, where translation modules are available for the data input and output interfaces to handle any computing technology available within the system under study.

A logical architecture for intelligent, agnostic multimodal transportation is presented schematically in Fig. 2, providing a visual understanding of its connections and interconnections. The description of each layer of the architecture is given below:

- Layer 1 – Data Collection: collects real-world information from multiple sources, such as:
  - Infrastructure sensors (safety and traffic cameras, air quality sensors).
  - Connected vehicles (GPS data, telemetry, vehicle status, and behavior).
  - Walkers (GPS data from mobile phones).
  - Others (weather information, special events, traffic news, public transportation schedules).
- Layer 2 – Processing and Analysis: information from Layer 1 is transformed into useful data. It uses big data techniques (real-time data ingestion and processing), machine learning using the proposed predictive mathematical model in equation 3 (predicting traffic patterns, transportation demand, congestion, delays, and transportation availability), and artificial intelligence (managing special events in real time, such as road closures, incidents, and accidents). It generates a virtual “Digital Twin”-type representation of the transportation network, simulating the system’s behavior in real time, allowing for testing possible scenarios and optimizing operations according to the indicated objective vectors.
- Layer 3 – Business Logic and Optimization: this is the “brain” of the system, where decisions are made and actions are executed. It uses the information processed from Layer 2 to coordinate

and optimize transportation from routing, fleets, fares, and payments to present optimal transportation management planning and multimodal payment to the end user's satisfaction and in line with the concept of sustainability.

– Layer 4 – Interface and Services: this layer interacts directly with the end user, operators, and system administrators through mobile applications, dashboards, and other tools, control, and information systems at stations, such as real-time interactive screens at stops that display schedules, delays, transportation alternatives, routes, among others.

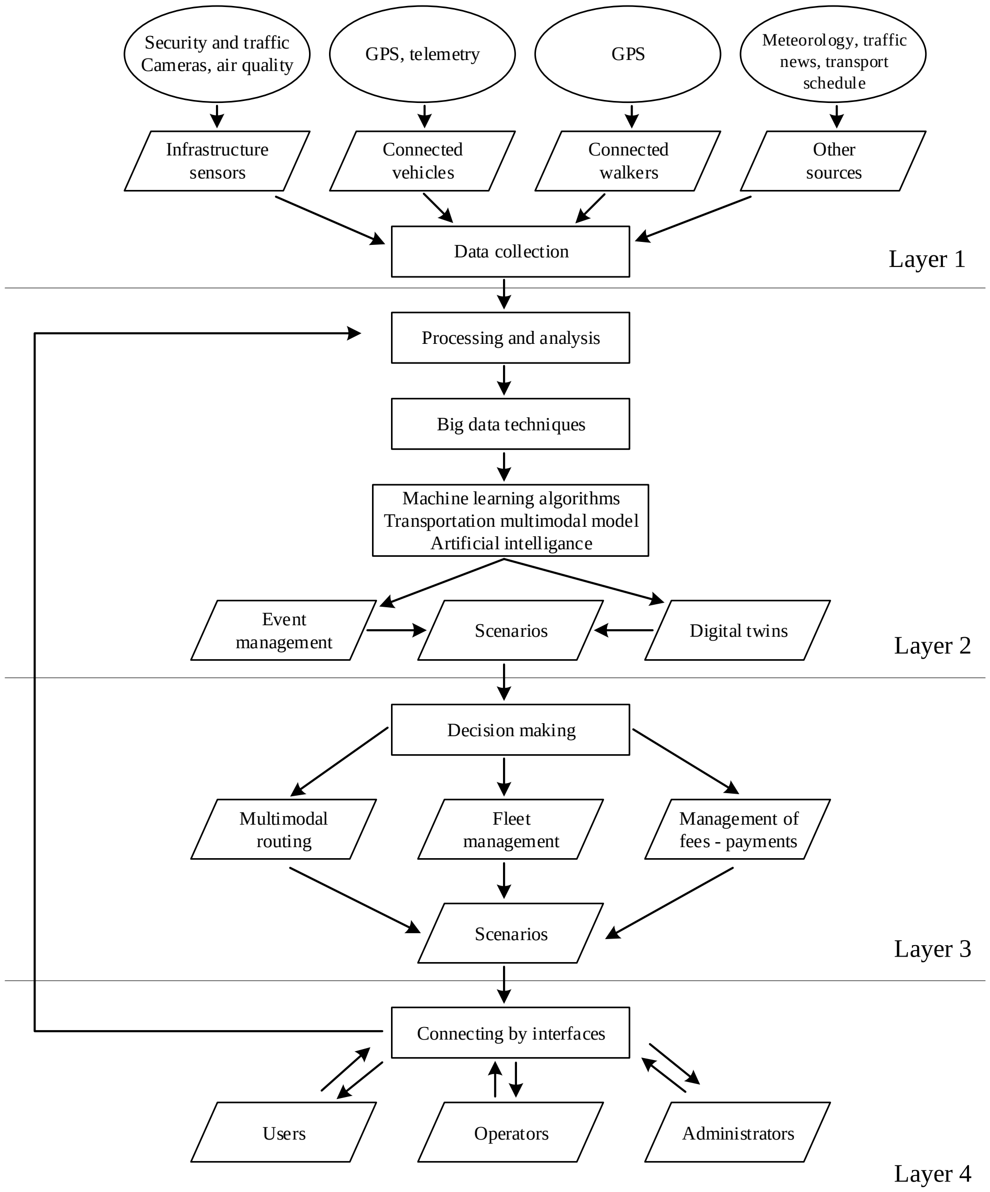


Fig. 2. Logical architecture for multi-layered multimodal transportation with intelligent systems

The application of this agnostic and intelligent logical architecture for a multimodal transportation system has its challenge in the understanding of sustainable multimodal transportation in decision makers and legislators in the transport area for the implementation of "IoT" devices (Internet of things) in each transport unit (bicycles, motorcycles, cars, buses, among others), as well as on the routes, presenting itself as a possible, and feasible alternative for connectivity to a "brain" that receives information from other areas of transport (maritime, rail, air), and walkers from their devices in the company of the use of high-speed technology in data navigation.

In this way, real-time information could be available to feed the logic of the architecture that, under agnostic programming in communication interfaces, allows the development of the most appropriate alternative in a given situation.

5. CONCLUSIONS AND PERSPECTIVES FOR FURTHER RESEARCH

This work presented a robust predictive mathematical model to optimize the decision-making on a multidimensional stochastic system, as it is the multimodal transportation, incorporating probability density distribution, integrating within the entropic maximization function.

A justification on the use of logical architecture for an intelligent agnostic system is presented and could be used within machine learning algorithms with the core mathematical model proposed in this work that harmonizes and orchestrates with the objective decision-vectors the most appropriate decision-making in the selection of routes and fleets that allow safety, decongestion, reduction of environmental emissions, more efficient use of energy and a transit time that satisfies the end-user in accordance with the cost associated with the selected transportation service.

The use of an agnostic system that allows us to obtain the best combination of technologies and cognitive predictive inference models supported by the entropic maximization theory of stochastic systems within of machine learning logical architecture, allowing an interactive artificial intelligence to more closely understand the end-user needs in advance in sustainable transportation systems.

For future research, alliances with government and private entities are planned to create a big database and generate a functional test within a selected locality.

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References

1. Dobbs, R., Smit, S., Remes, J., Manyika, J., Roxburgh, C., & Restrepo, A. (2011). Urban world: Mapping the economic power of cities. Retrieved from: https://www.mckinsey.com/featured-insights/urbanization/urban-world-mapping-the-economic-power-of-cities (in English).

2. Ma, Z., & Zhang, P. (2022). Individual mobility prediction review: Data, problem, method and application. *Multimodal transportation, 1*(1), 100002. DOI: 10.1016/j.multra.2022.100002 (in English).

3. Sharma, B. K. Zero Carbon Emission must be achieved at the Earliest for Sustained Growth of Our Planet Earth. *IRASS Journal of Multidisciplinary Studies, 2*(2), 8–16. Retrieved from: https://irasspublisher.com/assets/articles/1739430244.pdf (in English).

4. Sharma, S., & Mishra, S. (2013). Intelligent transportation systems-enabled optimal emission pricing models for reducing carbon footprints in a bimodal network. *Journal of Intelligent Transportation Systems*, *17*(1), 54–64. DOI: 10.1080/15472450.2012.708618 (in English).

5. Arya, A., Bachheti, A., Bachheti, R. K., Singh, M., & Chandel, A. K. (2024). Role of artificial intelligence in minimizing carbon footprint: A systematic review of recent insights. *Biorefinery and Industry 4.0: Empowering Sustainability*, 365–386. DOI: 10.1007/978-3-031-51601-6_14 (in English).

6. Qin, X., Ke, J., Wang, X., Tang, Y., & Yang, H. (2022). Demand management for smart transportation: A review. *Multimodal Transportation*, *1*(4), 100038. DOI: 10.1016/j.multra.2022.100038 (in English).

7. Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. *Sustainability*, *11*(1), 189. DOI: 10.3390/su11010189 (in English).

8. Barth, M. J., Wu, G., & Boriboonsomsin, K. (2015). Intelligent transportation systems and greenhouse gas reductions. *Current Sustainable/Renewable Energy Reports*, *2*(3), 90–97. DOI: 10.1007/s40518-015-0032-y (in English).

9. Yan, R., & Wang, S. (2022). Integrating prediction with optimization: Models and applications in transportation management. *Multimodal Transportation*, *1*(3), 100018. DOI: 10.1016/j.multra.2022.10001 (in English).

10. Sung, Y. L., Li, L., Lin, K., Gan, Z., Bansal, M., & Wang, L. (2023). An empirical study of multimodal model merging. Retrieved from: https://doi.org/10.48550/arXiv.2304.14933 (in English).

11. Regenwetter, L., Abu Obaideh, Y., & Ahmed, F. (2023). Counterfactuals for design: A model-agnostic method for design recommendations. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. Retrieved from: https://doi.org/10.1115/DETC2023-117216 (in English).

12. Singh, J., & Anand, A. (2019). Exs: Explainable search using local model agnostic interpretability. In *Proceedings of the twelfth ACM international conference on web search and data mining* (pp. 770–773). DOI: 10.1145/3289600.3290620 (in English).

13. Salazar-Cabrera, R., de la Cruz, Á. P., & Molina, J. M. M. (2020). Sustainable transit vehicle tracking service, using intelligent transportation system services and emerging communication technologies: A review. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(6), 729–747. DOI: 10.1016/j.jtte.2020.07.003 (in English).

14. Lopane, F., Kamargianni, M., Yfantis, L., Chaniotakis, E., Pappelis, D., Fermi, F., ... & Magoutas, B. (2021). Harmony Model Suite: an integratedspatial and multimodal transport planning tool to lead a sustainable transition to a new mobility era. In *ETC Conference Papers 2020* (2020). Association For European Transport. Retrieved from: https://discovery.ucl.ac.uk/id/eprint/10126358/1/ETC2020_HARMONY-paper.pdf (in English).

15. Lin, Z., Dong, J., Liu, C., & Greene, D. (2012). Estimation of energy use by plug-in hybrid electric vehicles: Validating gamma distribution for representing random daily driving distance. *Transportation Research Record*, *2287*(1), 37–43. DOI: 10.3141/2287-05 (in English).

16. Tokey, A. I., Shioma, S. A., & Jamal, S. (2022). Analysis of spatiotemporal dynamics of e-scooter usage in Minneapolis: Effects of the built and social environment. *Multimodal Transportation*, *1*(4), 100037. DOI: 10.1016/j.multra.2022.100037 (in English).

17. Yoo, S. L., Jeong, J. Y., & Yim, J. B. (2015). Estimating suitable probability distribution function for multimodal traffic distribution function. *Journal of the Korean Society of Marine Environment and Safety*, *21*(3), 253–258. DOI: 10.7837/kosomes.2015.21.3.253 (in English).

18. Casas, S., Gulino, C., Suo, S., & Urtasun, R. (2020, October). The importance of prior knowledge in precise multimodal prediction. In *2020 IEEE/RSJ international conference on intelligent robots and systems (IROS)* (pp. 2295–2302). DOI: 10.1109/iros45743.2020.9341199 (in English).

19. Jabari, S. E., Freris, N. M., & Dilip, D. M. (2020). Sparse travel time estimation from streaming data. *Transportation Science*, *54*(1), 1–20. DOI: 10.1287/trsc.2019.0920 (in English).

20. Guessous, Y., Aron, M., Bhouri, N., & Cohen, S. (2014). Estimating travel time distribution under different traffic conditions. *Transportation Research Procedia*, *3*, 339–348. DOI: 10.1016/j.trpro.2014.10.014 (in English).

21. Gupta, S., Garg, H., & Chaudhary, S. (2020). Parameter estimation and optimization of multi-objective capacitated stochastic transportation problem for gamma distribution. *Complex & Intelligent Systems*, *6*(3), 651–667. DOI: 10.1007/s40747-020-00156-1 (in English).

22. Wu, N., & Geistefeldt, J. (2014). Standard deviation of travel time in a freeway network--A mathematical quantifying tool for reliability analysis. In *CICTP 2014: Safe, Smart, and Sustainable Multimodal Transportation Systems* (pp. 3292–3303). DOI: 10.1061/9780784413623.316 (in English).

23. Zhang, Y., Cheng, X., & Reeves, G. (2021, March). Convergence of Gaussian-smoothed optimal transport distance with sub-gamma distributions and dependent samples. In *International Conference on Artificial Intelligence and Statistics* (pp. 2422–2430) (in English).

24. Ma, Z., Ferreira, L., Mesbah, M., & Zhu, S. (2016). Modeling distributions of travel time variability for bus operations. *Journal of Advanced Transportation*, *50*(1), 6–24. DOI: 10.1002/atr.1314 (in English).

25. Arroyo, I., Bravo, L. C., Llinás, H., & Muñoz, F. L. (2014). Distribuciones Poisson y Gamma: Una discreta y continua relación. *Prospectiva*, *12*(1), 99–107. DOI: 10.15665/rp.v12i1.156 (in English).

26. Gavilán Gonzales, M., & Gonzales Bohorquez, M. (2017). The Gamma Function: basic properties and some applications. *Selecciones Matemáticas*, 4(2), 177–191. DOI: 10.17268/sel.mat.2017.02.05 (in English).

27. Rivaud, J. J. (2004). La Función Gama. *Miscelánea Matemática*, *39*, 61–84 (in English).

28. Tasic, I., Porter, R. J., & Brewer, S. (2016). Applications of generalized additive and Bayesian hierarchical models for areal safety analysis: case study of an urban multimodal transportation system in Chicago, Illinois. *Transportation research record*, *2601*(1), 99–109. DOI: 10.3141/2601-12 (in English).

29. Shanon, C. (1948). A mathematical theory of communication. *The Bell systems technical journal, 27,* Retrieved from: https://people.math.harvard.edu/~ctm/home/text/others/shannon/entropy/entropy.pdf (in English).

30. Kieu, L. M., Bhaskar, A., & Chung, E. (2015). Public transport travel-time variability definitions and monitoring. *Journal of Transportation Engineering*, *141*(1), 04014068. DOI: 10.1061/(asce)te.1943-5436.0000724 (in English).

31. Kim, J., & Mahmassani, H. S. (2015). Compound Gamma representation for modeling travel time variability in a traffic network. *Transportation Research Part B: Methodological*, *80*, 40–63. DOI: 10.1016/j.trb.2015.06.011 (in English).

32. Arango-Serna, M. D., Serna-Urán, C. A., & Patiño-Rivera, B. E. (2017). Gestión de pedidos de medicamentos oncológicos usando programación estocástica. *Dyna*, *84*(201), 59–67. DOI: 10.15446/dyna.v84n201. 50467 (in Spanish).

33. Mo, B., Zhao, Z., Koutsopoulos, H. N., & Zhao, J. (2021). Individual mobility prediction: an interpretable activity-based hidden Markov approach. Retrieved from: http://arxiv.org/abs/2101.03996 (in English).

34. Jabari, S. E., & Liu, H. X. (2012). A stochastic model of traffic flow: Theoretical foundations. *Transportation Research Part B: Methodological*, *46*(1), 156–174. DOI: 10.1016/j.trb.2011.09.006 (in English).

35. Bellocchi, L., Latora, V., & Geroliminis, N. (2021). Dynamical efficiency for multimodal time-varying transportation networks. *Scientific reports*, *11*(1), 23065. DOI: 10.1038/s41598-021-02418-5 (in English).

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ОБҐРУНТУВАННЯ АРХІТЕКТУРИ ДЛЯ ІНТЕЛЕКТУАЛЬНОГО АГНОСТИЧНОГО МУЛЬТИМОДАЛЬНОГО ТРАНСПОРТУ

Анотація. *За оцінками, до 2050 р. приріст міського населення в сучасних міських просторах перевищить 50 %. Тому моделі переміщення людей і товарів стають фундаментальним елементом планування, контролю та прийняття рішень у мультимодальних перевезеннях. Використання агностичної системи, що дає змогу забезпечити найкраще поєднання технологій та когнітивних моделей прогнозування, які охоплюють усі сфери транспорту (автомобільного, морського та повітряного) без обмежень мови програмування, підкріплене функціями розподілу ймовірностей на основі теорії ентропійної максимізації складних стохастичних систем як основної моделі, яку можна ввести до логічної архітектури машинного навчання. Вона дає змогу вибрати найбільш ефективну, гармонійну та стійку траєкторію перевезення. Використана методологія є дослідницько-описовою та теоретичною, ґрунтується на досвіді, отриманому в інших країнах, та поєднанні теорії Шеннона з функціями гамма-розподілу в багатовимірних стохастичних системах для транспортного сектору, що є інноваційним внеском цієї роботи. Подано репрезентативну модель інтелектуальної агностичної логічної архітектури, із інтеграцією багатовимірної системи, що підкріплює аргументи на користь її використання. Її можна розглядати як пропозицію, що підлягає розробленню та впровадженню з метою зменшення заторів на дорогах, зниження рівня забруднення навколишнього середовища та забезпечення стійких альтернатив. Викликом є розуміння цієї інтелектуальної агностичної системи законодавцями у сфері транспорту для впровадження пристроїв "IoT" у кожній транспортній одиниці та маршрутах для підключення до "мозку", який отримує інформацію з інших галузей транспорту та від пішоходів із їхніх пристроїв за допомогою високошвидкісної технології навігації даних.*

Ключові слова: *мультимодальний транспорт, інтелектуальна архітектура, агностична система, ентропійна максимізація, гамма-функція.*