Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **70**, *1*, pp. 127–132, Bucarest, 2025

HISTORICAL VEHICLE TRACK VALIDATION IN AN ADAPTIVE ROUTE OPTIMIZATION SOLUTION

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Keywords: Route optimization; Machine-learning classification; Adaptive algorithm; Historical tracks.

This paper details the development of a robust solution for route optimization tailored for commercial vehicle fleets, with a particular emphasis on the specific requirements of small and medium-sized enterprises (SMEs). Our innovative platform integrates several components, including a data ingestion service for real-time GPS data, an integration layer for seamless connectivity with existing customer applications, a sophisticated route optimization engine, and user-friendly interfaces for both web and mobile platforms. A key distinguishing feature of our approach is the incorporation of machine learning (ML) techniques to validate historical route data. This process mitigates the impact of known road hazards, leading to an average reduction of 19.6 % in distance traveled and 14.2 % in route duration when comparing differences between planned and executed routes. Adjusting the optimal route necessitates reliable historical tracks, thus requiring the automatic validation of these tracks with minimal human intervention. In this paper, we describe the implementation of several machine-learning classification models over historical trips and compare the results to select the most suitable model.

1. INTRODUCTION

Routing optimization is critical in logistics and transportation, helping companies manage the challenges of cost efficiency, delivery time, and customer satisfaction. The Vehicle Routing Problem (VRP) is a central model for optimizing routes, aiming to solve constraints like vehicle capacity, time windows, and cost while dynamically adjusting to real-time traffic and delivery demands [1,2]. Traditional VRP solutions, using algorithms like Genetic Algorithms (GA) and Ant Colony Optimization (ACO), lay a strong foundation but face limitations in dynamic, real-time scenarios [3,4]. Recent advancements in adaptive and machine learning-based algorithms have demonstrated improvements in VRP, allowing for continual optimization and response to fluctuating conditions [5].

This paper proposes a machine-learning classification module for historical track validation to enhance VRP solutions. This module aims to determine route validity based on historical data and human-validated examples, using data-driven classification models to reduce manual route verifications. This approach could significantly streamline routing operations by automating route validation, thus enhancing the efficiency of adaptive routing algorithms that rely on historical data [6,7].

The study objective is to propose an advanced routing solution that merges standard VRP methodologies with adaptive algorithms and an ML-powered classification component to ensure the inclusion of high-quality historical routes. Additionally, usability testing will assess how well this comprehensive solution meets end-user needs.

The solution presented results from an extensive three-year international research and development project that the European Union founded through the Eureka Network program from 2020 to 2023. More information about the solution is available on the project website [8].

This paper is structured as follows: section 2 describes an overview of related work and background information, while section iii describes a high-level view of the solution's components. In section 4, we compare selected ML methods used to categorize the tracks. Section 5 presents the results and discusses them, and section vi concludes the paper with conclusions about the research work.

2. LITERATURE REVIEW

The VRP addresses various operational constraints to identify optimal vehicle routes, and traditional VRP solutions use metaheuristic algorithms to find feasible routes. However, modern applications often demand real-time adjustments, leading to the development of dynamic VRP algorithms, such as adaptive extensive neighborhood search (ALNS), which can modify the routes based on live data [9]. Incorporating machine learning into VRP frameworks allows solutions to "learn" from previous patterns and human input, making routing decisions that are both automated and contextually aware [6,10].

2.1 GATHERING USER REQUIREMENTS

User requirements are critical to designing efficient customer-oriented software solutions. Organizations can gather structured data on routing priorities for a route optimization solution by conducting quantitative surveys, such as minimizing costs or ensuring consistent delivery times. This data helps tailor routing solutions to operational needs, while surveys highlight user expectations for features like route adaptability and predictive accuracy [11].

2.2 ARCHITECTURE OF A ROUTE OPTIMIZATION SOLUTION

The architecture of a routing optimization system must support real-time data processing, modular scalability, and robust computing power. Often structured as a multi-layered or distributed system, routing solutions integrate real-time data, such as GPS and traffic updates, to optimize routes dynamically. Such an architecture allows continuous data integration across dispersed nodes and enables centralized control for complex routing decisions [12]. Distributed processing models, which split the problem into smaller, manageable tasks, are increasingly favored due to their scalability and adaptability, essential in urban logistics where route conditions change frequently [13,14].

2.3 TRADITIONAL VRP ALGORITHMS

Traditional VRP algorithms, including GA, ACO, and Simulated Annealing, are core methods for solving static

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DOI: 10.59277/RRST-EE.2025.1.22

VRPs. GA uses evolutionary principles to improve solutions by combining "parent" solutions, while ACO, inspired by ant foraging behavior, enhances routes based on historical paths [3]. Though effective for specific scenarios, these algorithms face challenges in dynamic VRP settings, where real-time decision-making and adaptability are essential [15].

2.4 ADAPTIVE ALGORITHMS BASED ON HISTORICAL TRACKS

Adaptive algorithms represent a significant advancement in VRP, allowing solutions to incorporate real-time adjustments based on live data and historical performance [16]. These algorithms can respond to dynamic factors such as traffic or weather, which is critical in urban logistics. For example, the adaptive extensive neighborhood search (ALNS) framework has been extended to handle real-time constraints, helping organizations optimize routes with fluctuating conditions by adjusting strategies according to ongoing evaluations [17]. Evolutionary and reinforcement learning techniques are also used to update route plans based on historical performance continuously and predicted traffic patterns, further improving efficiency in dynamic settings [18,19].

Recent adaptive methods leverage deep learning to enhance VRP solutions further. They employ neural networks to predict traffic patterns and optimize routes in response to these predictions [20]. Such advancements demonstrate significant promise, as they reduce computation times and increase solution robustness, making them suitable for complex, large-scale routing systems [21,22].

2.5 MACHINE LEARNING CLASSIFICATION

The machine-learning classification module is designed to automatically assess the validity of historical routes by comparing them to human-validated patterns, ensuring that only high-quality routes are incorporated into adaptive routing algorithms. Classification algorithms, such as support vector machines (SVM) and ensemble methods, are effective for analyzing historical data and distinguishing between valid and invalid tracks. For example, an optimized SVM model can reduce misclassifications and improve the selection accuracy of historical routes by analyzing relevant features and minimizing redundancy [23,24].

Recent studies demonstrate the efficacy of ML classification in handling imbalanced datasets standard in routing, where valid and invalid routes may not be equally represented [25]. This module can identify route validity patterns by leveraging historical data and employing methods like feature selection and clustering, supporting improved adaptive decision-making [26]. Reinforcement learning-based classifiers have also shown promise in optimizing routes based on learned behaviors from historical data, enhancing the overall adaptability of routing solutions [27].

2.6 USABILITY EVALUATION OF THE SOLUTION

Usability evaluation is essential to ensure that routing solutions are operationally effective and user-friendly. Usability assessments evaluate the interface's intuitiveness, ease of operation, and functionality. Feedback from these assessments allows designers to refine the system based on actual user needs, which may include features like real-time route modification, interactive visualizations, and error management [28]. Iterative usability testing ensures that the solution aligns with operational needs and supports efficient decision-making, increasing user satisfaction and solution reliability in the field [29].

Among the contributions made by our research, we can mention: a) an integrated solution for logistics companies that need to manage their vehicle fleets with software that can show a comparison between planned and executed routes, manages to minimize the difference between them by analyzing historical tracks and automatically learns to validate new trips; b) An adaptive algorithm that offers more realistic planned routes; c) getting user feedback in all the phases of the project: user requirements, testing of the optimization engine, and the usability of the final solution. To achieve higher scalability, techniques presented in [30] will be implemented in the future.

3. **METHODS – PROJECT IMPLEMENTATION**

The iRoute solution includes several technologies, from GPS data ingestion and processing to delivering status in real time and integrating with external customer solutions. All are presented in web and mobile user interfaces.

The iRoute solution engages four primary actors to support efficient data handling and route management. First, the GPS device collects data through a telematics system and sensors installed in vehicles, which then sends this information to iRoute's data acquisition endpoint. This endpoint processes the data, presenting it in maps and reports that help validate the route execution and assist in plan adjustments according to real-field conditions. Second, customer applications like ERP, WMS, and SFA systems communicate directly with iRoute through web services, facilitating automated data exchanges with minimal human intervention.

The solution includes mobile and web application users to manage route execution and oversight. As mobile app users, drivers access the planned routes, view the sequence of visits, and provide feedback on each delivery or collection. They can also address deviations, such as updating incorrect locations or selecting reasons for order rejections. As web app users, dispatchers manage the planning of imported customer resources and orders, adjust plans as needed, and track route execution. They also generate reports to analyze and improve planning outcomes.

3.1 USER REQUIREMENTS

Before developing the software solution, we performed a study to identify essential features and requirements, drawing from the constraints highlighted by potential users in the transportation industry [31]. A key challenge identified was the restricted number of stops the optimization algorithm could handle, posing issues for managing more intricate delivery routes. Additionally, many existing solutions limit dispatchers in assigning vehicles to optimized routes, particularly when configuring delivery time windows. The absence of tailored options often prevents companies from fully aligning the solution with their specific operational needs. In contrast, insufficient integration features with customer solutions complicate the generation of optimized routes in real time.

3.2 SOLUTION ARCHITECTURE

Our solution organizes data across three layers: the External Data Layer, the Application Core Layer, and the Presentation Layer. These layers interact with external data sources and users (Fig. 1).

The ***External Data Layer*** gathers and processes information from GPS and telematics sensors in vehicles, which is then transmitted to the central database. It supports remote configuration and provides real-time insights through bidirectional data connections, facilitating efficient planning and execution adjustments. This layer includes modules like Vehicle Data and Integration, which handle orders, resources, plan parameters, and route execution metrics.

In the ***Application Core Layer***, the central database, built on Microsoft SQL Server, is the foundation, storing data across categories like telematics, metadata, operations, and reporting. The Processing Services module cleans and transforms data for usability, while the User Profile module allows clients to set optimization preferences like time windows, vehicle types, and map settings. The Optimization Engine applies the VROOM algorithm, utilizing OpenStreetMap data, to create optimized routes that reduce costs and enhance efficiency. The data flow here supports custom configurations, adapting routes dynamically to meet clients' needs.

The ***Presentation Layer*** provides data access through both web and mobile applications. The web app includes essential features for administrators and dispatchers, such as authentication, system management, and report generation. The mobile app lets drivers view daily routes, track client locations, and provide feedback on field operations. This feedback loop enhances client-driver relationships and contributes to ongoing system improvements.

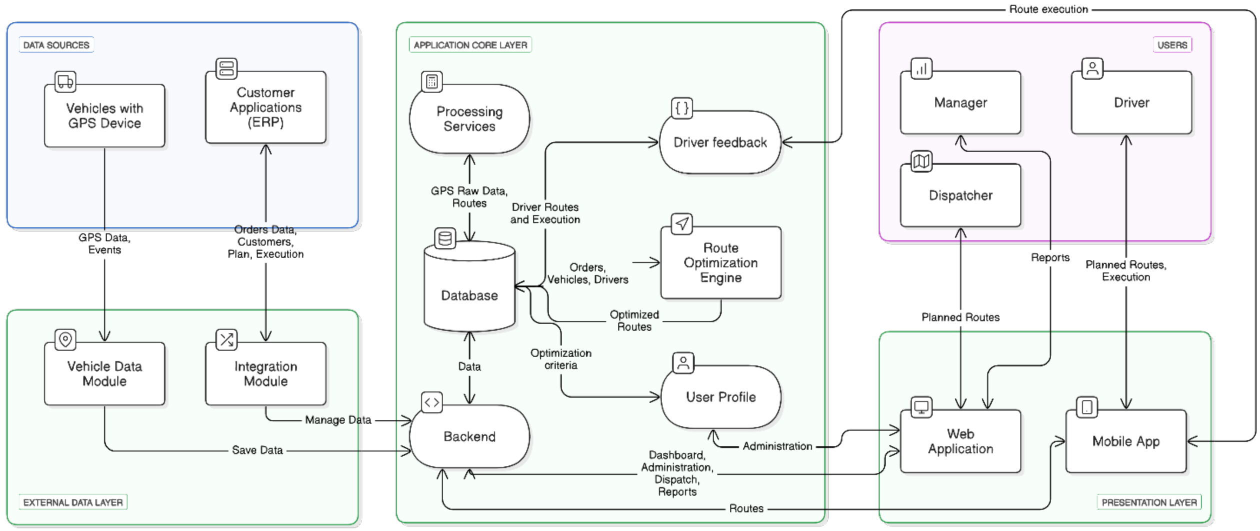

Fig. 1 – Solution's architecture.

Each module across these layers integrates seamlessly to optimize route planning, real-time monitoring, and dynamic adaptation, providing an effective and user-friendly tool for managing logistics and route execution.

3.3 ADAPTED ROUTE OPTIMIZATION ALGORITHM

In a previous article [28], we introduced a prototype for an adapting route optimization algorithm in the iRoute solution. The algorithm includes specific variables – user profile, customer locations, orders, driver and vehicle work schedules, delivery and route constraints, and planning parameters – that can contribute to even more effective optimization outcomes. By factoring in these elements, recurring road segments within routes can be reused to refine the optimal route offered by the algorithm.

The iRoute solution optimizes day-by-day operational routes by using real road conditions that drivers face on each delivery. For instance, when driving multiple times on a delivery route - each one with a different duration, distance, or road sequence used when comparing to the original optimal route - drivers are likely to favor alternative routes based on road familiarity, personal driving preferences (*e.g.*, choosing non-urban roads), or other practical conditions affecting the route's completion. When drivers must follow an overly theoretical route plan, they may struggle to follow it effectively, noting discrepancies due to unaccounted-for local factors like traffic, community characteristics, and road network peculiarities. This prompted us to leverage historical routes and incorporate driver insights, yielding a refined route that more closely aligns the plan with actual execution. This adaptation minimizes plan-execution differences while ensuring that all destinations on the route are covered. Dispatchers can also validate route execution or specific segments, ensuring drivers don't take extended paths without justification. Invalid historical segments are excluded from the final adapted route.

Route segment similarity was determined using the Curve Matching library. This approach involved normalizing each road sequence using Fréchet distance and Procrustes analysis between the polylines to compare route segments effectively, Fig. 2.

Fig. 2 – Fréchet distance (F.D.) for three tracks.

We've tested our algorithm on over 400 routes with fleets that involved more than 25 vehicles and obtained reduced duration and distance differences between what was planned and what was executed: an average of less than 19.6 % distance difference and less than 14.2 % duration difference [32].

3.4 AUTOMATIC VALIDATION OF HISTORICAL TRACKS WITH MACHINE LEARNING

The proposed adaptive algorithm depends on high-quality input data to achieve optimal results. An essential part of this process is validating historical route data, which can be particularly labor-intensive and time-consuming for dispatchers managing large fleets. This requirement has often led business owners and dispatchers to perceive our solution as potentially challenging to integrate into routine operations.

To address this concern and streamline validation, we incorporated a machine-learning classification approach to automate the validation of historical route data. For model development and evaluation, Python scripts were used to prepare and train several candidate models. The optimal model selection involved testing various classification algorithms to identify the best fit for the unique attributes of our dataset. Details of the model selection process and performance comparisons are outlined in Section IV. This automation improves data accuracy and enhances the feasibility of deploying the solution at a scale.

3.5 USABILITY EVALUATION

We assessed the usability of the iRoute solution using a methodology derived from the WAMMI testing approach, with modifications tailored for evaluating a web application designed for dispatchers and fleet managers. These users are the primary beneficiaries of such solutions, as their main objective is to effectively plan and optimize vehicle routes to minimize costs and enhance overall operational efficiency. It is crucial to ensure greater truck availability with minimal downtime, prioritizing this over minor savings in fuel consumption.

The usability questionnaire contained questions for user profiling, general feedback, usability feedback, and perceived efficiency feedback.

The evaluation was conducted over an extensive one-year period, with 112 respondents who completed the feedback form at the end of the test. The results were promising for the first version of the solution, with positive ratings for usability (3.79 out of 5) and perceived efficiency (3.67 out of 5), Fig. 3.

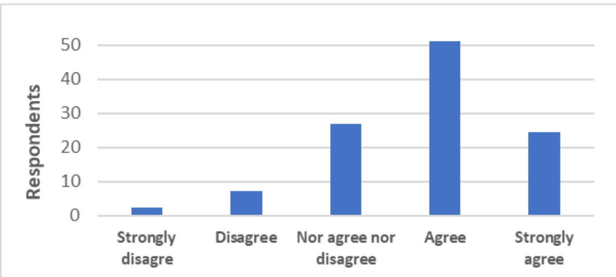

Fig. 3 – Average usability feedback.

4. COMPARING MACHINE LEARNING MODELS FOR VALIDATING TRACKS

As mentioned in section 3, we implemented several Machine Learning models to automatically classify historical tracks as valid or not valid.

First, we gathered a collection of historical tracks previously validated by manual feedback from some of our potential customers. The collection contained 65354 samples.

Before using the dataset, several operations were needed:

– Pre-process the data – summarizing nine different tables of data into a single table with all the useful information
– Eliminating irrelevant columns
– Converting data into a more ML-friendly format: Datetime converted in Timestamp, Percentage converted in Numeric.

After the pre-processing data, we had the following information for each track (Table 1).

Table 1

Dataset columns.

Column	Type	Description
TrackID	Integer	Unique code, identity of track
RouteID	Integer	The ID of a planned route (if any) that contained that track
Stationary	Bit	1 – the track is stationary; 0 – the track is a movement of the vehicle
EngineOn	Bit	1 – the track is for vehicle with engine on; 0 – the track is for vehicle with engine off
StartLatitude	Numeric (9,6)	The latitude of the start point
StartLongitude	Numeric (9,6)	The longitude of the start point
EndLatitude	Numeric (9,6)	The latitude of the stop point
EndLongitude	Numeric (9,6)	The longitude of the stop point
StartRecord	Timestamp	The timestamp for the start of the track
EndRecord	Timestamp	The timestamp of the end of the track
Distance	Integer	The distance of the track in meters
AvgDistance	Integer	The average truncated distance of similar tracks (same start, end)
Duration	Integer	The duration of the track in seconds
AvgDuration	Integer	The average truncated duration of similar tracks (same start, end)
SimilarTracks	Integer	Number of similar tracks (same start, end)
MaxSpeed	Integer	The maximum speed recorded on the track
AvgSpeed	Integer	The truncated average speed recorded on the track
MaxStopDuration	Integer	The truncated duration of the longest stop of the vehicle during the track
StationaryPoints	Integer	The number of GPS positions that were recorded as stationary during the track
TotalPoints	Integer	The total number of GPS positions recorded during the track
MaxSegment	Integer	The truncated length of the biggest segment (two consecutive GPS positions) that was recorded on the track
Valid	Bit	1 = track was valid; 0 = track was not valid – value used for training and testing

To evaluate the performance of the models, we split the dataset into training and testing subsets. This approach ensures the model is trained on most of the data sample while evaluating its performance on significant untrained data:

– 80 % of the samples were allocated for training.
– 20 % of the samples were allocated for testing.

We tested the following models:

– ***Support Vector Machine*** (***SVM***): a classifier that attempts to find a hyperplane separating valid and invalid routes. SVM is particularly effective in high-dimensional spaces and is well-suited for tasks where classes are separable.

– ***XGBoost***: Extreme Gradient Boosting, known for its ability to handle non-linear relationships, providing robust regularization to avoid overfitting, and it benefits from parallel processing, making it efficient for large datasets.[33]
– ***Random Forest***: An ensemble of decision trees that reduces overfitting and is particularly effective for handling large, complex datasets.[34]
– ***K-Nearest Neighbors (KNN)***: An instance-based learning model that works well for smaller datasets with localized clusters.
– ***Logistic Regression***: A linear model ideal for binary classification when the correspondence between input features and outcomes is linear.
– ***Decision Tree***: An intuitive model that splits data into decision nodes, making it interpretable and effective for more straightforward datasets with clear decision boundaries.

We used Python scripts to manage the models, separating preprocessing data from training and testing it, as seen in Fig. 4. The results of testing each model are detailed in section 5.

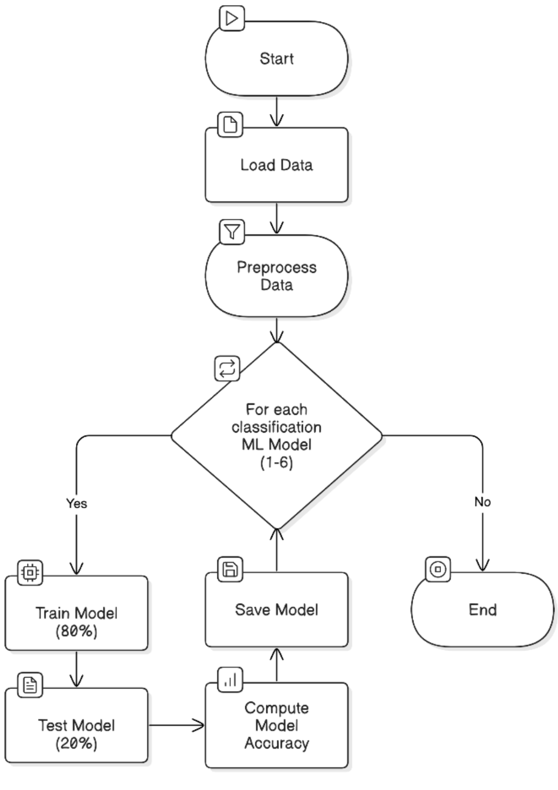

Fig. 4 – Training and testing ML models.

After training and testing the above models, we compare the accuracy and select the best one to use in production for real-time validation of tracks.

5. RESULTS OF ML TRAINING ON DIFFERENT MODELS AND DISCUSSIONS

To evaluate the performance of each classification model, accuracy was computed based on the predictions made on the test set. Table 2 summarizes each model accuracy, along with a brief description of when it is most suitable:

The **XGBoost** model emerged as the top performer, achieving an accuracy of **98.20 %,** making it the most suitable model for this dataset. Its capture of **complex, non-linear relationships** allowed it to outperform other models.

The **Random Forest** model performed with a similar accuracy of **98.17 %**, slightly trailing behind XGBoost. This suggests that ensemble methods like XGBoost and Random Forest are highly effective for this dataset.

Table 2

Machine Learning Classification Models Testing Results

Model	Accuracy (%)	Description and where to use
XGBoost	98.20	Ensemble learning method using boosting. Best for large, complex datasets with non-linear relationships.
SVM (Support Vector Machine)	76.09	Effective in high-dimensional spaces for classification tasks. Ideal for smaller datasets with distinct class boundaries.
Random Forest	98.17	Ensemble of decision trees, good for avoiding overfitting. Works well with large datasets and mixed feature types.
K-Nearest Neighbors (KNN)	88.77	Instance-based learning method. Suitable for datasets with locally clustered data, emphasizes interpretability.
Logistic Regression	77.78	Simple, linear model for binary classification. Best when the relationship between features and outcomes are linear.
Decision Tree	97.38	Intuitive model that splits data into branches. Good for simple datasets with clear decision boundaries.

The **Decision Tree** model also performed well, with an accuracy of **97.38 %**, indicating it can handle more straightforward datasets effectively, although it slightly underperformed compared to the ensemble models.

The **K-Nearest Neighbors (KNN)** model showed a reasonable accuracy of **88.77 %**, proving it helpful when the data has localized clusters or interpretable patterns.

Finally, models like **Logistic Regression** and **SVM** struggled to capture the complexity in the data, achieving an accuracy of **77.78 %**.

6. CONCLUSIONS

Small and medium-sized enterprises (SMEs) operating transportation fleets mainly focus on minimizing operational costs. However, they often encounter challenges when implementing existing algorithms to optimize vehicle routes. Many affordable routing solutions have significant limitations, including restrictions on the number of delivery locations and routes that can be planned simultaneously and a lack of integration with current customer applications, reducing their usability in real business scenarios.

In this article, we introduced a new, scalable solution featuring an optimized algorithm to generate more realistic route plans, resulting in route execution times that closely align with planned durations. Our tests revealed a reduction in route duration by 14.2 % and a decrease in average distance by 19.6 % when comparing planned with execution, demonstrating the effectiveness of our approach.

To improve the adoption of the iRoute solution, we developed and evaluated several machine learning (ML) models designed to automate the validation of historical tracks. The results from these tests were encouraging, demonstrating that the models achieved an accuracy rate exceeding 98 % in correctly validating the tracks.

The iRoute platform offers a complete software and hardware solution by equipping customers with an essential toolkit to increase their delivery or collection transportation business performance.

ACKNOWLEDGMENT

This scientific research project was funded by the Ministry of Education and Research of Romania, UEFISCDI agency, within the Eurostars Subprogram of Eureka Innovation Program - European Cooperation (project number PN-III-P3-3.5-EUK-2019-0210 contract number 191/2020).

CREDIT AUTHORSHIP CONTRIBUTION

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Nicolae Goga: conceptualization, supervision, validation, project administration.
Constantin Viorel Marian: formal analysis, corresponding author, writing - review & editing.
Dan Alexandru Mitrea: validating, writing – reviewing & editing.
Diana Scurtu: software, data curation, validation.

Received on 10 January 2025

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