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INFORMATION SYSTEM FOR ADAPTIVE TRANSPORTATION PLANNING WITH CONSIDERATION OF ROAD TRAFFIC VARIABILITY

This paper presents an information system for adaptive transportation planning that integrates the classical linear-programming transportation problem with a time-dependent cost model approximated by a combination of normal probability density functions. The proposed mathematical model implements discretization of the 24-hour interval into equidistant time steps, which enables correct accounting for diurnal variations in road conditions while preserving high computational efficiency. A unified operational algorithm was developed based on the classical Simplex method, and key methods for constructing an initial feasible plan for the transportation problem were implemented to allow comparative analysis of performance and accuracy in dynamic conditions.

The outcome of the study includes an intuitive web interface implemented with React, using react-vis for charting, Leaflet for interactive maps and OSRM for routing, together with a server module written in Go that employs the gonum/lp library for solving linear-programming problems. The proposed architecture provides fast interaction between client and server modules, high scalability and straightforward cross-platform deployment.

Experimental validation confirmed the correctness of the model both in cases with static cost coefficients and in the enhanced time-dependent transportation formulation. In particular, the system supports automated temporal analysis of solutions and identification of cost-optimal departure times. In the intercity scenario dynamic optimization yielded up to 7.2 % savings relative to the worst static scheduling alternative, while in the urban scenario accounting for time-dependent costs produced savings up to 47.8 % for evening departures compared to the typical morning peak — consistent with observed urban traffic patterns.

A comparative analysis with leading commercial transport management systems demonstrated that, despite its streamlined architecture, the proposed system delivers the required level of flexibility and adaptivity while markedly reducing implementation and maintenance costs. Consequently, it constitutes an accessible and transparent tool for educational institutions, research activities and local logistics projects in small and medium-sized enterprises.

Keywords: adaptive transportation planning, transportation problem, time-dependent cost, normal distribution, linear programming, interactive visualization, routing.

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ІНФОРМАЦІЙНА СИСТЕМА АДАПТИВНОГО ПЛАНУВАННЯ ПЕРЕВЕЗЕНЬ З УРАХУВАННЯМ ЗМІН ДОРОЖНЬОГО ТРАФІКУ

У роботі представлено інформаційну систему адаптивного планування перевезень, яка поєднує класичну транспортну задачу лінійного програмування з часозалежною моделлю витрат, апроксимованою комбінацією нормальних функцій розподілу. Запропонована математична модель передбачає дискретизацію добового інтервалу на рівні часові кроки, що дає змогу коректно враховувати коливання дорожніх умов упродовж доби за умови збереження високої обчислювальної ефективності. Розроблено єдиний алгоритм функціонування системи на основі класичного симплекс-методу та реалізовано ключові методи формування початкового опорного плану транспортної задачі для проведення порівняльного аналізу продуктивності та точності в динамічних умовах.

Результатом роботи стала розробка інтуїтивного веб-інтерфейсу на базі React із використанням компонентів react-vis для побудови графіків, Leaflet для інтерактивних карт та OSRM для маршрутизації, а також серверного модуля на Go з бібліотекою gonum/lp для розв'язання задач лінійного програмування. Запропонована архітектура забезпечує швидку взаємодію між клієнтською та серверною частинами, високу масштабованість і простоту розгортання на різних платформах.

Експериментальне тестування підтвердило коректність моделювання як у разі використання сталих коефіцієнтів витрат, так і в умовах динамічної транспортної задачі з часовою залежністю. Зокрема, система дозволяє автоматично проводити часовий аналіз розв'язків та визначати оптимальні години доби для виконання перевезень. У міжміському сценарії динамічна оптимізація забезпечила до 7,2 % економії порівняно з найгіршим статичним графіком перевезень, а в міському – до 47,8 % за вечірнього відправлення проти звичайного ранкового піка, що відповідає реальним даним міського трафіку.

Порівняльний аналіз із провідними комерційними системами керування транспортом продемонстрував, що запропонована система, попри спрощену архітектуру, забезпечує необхідний рівень гнучкості та адаптивності, водночас знижуючи витрати на впровадження та технічне обслуговування. Вона є доступним і наочним інструментом для навчальних закладів, наукових досліджень і локальних логістичних проєктів малого та середнього бізнесу.

Ключові слова: адаптивне планування перевезень, транспортна задача, часозалежна вартість, нормальний розподіл, лінійне програмування, інтерактивна візуалізація, маршрутизація.

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Introduction

Modern logistics systems are increasingly challenged by the instability of transportation costs caused by daily fluctuations in traffic intensity. Inefficient route planning leads to higher operating expenses, loss of time and resources, and a deterioration of environmental conditions due to additional carbon dioxide emissions. The classical transportation problem, formulated as a linear programming task, successfully operates with fixed cost coefficients but does not account for the temporal dynamics of road conditions. Existing commercial solutions are capable of modeling real-time traffic changes; however, they often require substantial investments in licensing, infrastructure, and qualified personnel, which limits their accessibility for small and medium-sized enterprises as well as educational and research institutions [1–4].

Recent studies indicate that daily traffic load profiles in large metropolitan areas typically exhibit a bimodal structure, characterized by morning and evening peaks. Approximating such profiles using combinations of normal distributions has proven to be sufficiently accurate and computationally straightforward [5, 6]. However, domestic research rarely combines the classical transportation model with detailed temporal analysis, and existing systems do not always provide transparency and flexibility in configuration for end users.

The aim of this study is to develop an information system for adaptive transportation planning that integrates the classical transportation problem with a time-dependent cost function accounting for the dynamics of road traffic. Additional system requirements include achieving high computational efficiency, supporting flexible parameterization of transportation scenarios, and implementing an intuitive web interface for user interaction.

The scientific novelty of the research lies in the improvement of the adaptive transportation planning model, which differs from existing approaches by employing a time-dependent cost function approximated by a combination of normal distribution functions. This enables the representation of real fluctuations in transport load throughout the day and increases the accuracy of generating optimal routes.

The practical significance of this work lies in the creation of an adaptive transportation planning information system that can be effectively applied under real urban conditions. The developed solution can be used in educational processes, research activities, and small to medium-sized enterprises to optimize logistics operations considering changes in road conditions.

Related Works

Recent research in the field of intelligent transportation planning increasingly focuses on modeling temporal uncertainty, traffic variability, and multi-criteria optimization approaches [7–12].

Specifically, [7] proposes a method for the simultaneous optimization of routing and pricing in same-day delivery scenarios, which takes into account the stochastic nature of travel time. The model demonstrates improvements in financial performance and a reduction in order rejection rates compared to traditional deterministic approaches. However, this approach does not integrate the classical transportation model with fixed supply and demand constraints, which limits its applicability for centralized freight flow management tasks.

The study in [8] develops a mixed-integer nonlinear transportation model considering CO_2 emissions and time-varying vehicle speeds. A hybrid adaptive genetic algorithm with an elite-oriented local search operator is proposed, showing advantages in avoiding local minima and achieving higher solution quality. Nevertheless, the implementation is research-oriented and lacks an interactive interface, restricting its use in practical business environments.

Research [9] targets multi-criteria optimization in refrigerated logistics systems. The authors propose a symmetry-based approach utilizing LNS-NSGA-III, which enables a balance among delivery cost, emission volume, and product freshness. The introduction of dynamic adjustment of congestion coefficients across regions enhances model stability. However, the absence of mechanisms for flexible real-time adjustment of time-dependent profiles limits the solution’s adaptability in dynamic environments.

In [10], a food delivery routing approach is proposed, which accounts for temporal variability of road network parameters by dividing the network into time-based subnetworks with variable speeds. The application of a genetic algorithm within each time layer results in a 39% reduction in total costs associated with order delays. However, the model does not consider uneven demand distribution throughout the day, which may reduce forecasting accuracy in cases of irregular loading.

Recent work [11] proposes a sustainability-oriented vehicle routing framework using time-dependent arc travel durations and a multi-stage heuristic (savings, modified tabu search, cycle-transforming optimization). Validated on benchmarks and a large e-commerce case, it reduces costs and emissions, but remains heuristic and targets vehicle routing problem variants rather than the classical balanced transportation problem, which limits direct integration.

Research [12] synthesizes contemporary advances in time-dependent vehicle routing, including travel-time prediction, real-time re-optimization on road graphs, efficient neighborhood exploration, dynamic discretization, and machine-learning-inspired methods. The review highlights remaining challenges in scalable data integration and deployable, user-facing systems.

Summarizing these approaches, it can be concluded that accounting for temporal variability in logistics models indeed improves planning efficiency. At the same time, existing solutions typically do not offer an integrated architecture that would combine a classical balanced transportation model; a flexible time-dependent cost model; an interactive web interface for result analysis and correction; and an open client-server architecture for scalability.

This gap defines a relevant niche for further research aimed at developing information systems that integrate adaptive transportation planning with the real-time state of the road environment.

Mathematical model of adaptive transportation planning

The improved mathematical model of adaptive transportation planning is based on an extension of the classical Frank Hitchcock linear programming transportation problem by incorporating a time-dependent cost component. The classical formulation minimizes:

$$\min_{x_{ij}} \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}^{0} \cdot x_{ij} \quad (1)$$

subject to the balance constraints:

$$\sum_{j=1}^{n} x_{ij} = a_i, \sum_{i=1}^{m} x_{ij} = b_j, x_{ij} \geq 0, \quad (2)$$

where a_i and b_j represent the supply at the i-th origin and demand at the j-th destination, respectively, and c_{ij}^{0} denotes the fixed transportation cost per unit from origin i to destination j.

However, in real-world conditions, daily fluctuations in traffic intensity lead to significant variations in transportation costs throughout the day. To account for this, the cost c_{ij} is considered as a function of time:

$$c_{ij}(t) = c_{ij}^{0} + f_{ij}(t), \quad (3)$$

where $f_{ij}(t)$ represents additional costs due to traffic congestion at time t.

Based on empirical observations, daily traffic profiles can be effectively and accurately described as sums of normal density functions with two or more peaks [5, 6], thus:

$$f_{ij}(t) = \sum_{p=1}^{g} A_{ij}^{(p)} \phi\left(t;\ \mu_{ij}^{(p)}, \sigma_{ij}^{(p)}\right), \quad (4)$$

where:

$$\phi\left(t;\ \mu_{ij}^{(p)}, \sigma_{ij}^{(p)}\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \quad (5)$$

is the probability density function of a normal distribution with mean μ and standard deviation σ, g is the number of congestion peaks, and $A_{ij}^{(p)}$ are their amplitudes. Unlike classical mixture models with weights π_p (where $\sum \pi_p = 1$), the amplitudes $A_{ij}^{(p)}$ are not normalized, allowing independent adjustment of each peak's height to fit real traffic conditions.

For numerical implementation, the daily interval is divided into K equal steps of duration Δt minutes ($\Delta t \in \{5, 15, 30, 60\}$). Let:

$$t_k = (k-1)\frac{\Delta t}{60},\ k = 1, \dots, K. \quad (6)$$

At time step k, the cost is given by:

$$c_{ij}^{(k)} = c_{ij}^{(0)} + f_{ij}(t_k). \quad (7)$$

After discretization, the optimization problem retains its linear form and can be expressed as:

$$\min_{\left\{x_{ij}^{(k)}\right\}} \sum_{k=1}^{K} \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}^{(k)} \cdot x_{ij}^{(k)}, \quad (8)$$

subject to:

$$\sum_{k=1}^{K} \sum_{j=1}^{n} x_{ij}^{(k)} = a_i,\ \sum_{k=1}^{K} \sum_{i=1}^{m} x_{ij}^{(k)} = b_j,\ x_{ij}^{(k)} \geq 0, \quad (9)$$

where $x_{ij}^{(k)}$represent the shipment volume from i to j at time step k.

Thus, the proposed model combines the classical transportation problem with a time-dependent cost component approximated by sums of normal distributions. The discretization of the day transforms it into a solvable three-dimensional linear programming problem, preserving computational efficiency while accurately reflecting the dynamics of real traffic conditions.

System architecture

The architecture of the developed adaptive transportation planning information system is divided into two interacting subsystems: client-side (Frontend) and server-side (Backend). The client-side, implemented in JavaScript using the React framework, is responsible for the user interface, collection and validation of the initial transportation matrix data, configuration of model parameters, visualization and animation of routes on an interactive map, as well as graph plotting and time management. The server-side, written in Go and utilizing the gonum/lp library, provides a REST API for request handling, formulates the discretized transportation problem with time-dependent costs, selects the solution method (simplex, northwest corner, minimum cost, Vogel's approximation, Russell's approximation), and returns results in JSON format.

JavaScript with React was chosen for the client due to a balanced trade-off between performance and bundle size, while Go was selected for the server considering its high request throughput, cross-platform support, and availability of the gonum/lp linear programming library. Among specialized technologies, open-source solutions offering an optimal balance between functionality and module size were adopted: react-vis for graph visualization, Leaflet for maps, OSRM for routing, Nominatim and BigDataCloud for geocoding, and Electron for desktop packaging.

Fig. 1 illustrates the UML component diagram of the client-side (Frontend) subsystem. The central component "App" coordinates initialization, user interface event handling, and API calls. The "TransportationMatrix" module manages dynamic construction and editing of the matrix; "MapSetup" integrates OSRM and Leaflet for route generation; "CellConfigModal" configures time-dependent cost parameters; and "SolutionDetailsModal" provides detailed visualization of solution analysis.

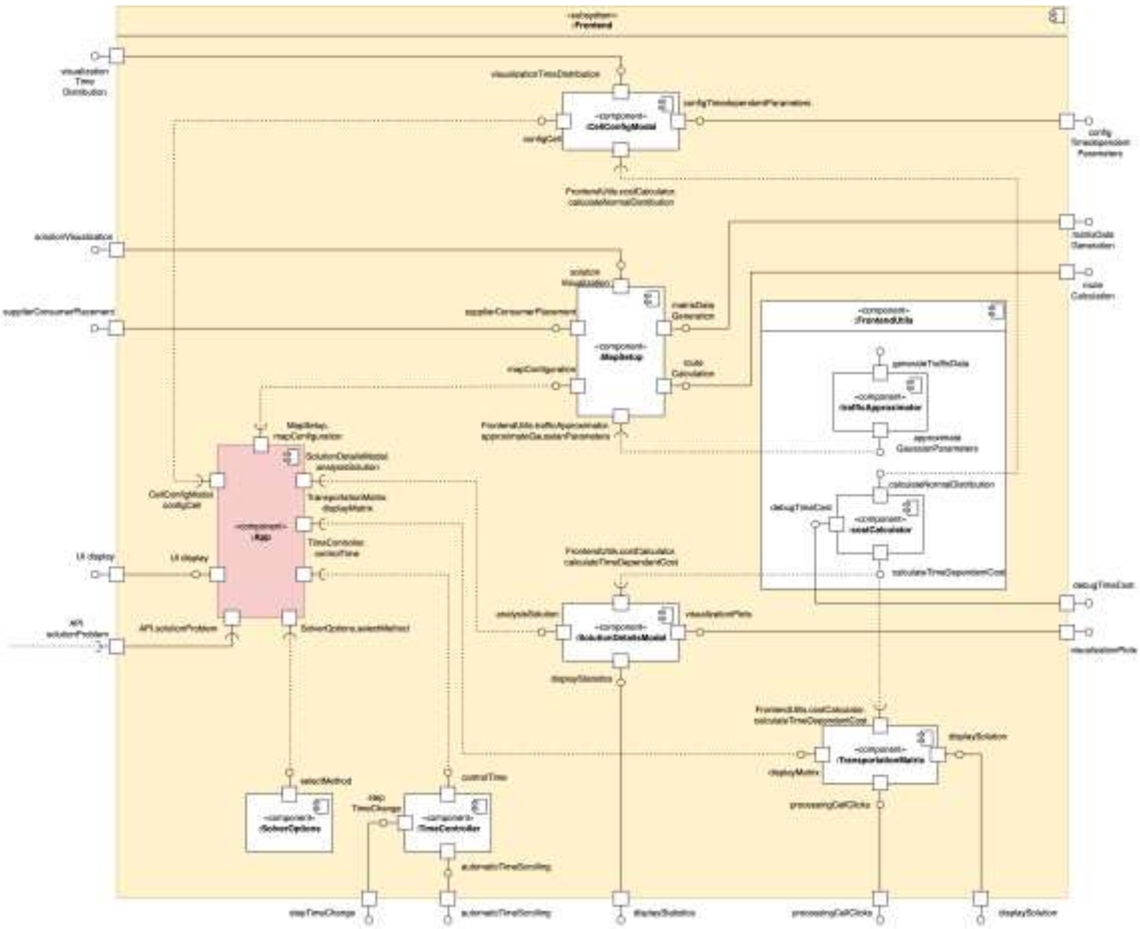

Fig. 1. UML component diagram of the client-side of the adaptive transportation planning information system

Fig. 2 shows the UML component diagram of the server-side (Backend) subsystem. The "Backend" modules are responsible for request handling, formulation of the discretized transportation problem with time-dependent costs, selection of the solving method, and returning results in JSON format. These modules are implemented in Go with the gonum/lp library, ensuring high computational performance and scalability.

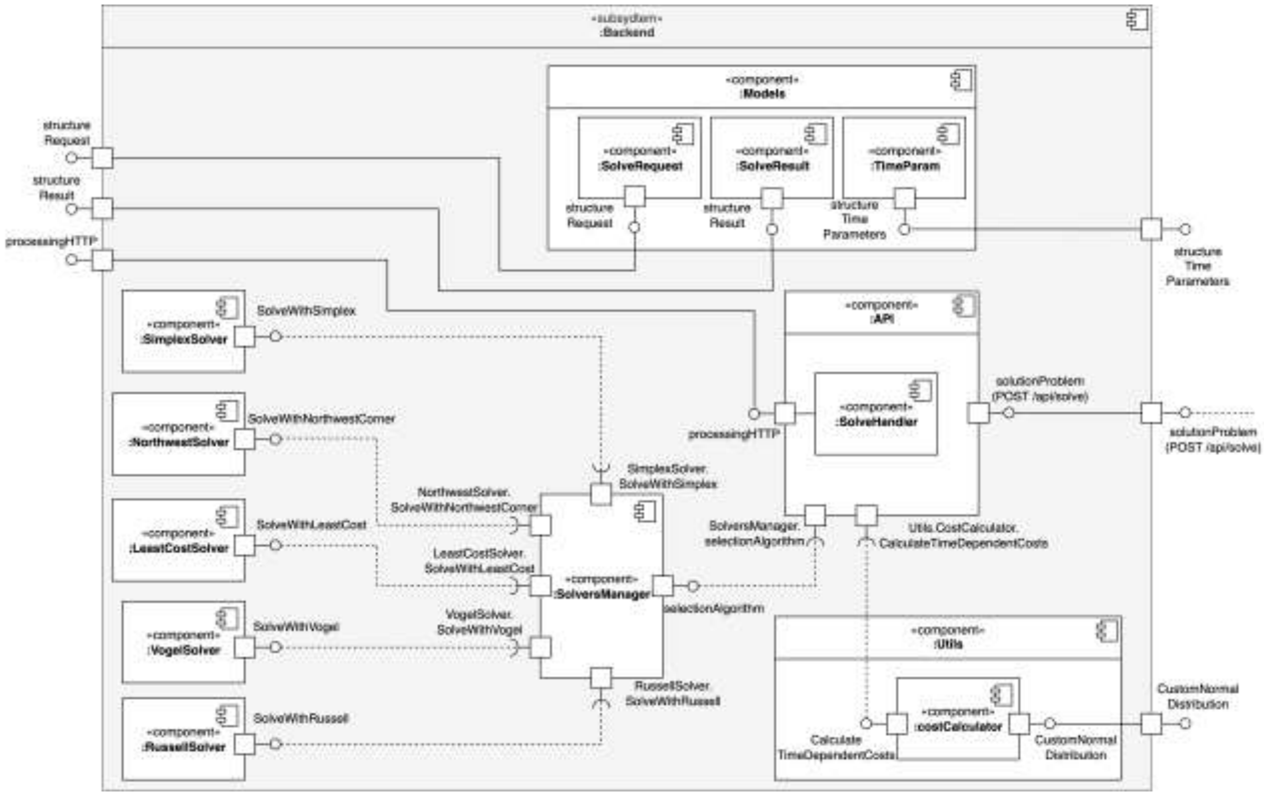

Fig. 2. UML component diagram of the server-side of the adaptive transportation planning information system

The system's operational algorithm includes initialization with selected parameters, loading or generating the transportation matrix, sequential invocation of the chosen optimization method for each discretized time interval, and a main modal window cycle encompassing matrix resizing, data saving and loading, view parameter management, and interaction with modal dialogs.

Thus, based on the aforementioned components and algorithms, the adaptive transportation planning information system "ChronoLogix" was developed, providing a scalable integration of the proposed mathematical model with an intuitive web interface.

Experiments

To verify the practical applicability of the developed adaptive transportation planning information system "ChronoLogix", a series of experiments were conducted in two scenarios: intercity and urban routing. Users specify geospatial points of suppliers and consumers directly on the map within the application, which allows automatic generation of the transportation matrix based on real coordinates and simplifies the preparation of input data. In both scenarios, the transportation matrix dimension was kept constant at 5×5, but the geographic locations of suppliers and consumers differed.

In the intercity scenario, suppliers were located in the cities of Kyiv, Dnipro, Lviv, and Kryvyi Rih, while consumers were in Kyiv, Kharkiv, Vinnytsia, Mykolaiv, and Chernihiv. In the urban scenario, all addresses were concentrated within London (United Kingdom). For both scenarios, a truck was chosen as the transportation mode with coefficients: +40% to travel time and +10% to distance; toll road avoidance was also enabled (+10% to time, +7% to distance) as well as ferry avoidance.

Fig. 3 shows a screenshot of the interface with supplier points (red markers), consumers (green markers), and generated routes in both intercity and urban scenarios.

Fig. 3. Generated routes for experiments in intercity and urban scenarios

After automatic route construction, the system generates a transportation matrix where each route corresponds to a single matrix cell. The fixed coefficients $c_{ij}^{(0)}$ are assigned as 10% of the distance in kilometers, while the time-dependent component $f_{ij}(t_k)$ is simulated depending on the route type (urban, suburban, highway), direction, length, and random factors.

Figure 4 presents the interface of the "ChronoLogix" adaptive transportation planning system along with the automatically generated transportation matrix for the intercity scenario.

Fig. 4. System interface and automatically generated transportation matrix for the intercity scenario

Using the detailed solution analysis functionality, the optimal transportation plan was computed for each of the 48 discretized intervals (step Δt = 30 minutes). After generating the matrix for every time interval, the system sequentially applied the simplex method to obtain the optimal flow distribution. The results are presented as transportation cost variation curves. Fig. 5 illustrates the intercity scenario.

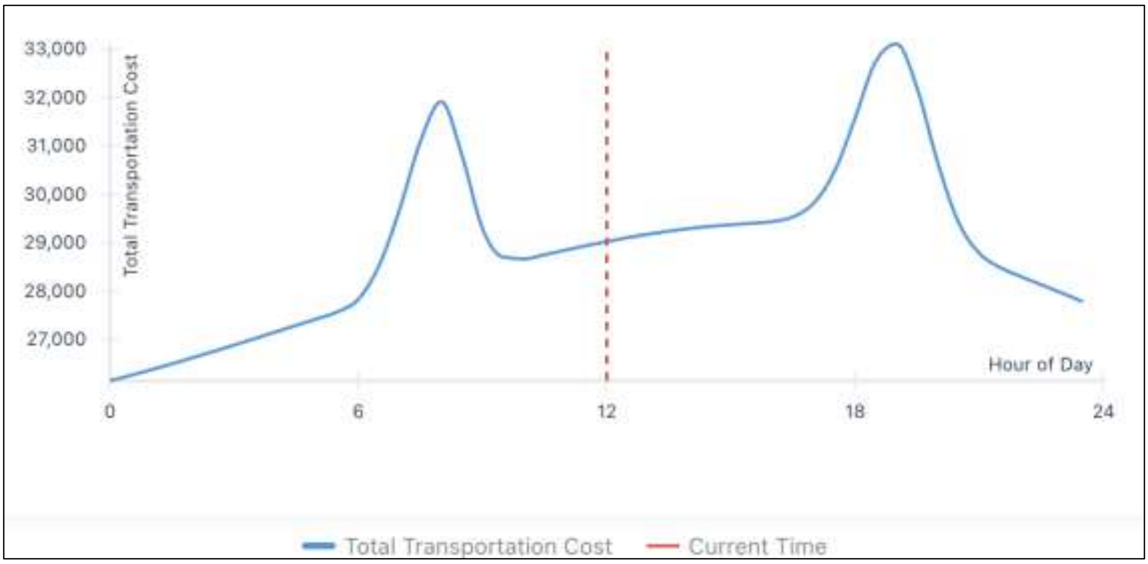

Fig. 5. Transportation cost variation curve in the intercity scenario

In addition, a separate analysis was performed for urban routes. The corresponding cost variation over the day is presented in Fig. 6, which highlights the much stronger influence of traffic congestion compared to the intercity case.

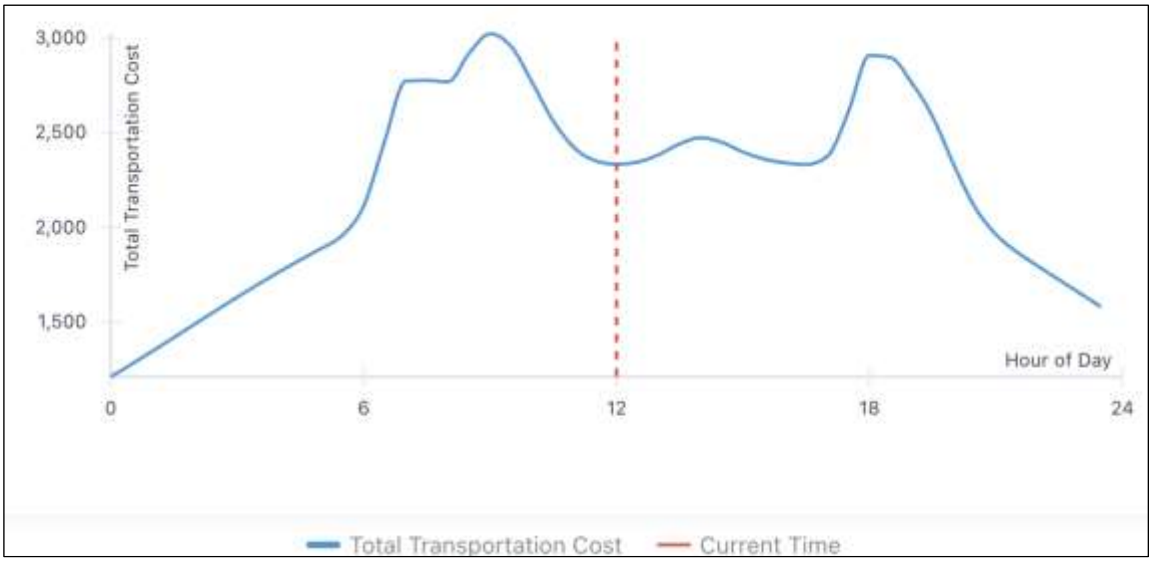

Fig. 6. Transportation cost variation curve in the urban scenario

For each of these two scenarios, the following were calculated:
transportation cost after adjustment of the chosen transportation plan (considering traffic $f_{ij}(t_k)$) – the route and departure time are selected to minimize the sum $c_{ij}^{(k)} = c_{ij}^{(0)} + f_{ij}(t_k)$;
static transportation cost (without considering traffic $f_{ij}(t_k)$) – the route and departure time are chosen based on fixed costs $c_{ij}^{(0)}$.

For each scenario, the actual costs of the static route without adjustment of the chosen plan were also calculated – i.e., the sum $c_{ij}^{(k)} = c_{ij}^{(0)} + f_{ij}(t_k)$ it would incur when applied to the matrix considering traffic. Cost savings were computed as the difference between the actual static transportation cost without adjustment and the transportation cost after adjustment of the chosen transportation plan considering traffic.

A comparison of the results from these experiments for intercity and urban scenarios is provided in Tables 1–2.

Apart from the calculated savings in hourly comparisons, a more important and significant factor is cost savings at extreme values. That is, the savings between the most accurate choice in the intercity scenario for the dynamic solution (29025,61) and the worst choice for the static solution (31276,43) already amount to 7,2%. Similarly, in the urban scenario, the maximum savings reach 47,8%.

Table 1

Comparison of the minimum transportation cost calculated considering road traffic and expected static estimates in the intercity scenario

Time	Transportation cost considering road traffic		Cost savings (%)	Static transportation cost without considering road traffic
	after adjustment of the selected transportation plan	without adjustment of the selected transportation plan		
8:00	31276,43	31276,43	0	25920,11
12:00	29025,61	29827,5	2,68	
17:00	29819,73	30400,52	1,91	

Table 2

Comparison of the minimum transportation cost calculated considering road traffic and expected static estimates in the urban scenario

Time	Transportation cost considering road traffic		Cost savings (%)	Static transportation cost without considering road traffic
	after adjustment of the selected transportation plan	without adjustment of the selected transportation plan		
8:00	2763,91	4364,91	36,68	1075,03
12:00	2333,03	4280,43	45,5	
17:00	2278,23	3650,16	37,59	

Considering the time component in the intercity scenario provides a relatively small economic benefit (maximum 7,2%), but it is crucial for the correct assessment of actual route costs (for example, actual costs of 31276,43 instead of 25920,11 calculated by route distance). In contrast, in urban conditions, the time factor becomes critical: without taking it into account, optimistic estimates (1075,03) significantly underestimate the actual costs (4364,91), as a significant part of the time is spent in traffic jams. Thus, the results of the experiment clearly confirm the feasibility of developing and applying an adaptive transportation planning information system with a time-dependent cost model to ensure economically sound decisions for both intercity and urban routes.

The next step was to test the impact of time discretization on solution detail and execution time. The Δt step was set to 5, 15, 30, and 60 minutes. For each step, the average route cost, minimum and maximum cost, cost variation, and total execution time for all steps were recorded (Table 3).

Table 3

Impact of time discretization on solution detail and execution time

Δt (min)	K	Total execution time (ms)	Average cost	Minimum cost (hour)	Maximum cost (hour)	Cost variation	Execution time per step (ms)
5	288	4750	2028,58	986,07 (23:55)	2982 (09:05)	1995,93	16,38
15	96	1563	2031,65	1024,54 (23:45)	2980,83 (09:00)	1956,28	16,28
30	48	764	2032,16	1028,1 (00:00)	2980,83 (09:00)	1952,73	15,91
60	24	367	2027,36	1028,1 (00:00)	2980,83 (09:00)	1952,73	15,29

The testing in Table 3 was conducted on a 5×5 urban matrix. Testing on an intercity matrix did not differ from the urban case in terms of key parameters. The key parameters in this experiment are the cost variation (solution detail) and total execution time. Discretization at five minutes is the most accurate but has a significantly longer execution time. Switching to 15 minutes speeds up calculations threefold with only a slight deterioration in detail. Further increasing discretization leads to even faster performance with only minor calculation degradation. Thus, depending on the objectives, it is reasonable to use a 5-minute discretization for maximum accuracy and savings, and a 60-minute discretization for maximum calculation speed. A compromise option is a 15-minute discretization, which balances execution time and cost variation.

From the perspective of computational complexity, the introduction of the time-dependent cost function does not change the problem class: the extended formulation remains a linear programming transportation problem and is solvable in polynomial time. The additional time dimension only increases the number of decision variables proportionally to the number of discretization steps, which effectively multiplies the execution time by a constant factor. Experimental results confirm this proportionality, as the measured computation time grows linearly with the number of time intervals K. Therefore, while the asymptotic complexity remains unchanged, the number of discretization steps directly determines the constant multiplier in execution time.

The third experiment compared all supported solving algorithms. For a fixed time of day (12:00), for 10×10 matrices of intercity and urban scenarios, the optimal cost and execution time were recorded for the simplex method and initial plan construction algorithms: the northwest corner, least cost, Vogel's approximation, and Russell's approximation. The deviation of each algorithm from the benchmark simplex solution was calculated. The results are shown in Table 4.

The simplex method is the most accurate and the only one that always returns the optimal solution. The northwest corner algorithm can be used only for educational purposes, as it is unacceptably inefficient (deviation of 137.48% for the intercity and 99.95% for the urban scenarios). Other heuristics showed varying degrees of compromise. The least cost method produces unstable results: relatively small deviation in the intercity scenario

(≈4.27%) but significant in the urban one (≈15.86%). Vogel's and Russell's approximations showed moderate deviations (≈5–8% intercity, ≈7–8% urban).

Table 4

Analysis of initial basic feasible solution algorithms for time-dependent transportation problems

Algorithm	Intercity optimal solution	Intercity execution time (ms)	Deviation from simplex (%)	Urban optimal solution	Urban execution time (ms)	Deviation from simplex (%)
Simplex method	203642,61	19,3	–	3664,11	20	–
Northwest corner	483605,75	5,4	137,48	7326,36	2,1	99,95
Least cost	212335,17	3,3	4,27	4245,22	4	15,86
Vogel's approximation	214866,88	3,7	5,51	3957,65	2,3	8,01
Russell's approximation	220362,42	2,1	8,21	3942,8	2,5	7,61

In terms of execution time, heuristics turned out to be much faster than the simplex: in the intercity scenario, average execution times were 2–6 ms versus 19.3 ms for the simplex (heuristics are 3–9 times faster). In the urban scenario, a similar pattern was observed – heuristics executed in 2–4 ms versus ~20 ms for the simplex (2.5–9 times faster). However, in absolute terms, these differences are measured in tens of milliseconds, and for interactive applications in modern hardware conditions, they are negligible; therefore, from a practical accuracy standpoint and with acceptable slowdown, it is reasonable to prefer the simplex method, using heuristics as quick initial approximations or for very large problems.

Comparative analysis with existing transport management systems

A comparative analysis of the developed information system "ChronoLogix" and leading commercial solutions was carried out based on several practically relevant criteria: implementation and licensing costs, code openness and deployment options, the level of required expertise for implementation and maintenance, route optimization methodology, configuration flexibility, scalability, and target audience.

Commercial transport management systems (TMS) provide an extended set of features for corporate and global supply chains (API, ERP integration, analytics and AI/ML modules, multimodal transport support). Their adoption is accompanied by significant capital and operational expenditures, the need to engage integrators and DevOps specialists, and a closed architecture that limits the research transparency of algorithms [1–4].

"ChronoLogix" is implemented as a lightweight, transparent, and economically accessible platform: local deployment, partially open APIs, a simple interface, and a mathematically formalized model (linear programming with time-dependent costs). This combination of attributes makes the system suitable for educational purposes, scientific experiments, and local logistics tasks for small and medium-sized businesses, where transparency of methods, rapid prototyping of transportation solutions, and a low entry threshold are critical.

Among the limitations, it is worth noting the absence of built-in scalable corporate modules, advanced ERP and telemetry integration mechanisms, as well as sophisticated AI capabilities. Thus, "ChronoLogix" is not a direct replacement for commercial TMS in large logistics networks but effectively occupies the niche of an affordable and illustrative tool for research, education, and local use.

Conclusions

This work presents an information system for adaptive transportation planning "ChronoLogix", which combines the classical transportation problem of linear programming with a time-dependent cost model approximated by a combination of normal distributions. The developed discretized model preserves linearity and computational efficiency while adequately reflecting the daily dynamics of road conditions.

The conducted experiments showed that accounting for the time component provides moderate savings (up to 7.2%) on intercity routes, yet it is critically important for the correct estimation of actual costs. In urban conditions, the time-dependent model demonstrates up to 47.8% savings compared to static planning, since without its integration, real expenses are severely underestimated. The discretization step analysis revealed that switching from 5-minute to 15-minute intervals speeds up computations threefold with minimal accuracy loss, while further increasing the step to 60 minutes yields an additional performance gain with an acceptable loss of detail. From a computational perspective, introducing the time dimension does not change the problem class: the linear programming structure is preserved, and the number of time intervals only proportionally affects execution time. It was determined that among the methods for constructing the initial plan, the northwest corner approach performs the worst, whereas the least-cost method and Vogel's and Russell's approximations show moderate deviations. At the same time, heuristics perform significantly faster in relative terms, but in absolute values, the difference is only in tens of milliseconds. Thus, heuristics are appropriate as quick initial approximations or for large iterative schemes, while the simplex method remains the optimal choice for final accuracy with acceptable delay.

The obtained results confirm the feasibility of using "ChronoLogix" for educational, research, and applied logistics tasks in small and medium-sized businesses.

In the future, it is planned to integrate the system with real-time data streams (road network telemetry), extend the model with fuzzy optimization to handle imprecise input data, and add support for multimodal transport (rail, water) as well as adaptive algorithmic approaches based on machine learning for traffic congestion prediction and further improvement of the economic efficiency of routing solutions.

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