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Data-driven Simulation in Transportation Management through Cross-Sectoral Collaboration

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Abstract: This article proposes an innovative integrated framework and research methodology for data-driven simulation in transportation management through cross-sectoral collaboration. The presented study is based on a real case of synergy in the transportation of products in two sectors - agriculture and forestry. The purpose of this study is to simulate the synergistic improvement of the planning and organization of transportation of agricultural and forest products by small businesses. The benefit for participants in both economic sectors is to ensure a more efficient use of their transport and labor resources by using the opportunities of intersectoral cooperation and emergent data driven-modeling and simulation technologies. The data-driven models such as symbolic regression are used to identify patterns in data and translate the underlying relationships into the modeling formalisms needed to build computer simulation models. The proposed study was tested in real-life conditions.

Keywords: Agriculture; Forestry; Cross-sector Collaboration, Data-driven Modeling; Web-based Simulation; Transportation Management.

1. Introduction

Modern digital platforms are radically transforming business models and changing inter-industry and inter-company relationships, opening up new areas of cooperation today (Veile et al., 2022). Simulation technologies provide an experimental approach to exploring the potential of cross-sectoral collaboration in transportation management and to developing and planning further transportation decisions (Castañer and Oliveira, 2020). Collaboration is a necessary prerequisite for synergy in the transportation of agricultural and forest products, which expands the collaboration process and takes the results beyond simple cooperation. Moreover, rapidly evolving data-driven computing technologies enable companies to realize the value of data and exploit the opportunities supported by data.

The objective of the presented study is to develop an integrated approach and methodology for data-driven modeling and simulation in transportation management through cross-sectoral collaboration. It is designed to process and interpret relevant data from various business areas (e.g. operations, economics) and provide meaningful and cost-effective analysis of the most important decisions.

Various methods and tools, including data science and modeling technologies, are considered and employed to model and analyze this synergy. The experimental part of the study was carried out using the example of synergy in the transportation of products from two industries – agriculture and forestry. In this example, the company is engaged in managing the transportation of not only agricultural or forest products separately, but both of them. The benefits of improved planning and organization of transportation of agricultural and forest products for small enterprises and farms are that it ensures a more efficient use of their transport and labor resources (in particular, vehicle drivers) by using the opportunities of inter-sectoral interaction and advanced computing technologies.

The modeling concept and research methodology are based on the well-established simulation-based approach to applications in logistics and supply chain management. In particular, practical examples of various case studies using the simulation approach to solve complex logistics problems can be found in (Merkuryev et al, 2009). This paper advances that methodology by integrating data-driven modeling and web-based simulation technologies. It also applies to a new application area, namely the planning and organization of transport across two industrial sectors.

Data-driven modeling involves using historical and other data to create models that identify trends and patterns in the data, and represent data in a structural form (Habib and Ayankoso, 2021). With the advancement of computational intelligence and machine learning techniques, as well as the wide availability of accumulated data, the use of data-driven models has increased in different application areas (Belmont Guerrón and Hallo, 2022; Merkuryeva, 2024).

Data-driven simulation is an emerging trend in the development of computer simulation technologies. It is based on the integration of different data models, complemented by computational intelligence and machine learning methods, changing the simulation from a model-based paradigm to data-driven one (Mütsch et al., 2023). In this study, data-driven modeling provides a data basis for guiding and controlling computer simulations throughout its life cycle, starting from defining the model structure and parameters for different experimental scenarios.

In the field of transport logistics in agricultural and forestry industrial sectors, one of the strongest influencing factors is the seasonality of demand for transportation. The seasonality of demand for agricultural transportation naturally depends on the harvest time, whereas the seasonality of demand for forestry transportation is associated with greater accessibility of forest roads during cold periods. This seasonality of demand presents important economic challenges. During busy seasons, large amounts of specialized and expensive resources are required in the short term and there is usually a shortage of skilled labor. At the same time, during low seasons, these logistics companies have idle resources and are forced to pay high wages to unemployed skilled workers in order to retain them for the next season.

Currently, small agricultural and forestry companies in developing EU countries are typically focused only on transporting products from a specific sector (agriculture or forestry) and have a conservative attitude towards collaboration opportunities. These businesses usually do not consider the possibility of sharing skilled labor and transportation resources in order to improve their economic efficiency. At the same time, small businesses, as a rule, have a fairly low level of digitalization and are not sufficiently equipped with modern information and communication technologies. Thus there is room for improvement through mutual collaboration of these businesses by using innovative data technology and data-driven modeling.

The development of innovative solutions to improve the planning and organization of transportation of agricultural and forest products by expanding cooperation between small enterprises was carried out within the framework of a research project, in which representatives of the industry from two sectors took part (Bolsakov et al., 2024). This project focused on small agricultural, forestry and transport companies. Consequently, the presented research methodology was tested in real-life conditions.

The following section provides a review of the literature on modeling and organization aspects of transport and logistics services in agriculture and forestry. Section 3 introduces the conceptual framework of the study and research methodology, including web-based data management, data-driven modeling, system dynamics modeling, stochastic discrete-event simulation, and a multi-user web environment. Section 4 describes the experimental part of the study and discusses the obtained experimental results. The conclusions of the study are given in Section 5.

2. Literature Review

An analysis of the organization of transport services and supplies in small enterprises in forestry and agriculture was conducted using the example of Latvia. Considering the seasonal demand for transportation in both sectors, it was found that the planning and organization of logistics in such enterprises could certainly be improved by sharing available vehicles and labor to transport produce as needed. Such a collaborative organization of transport logistics at SME level between different industrial sectors must not only be technically and economically justified, but also take into account all current relevant theoretical and technological developments. In addition, a comprehensive analysis of existing and new business processes in practice requires consideration of a large volume of detailed transport documentation and logistics data, followed by modeling possible scenarios for planning and organizing transportation.

To improve transport logistics in the forestry sector, both analytical and algorithmic models have been studied in (Alonso-Ayuso et al., 2020; Troncoso and Garrido, 2005; Sfeir et al., 2019; Alayet et al., 2018). The proposed models often do not take into account the factor of seasonal demand fluctuations when offering new solutions for the optimal use of existing transportation resources.

The literature suggests many factors directly and indirectly affecting forestry transportation companies as well as the environment. For example, the model proposed in (Mathur and Warner, 1997) takes into account direct transportation costs, as well as indirect costs such as investments in public infrastructure and financial assessment of the impact on the environment and ecology. The impact on the labor force and the labor market is assessed in (Boukherroub et al., 2013). Furthermore, a hybrid multi-criteria model for assessing the effectiveness of sustainable management of forest enterprises from economic, social and environmental points of view is proposed in (Deng et al., 2023).

Often, the proposed models (Boukherroub et al., 2013; Walsh et al., 2003; Bajgiran et al., 2016) do not focus only on the transportation process itself, but more specifically on the supply chain management of all products involved. This enables efficient planning and organization of the work processes of the participating enterprises for the benefit of all of them. In particular, models with cost uncertainty are described in (Walsh et al., 2003) and models with shared transport resources are presented in (Francois et al., 2017).

For modeling such a socio-techno-economic system, analytical models are often used (Buongiorno, 1996; Bajgiran et al., 2016; Francois et al., 2017; Oke et al., 2018). To solve various transportation problems, simulation models that imitate physical processes and allow computer experiments to be carried out with them are proposed (as, for example, in (Walsh et al., 2003; Boukherroub et al., 2013)).

The literature on logistics modeling in the agricultural sector mostly carries out process analysis. Priority is given to the transportation of agricultural products from farms to warehouses and further in the logistics chain to processing or transshipment points. Both system dynamics and discrete-event simulation models are used to analyze the transportation of agricultural products. Examples of several models based on system dynamics and their comparison are given in (Oliveira et al., 2022; Chen et al., 2022). Examples of discrete-event simulation models for the analysis of farm-scale grain transportation systems and the modeling of grain logistics from farms to ports are described in (Fioroni et al., 2015; Turner et al., 2019).

There are also studies in the literature, including quite recent ones, that use well-known discrete-event modeling formalism (Cavone et al., 2017), such as Petri nets, to analyze supply and production chains in the agricultural and forestry sectors. Hybrid Petri net models have been used to assess the logistic efficiency of forestry production chains (Cardoso et al., 2009) and to plan agricultural work processes under uncertainty (Ozgun and Kirci, 2015; Guan et al., 2008), and colored Petri nets were applied to model and analyze agricultural supplies to the European Union (Pavlenko et al., 2020).

In research on the organization of agricultural production, much attention is also paid to analytical models for ensuring the efficiency of logistics services. A large number of articles, for example (Xiao and Lang, 2009; Lamsal et al., 2016; Mehmann and Teuteberg, 2016; Mogale et al., 2019; Mardaneh et al., 2021; Trunina et al., 2021; Sgurev et al., 2022), present linear programming models for optimizing the transportation of agricultural products. Although there are quite effective methods for solving such optimization problems, these models contain many assumptions and simplifications that usually do not take into account the volatility and/or seasonality of demand. The use of complex optimization algorithms to organize efficient logistics is discussed in (Xiao and Lang, 2009; Lopez and Qassim, 2023), but these algorithms are always specific to certain transportation factors.

Although the linear programming models mentioned normally do not take the factor of seasonal demand into account, the fact that demand for agricultural products is highly variable, unstable and difficult to predict is one of the most important aspects of transport logistics in the agricultural sector mentioned in literature. There are studies covering both forecasting and modeling of demand for agricultural logistics services (e.g., (Li and Lu, 2015)) and transport models that take into account particularly short periods of high demand for agricultural crops (Sgurev et al., 2022).

Various key performance indicators (KPI) have been identified that need to be analyzed when organizing agricultural transportation. Cost efficiency (Diaz and Perez, 2000; Mehmann and Teuteberg, 2016; Nourbakhsh et al., 2016; Lomotko et al., 2019; Mardaneh et al., 2021) is the KPI most frequently selected, followed by energy consumption (Trunina et al., 2021) and supply chain efficiency (Nourbakhsh et al., 2016).

Collaborative data collection, analysis and processing for decision support in the agricultural and forestry industries are discussed implicitly or explicitly in several research papers (Zhu et al., 2009; Mehmann and Teuteberg, 2016; Gupta and Garima, 2017; Mardaneh et al., 2021; Oliveira et al., 2022). Although the methods proposed in these studies differ, the common point is that digitalization of agricultural and forestry transport companies is relevant and important in order to increase the efficiency of these companies and to improve their logistics processes. One of the widely recommended methods is the accumulation of process data in order to develop accurate and reliable models for further optimization of business processes.

The possibility of using a resource sharing approach in transportation is also being considered. In particular, relevant qualitative and quantitative productivity estimates based on an extensive study of the forestry sector are given in (Palatova et al., 2023). The impact of such resource sharing on sustainable economic development in the agricultural sector is analyzed in (Lin et al., 2022). However, the possibility of sharing resources between agricultural and forestry companies to create a flexible and diversified transport organization in such a case has not yet been widely discussed. In fact, the intersectoral cooperation and synergies between agriculture and forestry (Noordwijk et al, 2018) are analyzed mainly from the perspective of environmental sustainability.

3. Research Methodology

3.1. Rationale

Logistics and transportation of agricultural and forest products together constitute one fifth of all freight on Latvian roads (National Statistical System of Latvia, 2024). The current situation, where both agricultural and forestry transportation companies may suffer from seasonal factors and do not support each other, is due to several factors. Different technical specifications for the trucks, trailers and semi-trailers used in the transportation processes are the main cause. Additionally, transporting timber products, such as unprocessed logs, may also require additional skills from drivers as they will have to load the vehicle themselves.

Latvian forestry companies use three-axle trucks with three-axle trailers. These are also equipped with an hydraulic loader for cutting or open storage. Agricultural transport companies on the other hand use tractors with semi-trailers to transport bulk cargo, such as grain, fertilizers or peat. They do not require self-loading, as they are usually loaded from an elevator or agricultural machinery.

The agricultural enterprises may be interested in transporting timber during the winter period. Some even tried to do this with minor modifications to semi-trailers, but these were isolated cases. To provide agricultural trucks with the ability to transport timber, specialized semi-trailers equipped with an hydraulic loader can be used. By renting or purchasing such a semi-trailer, agricultural enterprises can ensure the loading and transportation of timber logs using the existing capacities and drivers when they stand idle during the off-season.

Furthermore, it can be envisaged that small businesses and farmers will be equipped with digital technologies and tools enabling the proper collection and analysis of relevant data for effective planning and organization of transportation of agricultural and forest products, thus taking advantage of the opportunities for cooperation between the two sectors.

3.2. Conceptual research framework

Simulation is widely recognized in literature and in practice as an effective and flexible approach to design efficient logistics and supply chain management. It should be noted that this approach can only provide reliable experimental results and estimates if the initial modeling data are reliable and if the model itself is based on a clearly formalized system structure and well defined processes. Preparing input data for small businesses in a target application can be challenging due to the lack of access to many of these data. The application of data mining using powerful machine learning methods to understand and interpret the available data and their integration with simulation technologies appears to be a quite reasonable solution for this problem in the context of this study.

The idea of integrating data science and modeling technologies is not new to either management or logistics. For example, integrated solutions based on cluster analysis and simulation-based optimization have been introduced for planning and scheduling product deliveries to a distribution center (Merkuryeva, 2012). The integration approach was subsequently supplemented by fitness landscape analysis (Merkuryeva and Bolshakov, 2015) and extended by applying computational intelligence methods to simulation-based planning and optimization in multi-echelon supply chains (Merkuryeva et al., 2011).

In our study the modeling concept and research methodology are enhanced by integrating data-driven modeling and web-based simulation. Extracting useful information from historical and operational data of a real system, identifying dependencies within these datasets, and transforming them into modeling formalisms (e.g., formulas) enables the definition of the structure and parameters of simulation models for subsequent experiments. In this approach, the simulation is dependent on and driven by the actual behavior of the system.

The proposed conceptual framework (Fig. 1) describes the principal components of the research methodology, as well as the interrelationships and data flows among them. It provides a structured foundation for the study, ensuring alignment between the proposed methodological approach and the application example presented in Section 4.

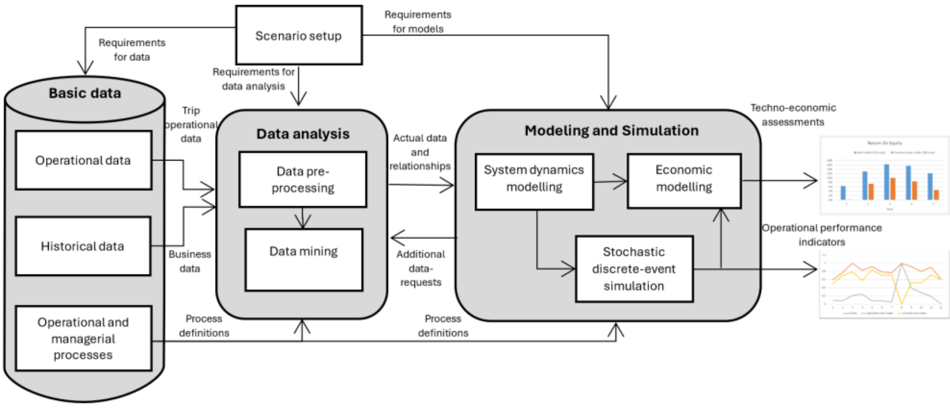

Figure 1. Conceptual framework of the study

An essential data preprocessing component in data analysis, especially in machine learning, involves the cleaning of raw data and the normalizing of attribute values to the same units of measurement. Then, a machine learning-based symbolic regression method (Kronberger et al., 2024) is used to find dependencies in historical and operational datasets and represent them in the form of analytical expressions. The obtained analytical models serve as the basis for the construction of system dynamics models.

In particular, the operational processes include transportation, loading, unloading and dispatch of vehicles, their maintenance and replacement. The system dynamics model is combined with an economic model to assess the economic viability of potential cooperation scenarios using technical and economic estimates. Additionally, the stochastic discrete-event simulation model provides a virtual simulation of real processes of transportation of agricultural and forest products. This simulation in turn takes into account random factors and events that influence the implementation of the developed scenarios, as well as the assessment of corresponding transport solutions using operational efficiency KPIs. Feedback loops between the basic components make the proposed framework both flexible and interactive.

Scenario setting plays a key role in the study. Possible options for cooperative scenarios and transport solutions for the use and configuration of transport resources are based on previous experiences of the involved companies and take the benefits of the cooperation between the two industrial sectors into account. These scenarios may include both existing and potential workflows, as well as available or leased vehicles.

Validation of the proposed models and tools was carried out during the development process. The purpose is to ensure that at a certain stage of development the results of modeling and simulation meet the initially defined requirements (Zenina et al., 2020). For example, in the case of symbolic regression, 80% of the available data were used to train the model, and then 20% were used to test the resulting model. Finally, the results of the experimental scenarios were tested in real-life conditions, allowing them to be compared with practical ones.

Since no single tool to address all these components exists, various tools and methods are proposed and combined to implement the developed research framework in the target application.

3.3. Methods and tools

The proposed research methodology offers a combination of methods and tools for web data management, data mining, system dynamics modeling, stochastic discrete-event simulation and multi-user web environment.

Web-based data management. As mentioned above, the study focuses on small businesses and farms in the agricultural and forestry sectors. Most of them have one to several trucks and carry out local transportation in the agricultural sector. These small business often have a relatively low level of digitalization and lack modern information technology tools.

The required data are obtained using the digital web platform for agricultural logistics management (Graudvedis, 2024). This web platform allows collecting and storing business data of small businesses and operational data on completed trips. Moreover, it provides data management for overall control of transport logistics and improved cost efficiency.

An example of statistical data on the transportation of agricultural products obtained from the digital management platform is shown in Fig. 2. In particular, the data records in the table include loading and delivery data, the total length of the route, the types and volumes of transported products, the time of contact between the dispatcher and the driver, overtime work, as well as data on the driver and the vehicle, and fuel consumption.

Data-driven modeling. Symbolic regression is one of the most powerful machine learning methods that allows extracting key underlying relationships as analytical expressions directly from data without making assumptions about the model structure (Kronberger et al., 2024). Moreover, it is applicable to small datasets.

One of the widely discussed methods in the literature for constructing symbolic regression is genetic programming with the representation of evolution by tree-like data structures (Affenzeller et al., 2009). This method is applicable in various fields, since it allows to obtain mathematical relationships regardless of the data context. For example, it was used to forecast river floods in (Merkuryeva et al., 2015) and to forecast demand for pharmaceutical products in (Merkuryeva et al., 2019). To construct symbolic regression models for the output variables in the study, the HeuristicLab software environment (Kronberger et al., 2012) was used.

Vehicle	Carrier	Reference ID	Cargo type	Units of measure	Volume	Total distance, KM	Loaded distance, KM	Empty distance, KM	Date	Filled fuel, L	Notes
RZ-79	Pan-Trans	22LV709762	Cutter chip	Bulk m³	99	250	125	125	06.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV709790	Cutter chip	Bulk m³	99	250	125	125	07.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV709853	Cutter chip	Bulk m³	99	250	125	125	11.12.2022	430	Pine
RZ-79	Pan-Trans	22LV709854	Cutter chip	Bulk m³	99	250	125	125	11.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV709873	Cutter chip	Bulk m³	99	250	125	125	12.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV709874	Cutter chip	Bulk m³	99	250	125	125	12.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV709897	Cutter chip	Bulk m³	99	250	125	125	13.12.2022	410	Spruce
RZ-79	Pan-Trans	22LV709898	Cutter chip	Bulk m³	99	250	125	125	13.12.2022	0	Spruce
RZ-79	Pan-Trans	22LV7557	Cutter chip	Bulk m³	99	250	125	125	08.09.2022	0	Pine
KB7960	RANPO	22R1776	Grains	t	24.012	62	31	31	14.08.2022	0	Wheat
KB7960	RANPO	22R2002	Grains	t	25.68	62	31	31	15.08.2022	0	Wheat
KB7960	RANPO	22R2694	Grains	t	24.78	62	31	31	18.08.2022	0	Wheat
KB7960	RANPO	22R2980	Grains	t	16.54	62	31	31	19.08.2022	0	Wheat
KB7960	RANPO	22R3108	Grains	t	26	62	31	31	19.08.2022	0	Wheat
KB7960	RANPO	22R3240	Grains	t	25.2	62	31	31	20.08.2022	0	Wheat
KB7960	RANPO	22R3280	Grains	t	25.06	62	31	31	20.08.2022	0	Wheat
KB7960	RANPO	22R3305	Grains	t	25.53	62	31	31	20.08.2022	0	Wheat
KB7960	RANPO	22R3396	Grains	t	25.44	62	31	31	21.08.2022	0	Wheat
KB7960	RANPO	22R3430	Grains	t	25.02	62	31	31	21.08.2022	0	Wheat
KB7960	RANPO	22R3452	Grains	t	25.34	62	31	31	21.08.2022	0	Wheat
KB7960	RANPO	22R4105	Grains	t	25.82	62	31	31	24.08.2022	0	Wheat
KB7960	RANPO	22R4287	Grains	t	18.488	62	31	31	25.08.2022	0	Rapeseed

Figure 2. Examples of data records

An example of the analytical extract encoded in a tree-like data structure is shown in Fig. 3. The leaf nodes of a tree data structure represent specific input variables multi-plied by constant coefficients, and the internal nodes represent binary operations on their values or the results of other binary operations. The resulting symbolic regression model is presented by an analytical expression. For more information, see Section 4.

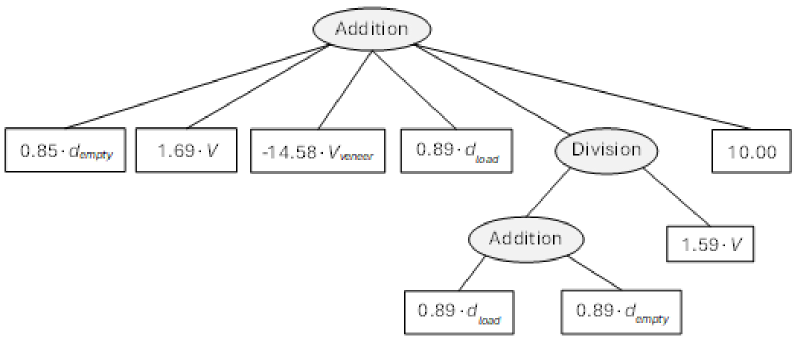

Figure 3. An example of the analytical extract encoded in a tree-like data structure

In fact, the use of the symbolic regression method has the advantage that the obtained dependences in the form of analytical expressions can be directly integrated into simulation models of the system.

The symbolic regression model is deterministic and reflects the past behavior of the system being analyzed by mathematical expressions. In the presented study, these mathematical expressions are updated as new data becomes available. The obtained dependences in the form of analytical expressions are then directly integrated into the system dynamics model for calculating nodes.

System dynamics modeling. The conceptual system dynamics model is constructed by identifying causal relationships between input variables and key performance indicators of the system. The model assumes that the company can use both its own trucks and trailers and rented vehicles.

The model contains more than 20 nodes that represent input, intermediate and output variables. The input variables define parameters of trips to be performed (e.g., numbers of owned and rented semi-trailers, average transportation distance, loading time, etc.), as well as parameters that affect costs and revenues, such as fuel costs and prices, taxes and wages. The intermediate variables represent the results of intermediate calculations of economic and operational performance indicators, e.g., time-dependent costs and total travel distance. The output variables are final calculations of economic and operational performance indicators such as fixed and variable costs, revenue, average vehicle utilization, and driver workload.

In Fig. 4, a cause-and-effect diagram created in AnyLogic shows how the various variables of the modeled system are interrelated.

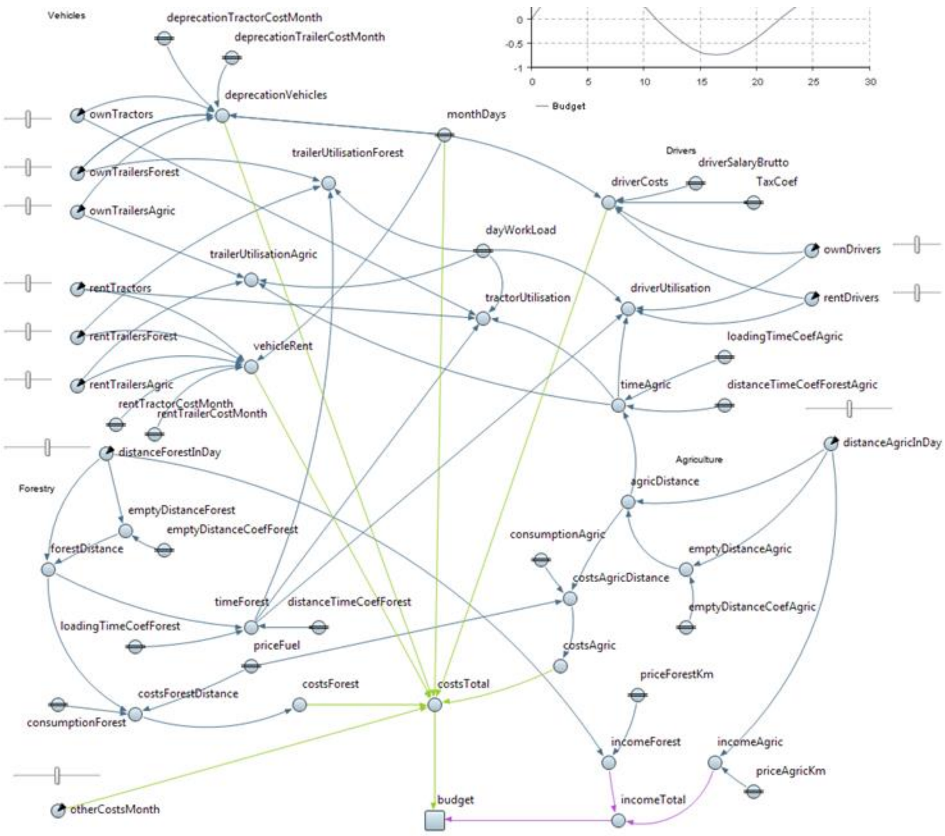

Figure 4. Causal loop diagram of the modeled system

The node connection logic and node calculations are based on assumptions derived from the results of symbolic regression analysis as well as from business process analysis. The dependencies and relationships between variables that can be derived from data-driven models (such as the relationship between empty and loaded route distances) are substantiated through data analysis. Other relationships that could not be identified in this way are determined based on analysis of the cost and income structure of the analyzed enterprise.

The computational modeling is carried out separately for the transportation of timber and for the transportation of agricultural products. The developed system dynamics model is deterministic and does not take into account randomness in the behavior of the system and its processes. If the computational model does not have a value for a particular output or it is unclear how to calculate it, it can be obtained using a symbolic regression formula derived from the available data.

Stochastic Discrete-Event Simulation. A stochastic discrete-event simulation model is developed to generate, simulate and evaluate transportation decisions for potential vehicle trips according to a given scenario. The model takes into account the input and output data of the system dynamics model and is partly based on its calculations. Specifically, input data include the company's geographical location, employee wages, costs and depreciation of vehicles (tracks, trailers and semi-trailers), equipment maintenance and repair costs, fuel consumption and price.

In particular, the model ensures modeling of stochastic input variables and processing of random events. For example, the influence of seasonality on the distance of transportation of agricultural products is described by the probability distributions, which depend significantly on the month of the year. Finally, the model provides values of key performance indicators.

Moreover, the model provides industry representatives with graphs of economic efficiency and operational performance indicators for a given scenario, and also displays the transport processes themselves online. This provides a holistic view (Fig. 5) for a better understanding of potential organizational scenarios and corresponding transport solutions.

Figure 5. Screenshot from discrete-event model visualization

Multi-user Web-based Environment. To make modeling and simulation services widely available to all stakeholders (e.g. managers, planners, drivers, etc.), a multi-user web-based modeling approach is proposed. Web modeling allows these services to be used over the internet and provides multi-user access to models, simulation experiments, their results and visualizations.

To enable multiple users to conduct independently experiments online, it was proposed to split the simulation model application into front-end and back-end system components. The front-end component is designed to provide the user with web access to the model, data entry, visualizations and process diagrams. The back-end component is designed to work with the simulation model, store user data and modeling results, and process the corresponding system behavior. The multi-user approach in the back-end component is organized by storing the model configuration for each user in a separate session. The simulation model updates these sessions in a loop (see Fig. 6).

The software is developed using the general-purpose PHP 7.4 scripting language for Windows web development.

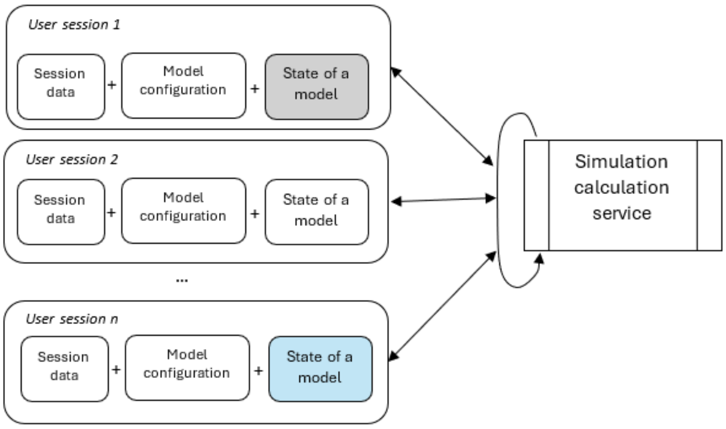

Figure 6. Multi-user web-based simulation

Economic Feasibility Assessment. A cooperative business model was developed to assess the economic feasibility of using different types of trailers. It is estimated that transport utilization and cost optimization strategies determine operating cost variations in the range of approximately 30%. The cost of purchasing equipment and driver comfort requirements affect the investment amount by approximately 15%.

The model allows appropriate adjustment of parameters to compare alternative solutions and determine the expected return on investment as well as the cost of carbon emissions. Moreover, it provides the calculation of the internal rate of return, the borrowing rate, as well as the calculation of the return on equity under certain conditions. Finally, the model uses the experience and knowledge of the industry experts who participated in the study, and the calculations are performed in Excel spreadsheets.

4. Case Study

This section presents an example of application of the proposed research methodology to model and simulate the benefits of cooperative scenarios in the transportation of products from two industrial sectors by a small agricultural company. The description of the experimental results obtained follows the proposed methodology step by step.

Preliminary data analysis. The initial experimental dataset contained data from over 61 forest companies with a wide range of used vehicles from 1 to 29 and 12 agricultural companies with 1 to 8 vehicles. These data sets include historical performance data, such as delivery date and location; travel distance for empty and loaded trips; type, weight and volume of transported products; vehicle and driver identification; supplementary time needed if any, etc.

The demand for transportation in the agricultural sector is largely dependent on seasonal factors. The probability distributions of the delivery distances for the agricultural products are shown in Fig. 7. The likelihood of short or nearly identical trips is higher during peak seasons, and the spread of distances is higher during off-peak seasons. This may be due to the sporadic, irregular nature of trips. The histogram of timber delivery distances for timber transportation in different months is presented in Fig. 8.

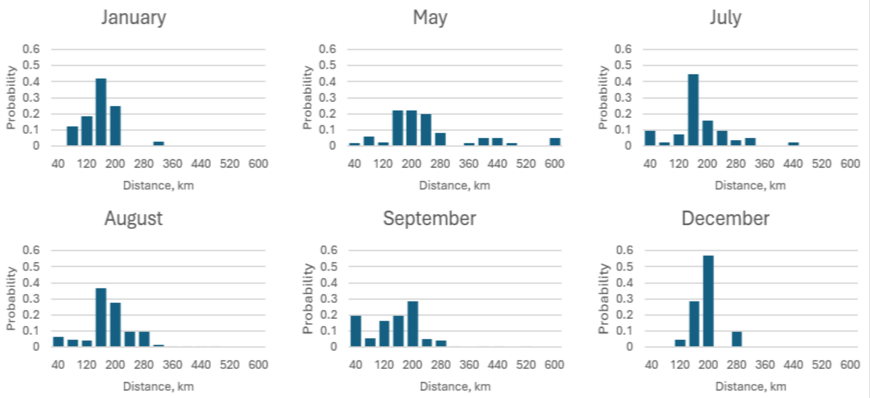

Figure 7. Histograms of delivery distances (in km) for agricultural products transportation in different months

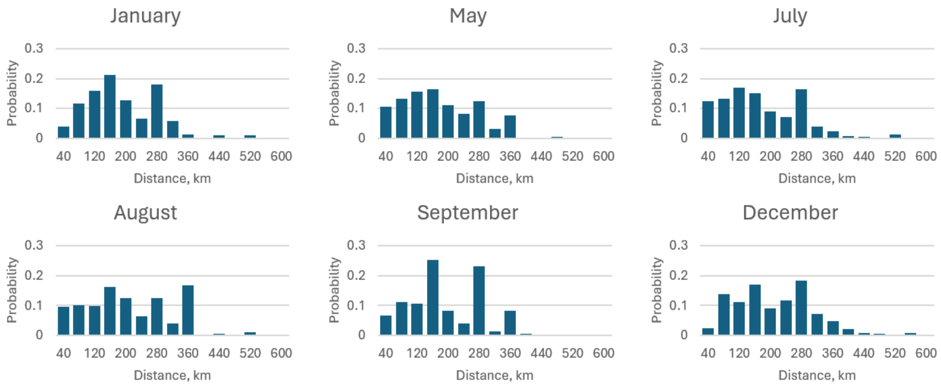

Figure 8. Histograms of delivery distances (in km) for forest products transportation in different months

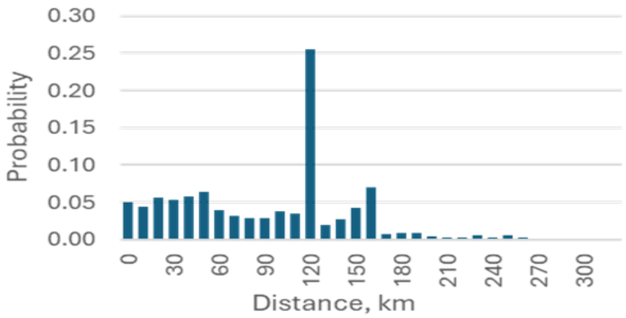

Figure 9. Histogram of length of loaded trips

In addition, a preliminary analysis of the data shows a rather complex nature of the empirical distributions of other random variables. For example, a fairly large portion of loaded trips have a length of about 120 km, and the possible distances of the remaining trips are evenly distributed over the range of possible values (see Fig. 9).

Among the different types of products analyzed in the life example by using traditional statistical techniques, the greatest dependence was found for grain.

Data-driven modeling. The seasonal factors influence the potential order volumes, distances and deliveries included in the model. At the stage of data-driven modeling using symbolic regression, various dependencies were obtained, such as the cost of the trip, the number of registered transport trips, the number of trips by product groups as well as the average volume of transported products in different months, etc. For example, the resulting symbolic regression model of the trip cost is presented by an analytical expression showing the dependence of this cost on the distances of travel with and without goods, as well as on the volume of transported goods, which turned out to be the most significant factors:

$$C_{trip} \approx 0.85\, d_{empty} + 1.69\, V - 14.58\, V_{veneer} + 0.89\, d_{load} + \\ + \frac{0.89\, d_{load} + 0.89\, d_{empty}}{1.59\, V} + 10, \tag{1}$$

where C_{trip} is the cost of the trip; d_{empty} and d_{load} – the distance of travel without and with transported timber, respectively; V is the volume of transported timber; V_{veneer} is the total volume of veneer blocks in the transported cargo. The formula (1) was obtained directly as a result of the analytical extract, encoded in a tree-like structure presented in Fig.3.

Similarly, mathematical expressions were obtained for various factors and parameters required for further development of the simulation models. In particular, to justify the calculation of the cost of a specialized semi-trailer in simulation experiments, based on the analysis of the collected data, the following model to estimate the provisional unit cost per km was obtained:

$$C_{dist} \approx \frac{2.092 \cdot d_{empty} + \log(115.2 \cdot d_{load} + 933.2 \cdot d_{empty})\,(0.149 \cdot V + 0.055 \cdot t_{load})}{1.7993 \cdot d_{load}} - \\ - \frac{1}{0.0172\, d_{load}^2} + \frac{1}{0.0142\, d_{load}^3} + 0.942, \tag{2}$$

where C_{dist} represent a unit cost in euros per km.

To assess the fitness of the obtained symbolic regression models, a cross-validation method was employed by splitting the data into a training (80%) and a testing (20%) subset. Accordingly, numerical accuracy metrics scores were estimated for each subset. E.g., for the data model expressed by equation (1) above, the following estimates were obtained: normalized root mean square error of 0.0229 and 0.0265, respectively; and Pearson coefficients (R2) of 0.973 and 0.977, respectively. Therefore, this model is considered reliable.

Setting up cooperative scenarios. The baseline scenario is one in which a small agricultural company is engaged in the transportation of agricultural products. It owns a certain number of trucks and semi-trailers, which are used for transportation purposes in certain months and employs a certain number of drivers. Key costs are estimated, including transportation, labor, and equipment maintenance.

This scenario is compared with new cooperative scenarios.

In the new scenario (called 'Scenario 1'), a company that primarily transports grain has one specialized semi-trailer that can be used to transport wood. This scenario was introduced to simulate the synergies of transporting products (i.e. grain and timber) from the two industrial sectors by a company and the impact on its performance.

In the following scenarios (called 'Scenario 2'), this company is primarily engaged in the transportation of grain. But it can use or share a certain number of semi-trailers (more than 1), either owned or rented, for the transportation of timber. The priority is the transportation of grain, but if the drivers are free and the specialized semi-trailers are idle, they are used to transport timber. In this scenario, different configurations of the enterprise's transport vehicles and drivers can be analyzed, taking into account the benefits of diversifying the transported products from the two sectors.

It should be noted that small agricultural companies typically employ as many drivers as trucks. Having more drivers than vehicles can result in unnecessary driver downtime.

Simulation-based analysis of cooperative scenarios. The results of the stochastic simulation by month during the year for the baseline and cooperative scenarios for the agricultural company are presented in Fig. 10. In particular, the figure presents the results for the cases with 1 and 3 drivers (and trucks, respectively) and different configurations of agricultural and forestry semi-trailers, simulated over the year. Fig. 10a shows the results of the simulation experiments for the case of one driver, one truck, one agricultural trailer and one forestry trailer. Fig. 10b shows the results for three drivers, three trucks, three agricultural trailers and one forestry trailer. In Fig. 10a and 10b, the dark green line represents the utilization rate of agricultural trailers, whereas the light blue line represents the utilization rate of forestry trailers and the brown line the utilization rate of trucks (and drivers). Note that in the baseline scenario, where the company is only engaged in the transportation of agricultural products and does not have a specialized semi-trailer for transporting timber, the loading of trucks, as well as drivers, will correspond to the dark green lines. Finally, the results of the simulation experiments comparing different transportation scenarios over the year are summarized in Table 1.

In scenario 1, the average utilization rates of trucks and specialized semi-trailers for timber transportation increase significantly compared to the baseline scenario, reaching values of 0.47 (up from 0.23) and 0.72 (up from 0.00), respectively. The highest average utilization rate can be achieved in a configuration of six semi-trailers. It will provide the greatest diversification of deliveries. But it will also be the most expensive configuration in terms of both fixed and operating costs. Thus, assuming that the company can operate in accordance with the demand model obtained from the analyzed data, the provision of timber transportation with just one semi-trailer will already significantly improve the use of the company's resources.

(a) (b)

Figure 10. Utilization rates of different vehicles with 1 (a), with 3 drivers (b), simulated over a year

Table 1. Results of simulation experiments for the baseline and cooperative scenarios

Number of semi-trailers		Trips per year		Total distance in thousands km per year		Average vehicle utilization rate		
Agriculture	Forestry	Agriculture	Forestry	Agriculture	Forestry	Trucks	Agriculture semi-trailers	Forestry semi-trailers
Baseline Scenario								
3	0	173	0	28.7	0	0.23	0.23	0.00
Scenario 1								
3	1	173	176	28.7	30.2	0.47	0.23	0.72
Scenario 2								
3	2	173	348	28.7	60	0.70	0.23	0.71
3	3	173	439	28.7	75.7	0.83	0.23	0.60
2	3	115	485	19.1	83.9	0.81	0.23	0.66

Furthermore, maximum resource utilization throughout the year can be achieved by having a diversified access to both agricultural and forestry transport (as described in different possibilities of scenario 2). This means that if a transport company is primarily engaged in the transportation of agricultural products, then by diversifying the types of goods transported with forest products, the existing and shared transportation resources (and the corresponding drivers) will be provided with additional work, even outside the harvest season. Indeed, the average vehicle transportation load for trucks and forestry semi-trucks increases in the simulation model for each of the studied numbers of semi-trucks used for transporting agricultural and forest products. However, assessing the cost-effectiveness of using additional vehicles requires a more complete examination of the model's input data for individual item costs, as well as clarification of fixed and variable costs for different trailer categories.

5. Conclusions

Modern digital platforms and modern computing techniques are radically transforming the business models of small and medium-sized businesses and changing the relationships between them. One of the new opportunities that can be considered is intersectoral and intercompany cooperation.

At the same time, modern digital technologies provide opportunities for the accumulation of large volumes of data. These data are widely used to extract useful information and understand the cause-and-effect relationships in the behavior of a real system. The latter enables the implementation of data-driven approaches to support decision making, amongst others in transportation management.

This article proposes a new integrated research framework and methodology for data-driven modeling and simulation in transportation management through cross-sectoral collaboration. It is designed to improve the planning and organization of transportation of agricultural and forest products by small agricultural and forestry businesses. The presented study is based on a real life case of synergy in the transportation of products in two sectors - agriculture and forestry. The benefit for participants in both economic sectors is to ensure a more efficient use of their transport and labor resources (in particular, vehicle drivers) by using the opportunities of intersectoral cooperation and emergent data driven-modeling and simulation technologies. The synergy effect is demonstrated through simulation-based analysis of cooperative scenarios between involved participants.

The proposed methodology offers a combination of methods and tools for web data management, data mining using powerful machine learning methods, system dynamics modeling, stochastic discrete-event simulation and a multi-user web environment. Data-driven models such as symbolic regression are used to identify patterns in data and translate the underlying relationships into the modeling formalisms needed to build computer simulation models. The system dynamics model is coupled with an economic model to assess the economic viability of potential cooperative scenarios and transport solutions. The discrete-event simulation model provides virtual simulation of real processes of transportation of agricultural and forest products, taking into account random factors and events that influence the implementation of these scenarios, as well as their assessment using operational performance indicators.

In the article, the life example is given for a small agricultural company that owns its own fleet of vehicles and thus has its starting point in the industries that have a need for transportation and are creatively looking for cross-sectoral collaboration. But the advantages of such inter-sector synergy may also be explored by small businesses in the transportation industry or third-party logistics companies that provide transportation of a wide range of goods. The proposed work may also be useful for researchers working in the field of data-driven modeling and simulation. Future research will also explore the potential for wider use of artificial intelligence and blockchain technologies to improve transport management in agriculture and forestry for small businesses, such as collecting, storing and analyzing data on handling conditions during transportation (e.g. temperature control, storage conditions) and ensuring that transported products meet required standards.

Finally, data-driven simulation, which is based on the integration of various data models, supplemented by computational intelligence and machine learning methods, can certainly be regarded as a new trend in the development of computer modeling technologies.

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