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An agent-based simulation and logistics optimization model for managing uncertain demand in forest supply chains

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ABSTRACT

This paper aims to model and minimize transportation costs in collecting tree logs from several regions and delivering them to the nearest collection point. This paper presents agent-based modeling (ABM) that comprehensively encompasses the key elements of the pickup and delivery supply chain model and presents the units as autonomous agents communicating. The modeling combines components such as geographic information systems (GIS) routing, potential facility locations, random tree log pickup locations, fleet sizing, trip distance, and truck and train transportation. ABM models the entire pickup and delivery operation, and modeling outcomes are presented by time series charts such as the number of trucks in use, facilities inventory, and travel distance. In addition, various simulation scenarios are used to investigate potential facility locations and truck numbers and determine the optimal facility location and fleet size.

1. Introduction

Agent-based modeling (ABM) is a simulation technique which enables modelling of various configurations and environments related to operations. The approach can be combined with geographic information systems (GIS) and various sources of external data. This paper presents a real study in forest supply chain for decision support for tactical decisions related to wood collection point related facility locations, the number of trucks needed and comparing the scenarios with key performance indicators. Agent-based modelling approach has shown applicability in solving complex problems, such as testing resiliency in supply chains [28], modelling disruptions in supply chains [48,20].

The designing task of supply chain structure and operations typically combines several questions and needs to be flexible to answer various questions. The problem presented in this paper is related to collection of woods from forest and then firstly determining suitable collection points for long haul transportation. The first part of the collection from the harvesting sites to the collection points have cost and time parameters related to fleet. The second part, the long-haul transportation from collection point to factory has its own cost and time related parameters. The process behind defining the best alternatives for collection points is based on total cost minimization. Geographical information systems can provide geospatial information and estimate of timber availability for each area. The parameters may include uncertainty in terms of distribution of supply. One of the significant challenges for companies is to choose the location of wood collection related facilities to minimize the total cost of fulfilling demands for products. There are fixed costs for locating facilities and logistic costs for distributing between facilities and demand points. The demand from the factory side may have variability which is seen as demand uncertainty in the supply chain side. Once the collection points are defined, the number of trucks in the fleet can be defined and their daily operation schedule should be estimated.

Fleet management and facility location are critical disciplines in supply chain management and logistics, and they can lead to economic benefits and higher customer service quality for companies. Selecting the best approach to resolve facility locations and fleet management in forest supply chains can be a challenging task for companies. There are mathematical algorithms to set and optimize the solution for these problems. On the other hand, simulation approaches are more flexible and pragmatic modelling methods, particularly in supply chain problems.

This paper addresses the research gap on combining simulation-based approach with optimization to solve a set of inter-coupled logistics decision making problems. The research problem of this paper is to demonstrate how a simulation model can combine multiple concepts such as facility locations, vehicle routing, policies assignment, fleet sizing and inventory management into a single model, and how to provide this operational information to managers by using agent-based

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approach. The problem is based on a real case, where decision makers have estimates for the future demand flows and patterns, cost parameters and seek for two alternative scenarios either direct collection from forest to factory by using trucks or multi-modal transportation using train. For both scenarios, the solution should have a proposed setup of collection areas and fleet size operational estimates.

The remainder of this paper is as follows. The literature review section presents prior works related to wood and related biomass supply chains with the focus of fleet optimization, inventory routing problem, pickup and delivery problem, and transportation dispatching methods are reviewed. The problem description and solution approach are discussed in materials and methods. The results are presented in the following section. Finally, the research discussion and conclusion are explained in end.

2. Literature review

In the past, various decision support systems have been proposed for tactical logistics planning in the bioeconomy related supply chains. These problems are generally similar to log collection, which is the scope of this paper. The prior works show that similar kind of problems have been solved by using various modelling methods, which have basis in operations research and operations management. Mobtaker et al. [32] reviewed studies from the past years, and use of mathematical optimization modelling and found recent focus areas on recycling logistics e.g. waste paper, integrated value chains from forest biomass to sawmills. Mobtaker et al. [32] suggest building new type of decision support systems combining approaches from forestry, management science, industrial engineering, computer science and graphics and social science experts. The following section analyses some optimization approaches related to biomass supply chains, related problems and approaches to solve the problems.

2.1. Optimization in biomass related supply chains

Mathematical optimization has been used in several earlier studies in biomass supply chains, which is a closely related application area of this paper. Logs are collected from forest employing possibly several types of transportation methods, biomass applications have similar properties, for example in case of woodchips, tree stumps or other by-products. Melchiori et al. [31] proposed a model combining the scheduling and routing problems of logging trucks. This approach used mixed integer linear programming. Very often the problems become complex and metaheuristic is used to solve the problem. For example, She et al. [39] presented a cost and emission based optimization model of forest supply chain and compared mixed integer programming with metaheuristics solver. The results showed the efficiency and simplicity of modelling. Ahmadvand et al. [1] presented a cost minimization problem of biomass stocks in the supply chain. Complexity of real-life decentralized planning has been recognized by Ghasemi et al. [13]. Integrations may have variabilities and be temporal during the planning periods. The paper by Ghasemi et al.[13] presented a real life case of wood company and presented an optimization based solution, which can be generate a solution within a reasonable time period. Babaeinesami et al. [2] used genetic algorithm to solve closed loop supply chain problems considering the environmental effects. This approach showed a practical approach to finding suitable solutions in fast time.

The forest-based supply chain encompasses a temporal series of spatially referenced activities from the forest to the customer, transforming the woody raw materials to forest-based products. Researchers have proposed various approaches to optimize the forest supply chain design and its key elements; Karttunen et al. [19] investigated the profitability and competitiveness of intermodal container supply chain compared to multimodal one in long-distance transportation of forest chips by rail and trucks. Availability analysis and agent-based simulation methods were utilized to estimate and compare logistics costs in different scenarios. Correll et al. [8] applied a simulation approach and metaheuristic optimization to re-design the forest supply chain by adding multiple crops to save in logistics and inventory costs. Another multimodal problem was presented by Zhang, Johnson, and Wang [47] employed an integrated multistage, mixed integer programming model to manage multimodal logistics, truck and train, for a forest biofuel supply chain. The model objective is set to minimize the total cost including infrastructure, transportation, feedstock procurement harvest, storage and process. Also Gautam, LeBel, and Carle [11] assessed the benefits of incorporating a terminal to overcome the forest supply chain challenge of delivering high-quality feedstock. The mixed-integer programming model was utilized to quantify the benefits, integrating information on biomass quality, harvest schedule, and seasonality in supply and demand.

There is a need for various types of optimization problems and specific types of wood, biomass or impacts on wider bio-economy. Agent based models have been also proposed to solve forest related problems. Holzfeind et al. [18] studied cable yarding and transport supply chain by building an ABM model. According to this study, agent-based techniques enable testing various real-life configurations in an efficient way. Simulation and optimization are not excluding each other.

In addition to using cost minimization type of objective functions, also environmental parameters such as greenhouse gas emissions have become part of the problems. According to Gazran et al. [12] fuel is still the top priority of objective functions and other approaches such as greenhouse gas emissions and platoon formations are still novel concepts. Basile et al. [4] analysed biofuel production supply chain and introduced greenhouse gases as part of the objective set in addition to traditional cost related objectives. Dashtpeyma and Ghodsi [9] introduced resilience need for the supply chains in case of shocks in demand and supply. Lo et al. [27] also pointed out the need to include uncertainty parameters such as biomass attainability, price fluctuations in the market and demand variability.

2.2. Fleet size related approaches

Forest supply chains have various types of tactical and operational decisions which organizations need to make on weekly or daily basis. Definition of fleet size has been typically part of the problems. Determining the fleet number in supply chains also has been vastly studied in the literature. Golden et al. [14] explicated the fleet sizing term, developed several classes of vehicles and revised the Clarke-Wright savings approach to resolve a fleet sizing problem. Ball et al. [3], one of the first authors who discerned the fleet sizing problem from conventional vehicle route planning, employed route first, cluster-second method and a greedy insertion heuristic to determine the fleet number. Klincewicz, Luss, and Pilcher [22] developed a mathematical model to determine the fleet size in a problem that a warehouse fulfills customers' demands by a combination of private delivery fleet and outside carrier service. A "single-source capacitated facility location formulation" is utilized as a solution approach in which each vehicle is considered as a facility to serve several customers. Wu, Hartman, and Wilson [45] utilized mathematical modelling to determine the number of a rental fleet with different trucks in age and types. In phase one of the solution, customer demands were assigned to available trucks, and in phase two, the solution was enhanced by Lagrangian relaxation. Diana, Dessouky, and Xia [10] set the optimal fleet size with continuous approximation approaches for many-to-many demand-responsive transit services with maximum detours. Klosterhalfen, Kallrath, and Fischer [23] proposed a mixed-integer linear programming model to determine the optimal size of rail cars by employing approximation from inventory theory.

On the other hand, simulation modelling has been considered as an established method to perceive complicated dynamics in the supply chain and logistics system [29,43,15]. Discrete-event-simulation was used by Lesyna [25] to optimize the rail car fleet for product delivery to end customers. Shi et al. [40] utilized the simulation approach to model the process of collecting products and delivering them to distribution centers. The sequential bifurcation was used to define the most important factors on cycle time and throughput such as truck number, loading and unloading time. In the post-screening phase, the response surface methodology is employed to determine the optimal level of key performance indicators. Sha and Srinivasan [38] applied an agent-based simulation approach to determine the fleet size in a multisite chemical supply chain. Autonomous decision-making of each agent, replenishment planning, and order assignment were considered in the simulation modeling. Sakai et al. [37] proposed a new agent-based modeling system for urban freight simulations in SimMobility which utilizes inputs such as establishment and vehicle population, without relying on economic data such as make-use and input-output tables, and predicts commodity flows, vehicle operations, and traffic conditions. As SimMobility Freight due to the agent-based structure is a fully disaggregate model, it allows assessing the operational efficiency at the most disaggregate level such as individual establishments, commodity contracts, shipments, and goods vehicles. Sakai et al. [37] applied the agent-based modeling system for policy analysis, which underlines the practicality of the framework.

2.3. Routing and inventory related approaches

For the forest related supply chains, inventory levels are important to ensure that downstream of the supply chain will have a continuous stream of materials. Routing related problems are often related to the concept. The literature on these problems is generic and non-industry specific. Advances in communication technologies such as Geographic information systems and satellite-based positioning systems has contributed to resolving dynamic vehicle routing problem, which is the generic basis of combining spatial map data with an optimization engine.

The systemic direction of the supply chain suggests that when broader supply chain components are involved in the modelling and optimization, the more efficient solution for problems can be determined. For instance, the location-routing problem which optimizes the location and routing; vehicle routing problem which identifies the routes of vehicles and considers given locations, time windows and customers demand; vendor managed inventory concept in which a supplier distributes the products and controls the customers' inventory, is an example of the integrated management style of supply chains [5, 42].

The generic problems related to this study may be also related to integration of routing problems to inventory levels [34]. This type of studies combine typically the fleet sizing and coordination of routes frequencies into the same optimization problem. Sometimes a cost minimization approach is presented (e.g. [44], or alternatively the objective is on minimizing the fleet size required to make strictly periodic, single destinations deliveries to a set of customers under the assumption that each vehicle can carry out one trip a day Campbell and Hardin [7] Transportation fleet collection from locations of origins and delivering them to destinations without any transshipment including time and vehicle constraints is another type of related combined problem [26].

2.4. Geographical information systems

Including geographical characteristics in the decision making has been also in the research agenda. Tahvanainen and Anttila [41] proposed a GIS-based model to estimates the cost of ten different forest supply chains and developed an additional eleven modified supply chains for sensitivity analysis. The cost calculation modelling was split into distance-dependent and distance-independent cost factors. Similarly, Kinoshita et al. [21] conducted a spatial evaluation of forest biomass usage applying a geographical information system(GIS). Operational costs for various stands were estimated using GIS and paired with the total demand of the subject region. Laasasenaho et al. [24] applied road-network-based route optimization, hierarchical clustering, location optimization and kernel density estimation to identify bioenergy production sites and to further optimize wood terminal locations. The location optimization tool of R software logistically determined feasible sets of farms and other biomass source locations for future biogas production. In addition, the kernel density tool in the ArcGIS software located the densest forest biomasses near road networks for future wood terminals. Yu et al. [46] proposed a new site selection approach with GIS modelling and road delivery method for biomass supply chain and developed an additional mathematical model with straight-line delivery. The combination of the models increased optimization performance. Embedding real maps of raw materials, terrain data, possible roads, transportation routes or any other geospatial information can bring a useful and practical set of input data for the decision support.

2.5. Synthesis from literature

The literature analysis shows that biomass related supply chains are complex and integrated approaches combining the harvesting, collection, transportations and various steps of production present need for solving several intercoupled problems. The problem of this paper related to organization of log collection shares similarities of other biomass collection papers presented in the literature. Various studies on specific product and context related problems have been presented in the literature. Geographical information systems and real time feedback from positioning systems give feedback for planners in a visual context. The literature also shows the importance of environmental aspects in combination with traditional cost and time related objectives. Solving complex problems require new types of computational approaches such as metaheuristic approaches including genetic algorithms. Also, Industry 4.0 and other digital technologies are expected have an impact on the wood supply chain [33]. Based on this we believe that an agent-based modelling approach can help to create models of complex and dynamic scenarios and combined with approaches presented in the existing literature.

3. Material and methods

This paper presents an agent-based modelling approach and applies the solution method to the case company data. The case company performs tree log pickup and delivery operations within different regions in Finland. Each region has certain amount of log products available, which need to be transported according to the need of the factory. This is modelled by using agent based modelling, more specific AnyLogic PLE simulation software, and combined with geographical information for each region.

Agent based modelling is an efficient approach when various participants are acting independently, interacting with each other, and responding to system alteration collectively [16,17]. In addition, when the total activity of system participants is nonlinear and is not derived from the aggregation of each entity behavior, ABM can be utilized as a concrete modelling method. Agent-based models are developed with entities, called Agents, which interact within an environment. Agents are independent and live in an environment in which communicate with other agents and they can make decisions and have goals to achieve considering their behavior. Each agent in the system behaves as an intelligent entity that has its interests and conditions and can make decisions based on a set of rules. Additionally, the agent behavior can diverge from primitive reactive decision rules to complex adaptive artificial intelligence. [6,30,36].

The justification for using simulation-based approach is the flexibility it can bring for the modelling. Complex non-linear and dynamic behavior can be introduced for agents. Geographical features can be

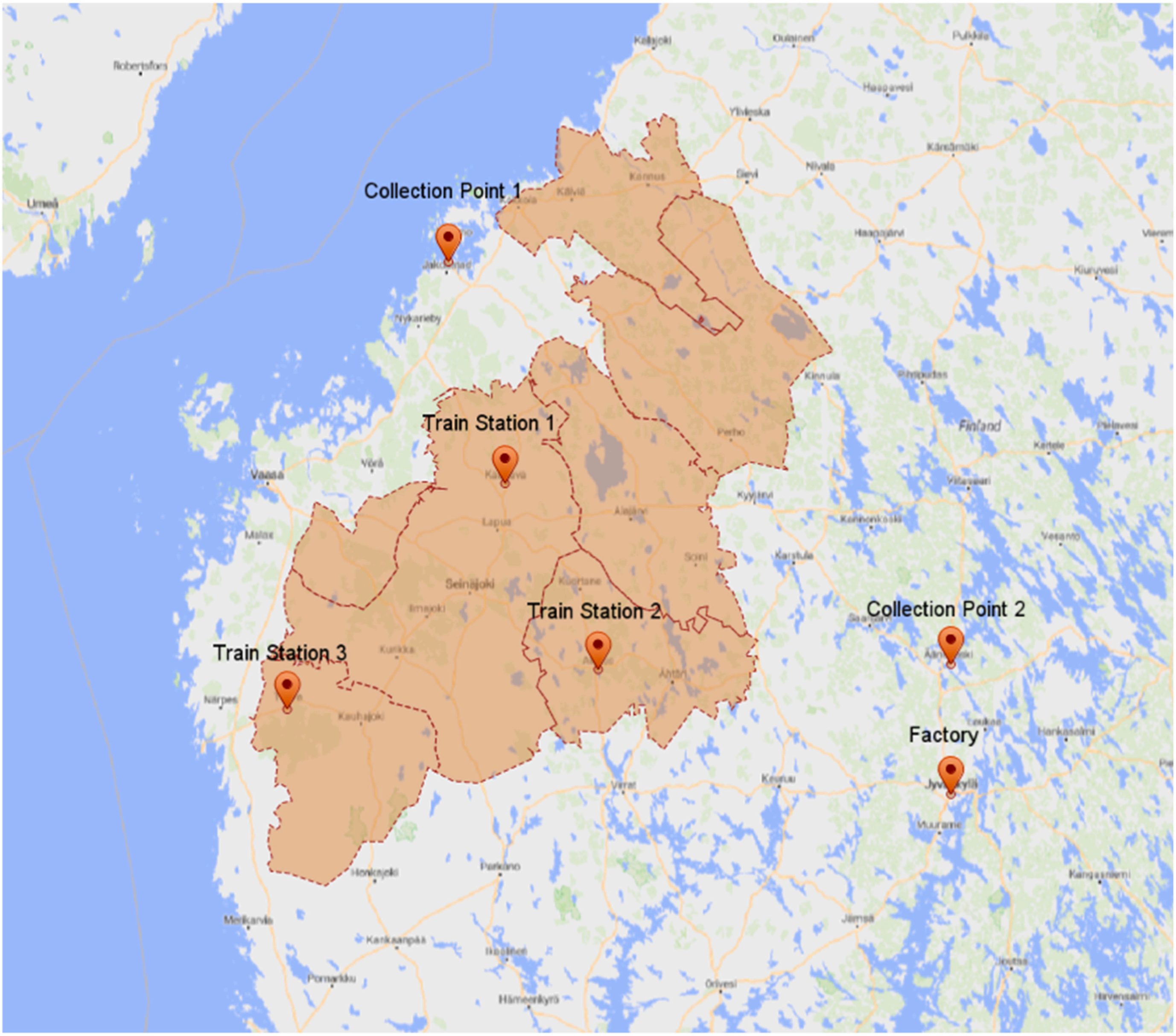

Fig. 1. A sample of potential wood collection point facilities location in the map.

embedded by using maps. Cost and time related indicators can be linked on an agent level such as a single transportation truck, on collection regions or as system level indicators. Simulation can also provide visualizations, which are useful when building the model and communicating with the end-users and other decision makers.

The research problem of this paper combines several aspects into a simulation model. Two scenarios are outlined as it is not obvious if using train connection makes sense in all cases or if direct transportation structure would yield a better solution. These scenarios were outlined together with the industrial partner for decision support. Comparison of direct transportation model with multi-modal was one of the important things to be analyzed in a new situation where a new factory location with higher demand was introduced and the flows would change. Also, the potential wood collection points was a new information received from a survey and actual implementation and decision of construction needed to be based on simulated analysis.

In the first step, we analyze the potential wood collection points on the map for direct transportation. In the first scenario, we expect the solution to have two potential collection points to which logs are delivered from seven regions from which logs are harvested. Tree locations (the supply) are dispersed within each region, therefore, there is no predefined point of pick up but the average number of pickups per day for each region is provided by the case company. The transportation trucks are located at collection points. Each region has a required number of pickups for each day. Based on this input, the optimization assigns a random geographical location point of tree logs is sent to the nearest factory based on driving routes. If available, a truck will be sent to the tree log location to load and transport the trees to the collection locations. The total costs are calculated and alternative locations are evaluated until the solution shows the desired level of total pickup costs. By using this process the locations of collection point facilities are determined and the truck agent assigned for their tasks. Additionally, in scenario one, logs are delivered from two collection points to the factory by using train transportation in combination with trucks. To evaluate and minimize the transportation cost, three types of costs are considered: truck fixed cost calculated based on the number of trucks assigned to each location, train trip costs and truck distance cost calculated from the total driving distance in kilometers between tree collection points

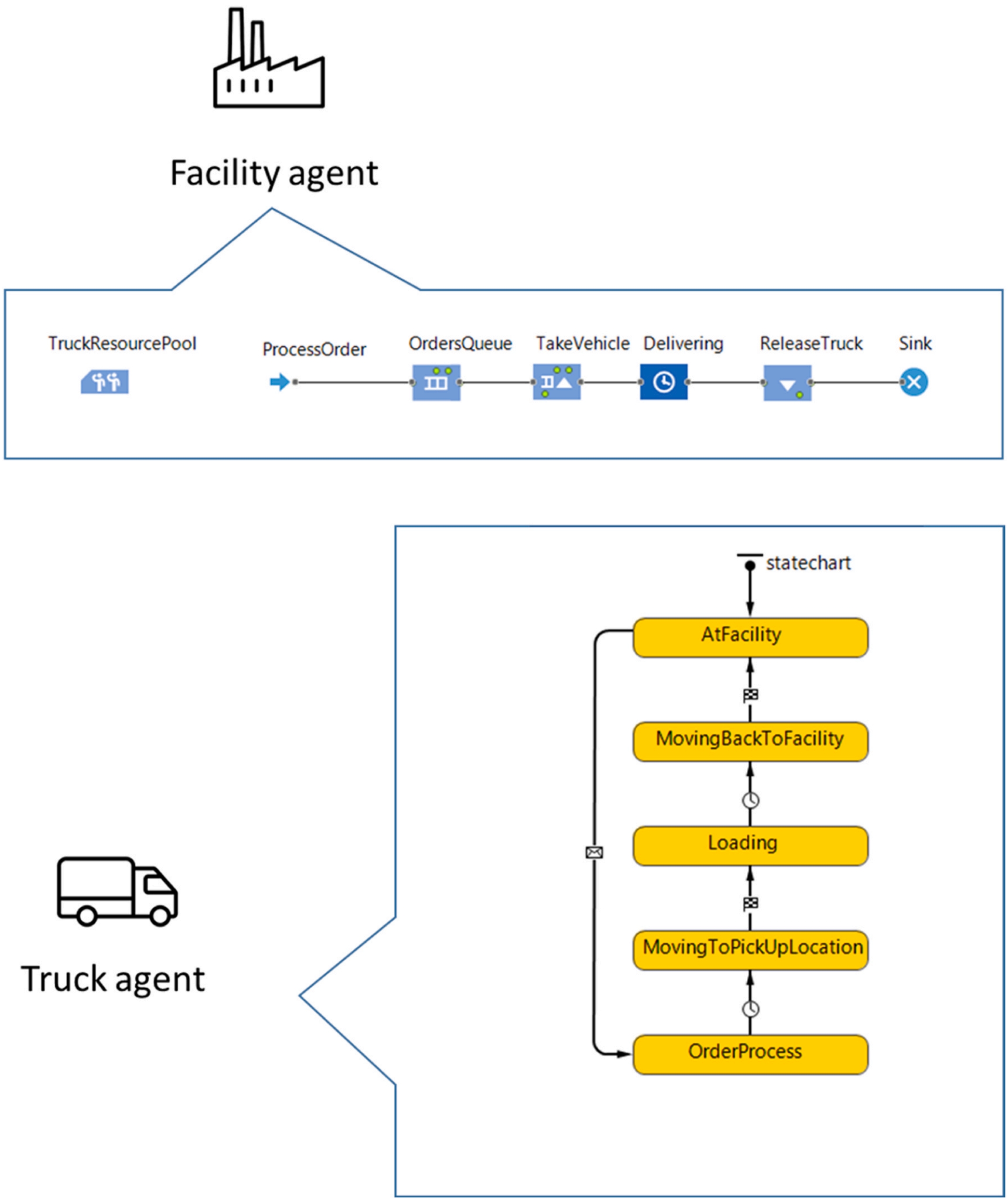

Fig. 2. Facility agent and truck agent simulation blocks in agent based modelling.

and facilities.

In the second scenario of modelling, we expect to have three train stations to which trucks deliver the logs from regions and try to define an optimal location for each of these. In addition, the factory receives the logs from three train stations by rail transportation or directly from regions by trucks. The other parameters of the second scenario are as same as the first one. The purpose of the modelling is to determine the minimum transportation cost for each scenario and evaluate how the selection of facility location impacts the logistics expense. Fig. 1 presents the potential facility locations, regions and the main factory location for both scenarios.

In addition, the availability of public geographical information such as maps, geotagged location data and population information has created new opportunities for researchers to model and visualize data. Geographical information system (GIS) has been immensely utilized in various scopes such as analyzing the client's location, allocating resources to regions to fulfill the customer demand and assessing logistics performance and trip costs. For instance, OpenStreetMap (OSM) data source, retrieving information such as route types, directions, speed limits and distances can be employed for logistics analysis. [35].

Collection points for tree log delivery are represented as Facility agents and are located on particular points through the GIS map. Seven instances of Region agents are generated to represent each particular region. The region agent consists of a Shape parameter storing the region name, a Center parameter presenting the assigned facility agent to link the collection point and the region. Each region agent also stores an

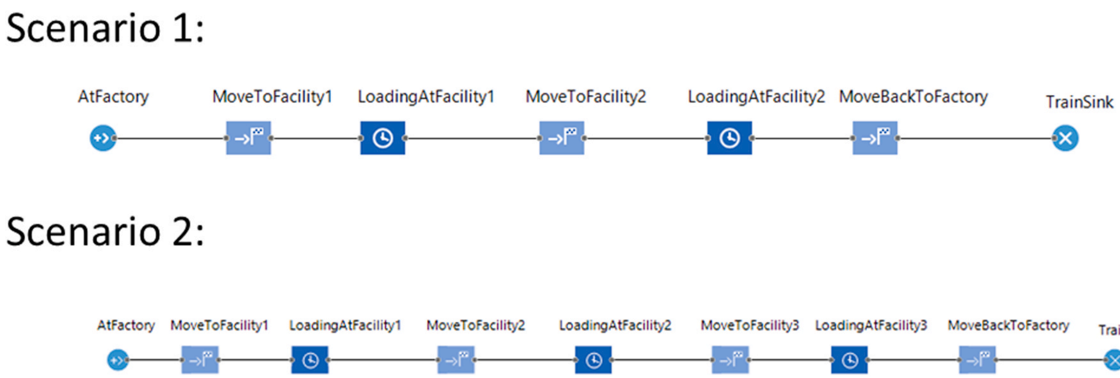

Fig. 3. Scenario 1 and scenario 2 - Train transportation simulation blocks.

Event object scheduling the Order agent creation time. Each of the Event object generates an Order agent based on the number of pickups per day for each region. The Order agent contains the TreeLocation parameter which stores pickup point geographical information. When the Event object creates an Order agent, a random point within the specific region is assigned to the TreeLocation parameter of the Order agent. The random point generation method is utilized since the location of tree logs for pickup is arbitrary within every region. The assigning policy of orders to facilities and trucks is based on the nearest neighborhood, each order links to closes collection point facility based on distance. According to the geographical location of facilities and orders, the GIS map utilizing the most recent routing information determines the closest facility to the order by computing route distances between two agents. Then the order agent is dispatched to the facility.

The facility agent modelling is generated by discrete event simulation, Fig. 2. Orders received by the ProcessOrder block are placed in

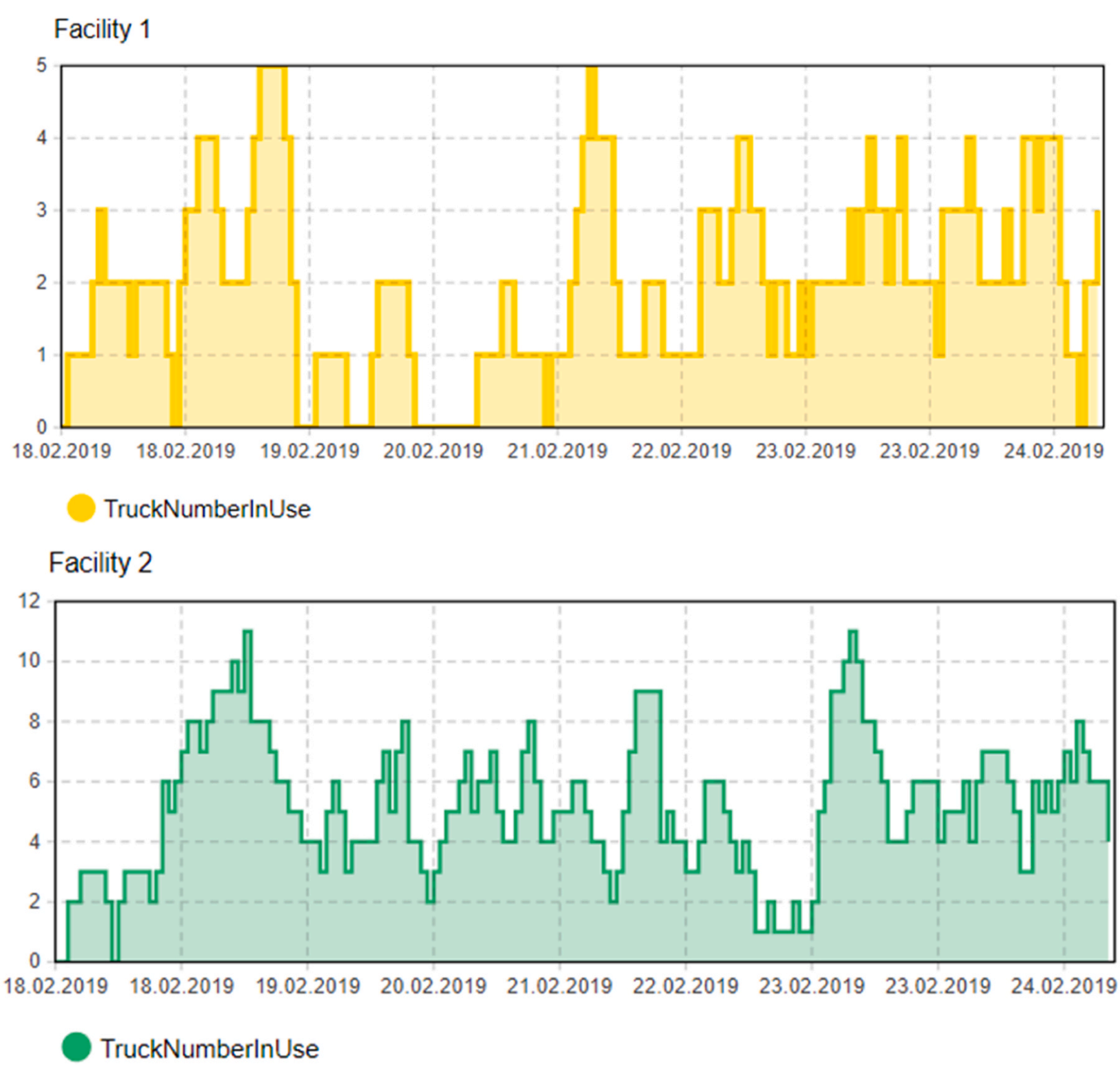

Fig. 4. Number of trucks in use for two collection point areas at each time of the day and week.

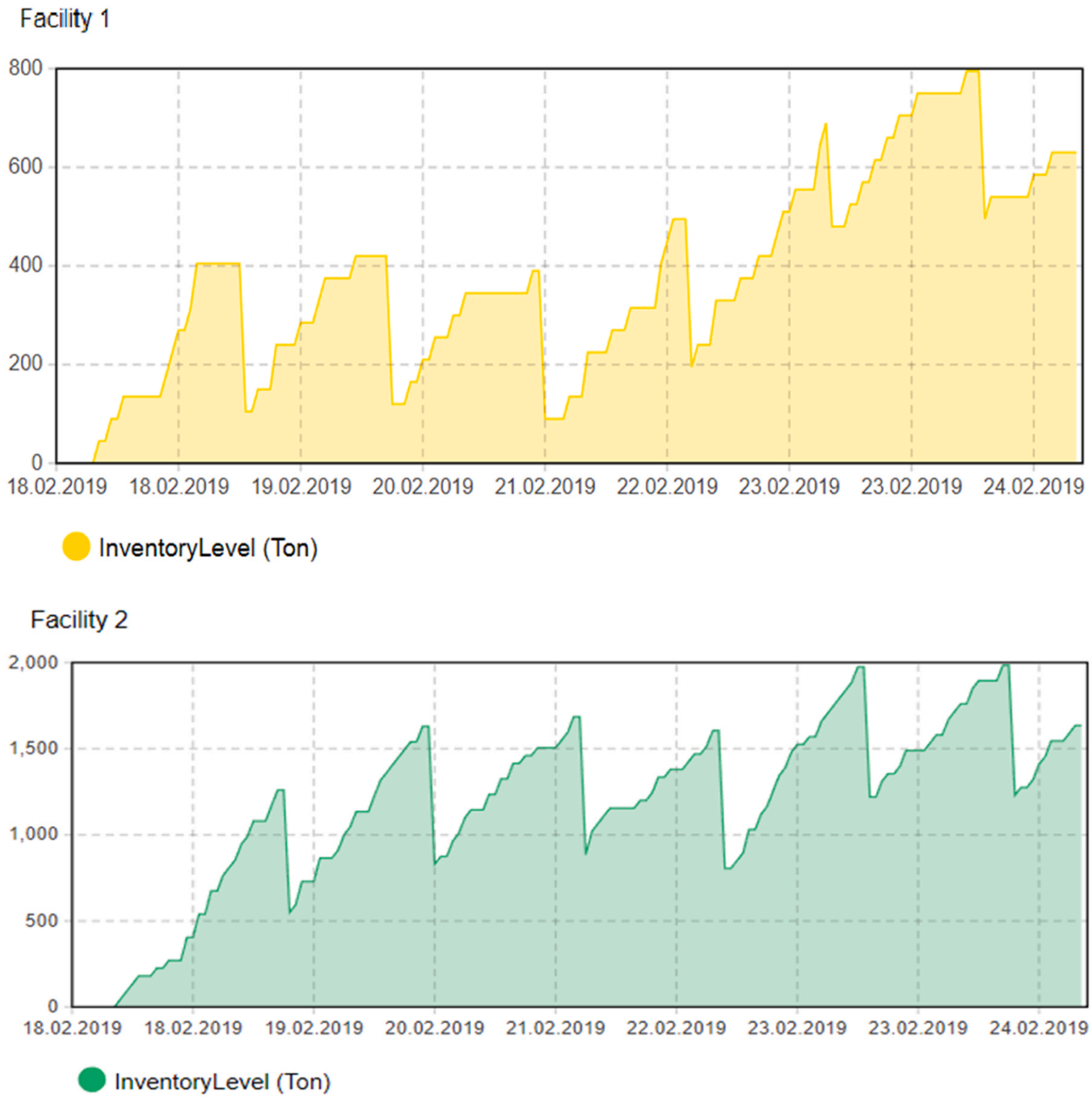

Fig. 5. Inventory level (tons) at collection point facilities at each period of time.

OrdersQueue which proceeds orders based on the first-in-first-out (FIFO) policy. The TakeVehicle block seizes one truck from the Truck-Resurce pool which stores the total trucks number and links simulation blocks to the Truck agent. If there is a truck available for transportation, the TakeVehicle block transfers the Order agent to the Truck agent.

Trucks are stationed originally at the location of facilities. When an Order agent is received, the OrderProcess stage begins and sends the truck to the Order agent location or the pickup point. The routing method options can be selected as shortest which determines the route between two points with minimum distance or as fastest which pinpoints the route with the least travel time. In this paper, the shortest routing method is selected and the GIS map retrieving the most updated route and traffic data is utilized to identify the driving route.

When the truck arrives at the pickup point, the process of loading tree logs is performed. The loading time is defined based on a probability distribution computed from the case company's raw data. In the next step, the truck moves back to the original facility location to deliver the tree logs, and the truck agent transfers the Order agent to the Delivering block of the Facility agent. The Delivering block transmits the Order agent to the Release block which makes the truck available for the next trips. Since the tree log delivery for a particular pickup location is completed at this stage, the order agent instance is removed with the Sink block.

Tree logs are also required to be collected from facility locations and delivered to the factory. The train transportation process is modelled by discrete event simulation, Fig. 3.

Train trips are performed once a day from the factory to facility locations and completed with a return to the factory. Trains, similar to trucks, take the real-world railroads by using the GIS map. The tree logs inventory at facilities and factory with every loading and unloading is updated.

Since there are dynamic factors such as tree log pick up location, pick up time in a day, routing and trip time, a transportation cost modelling and optimization method are utilized to minimize the logistics cost according to facility locations and the number of trucks in each scenario. Total driving distance is calculated for each truck simulation round (Eq. 1). For this study the model cost parameters were estimated for the train transportation to be in line by study Tahvanainen and Anttila [41]. (Eq. 2) and coded into the agent. The train trip cost is estimated based on an average of five wagons and the distance parameter is computed by GIS railway routing between the train stations and factory. Total cost (Eq. 3) is the sum of all transportation including both trucks and trains from the

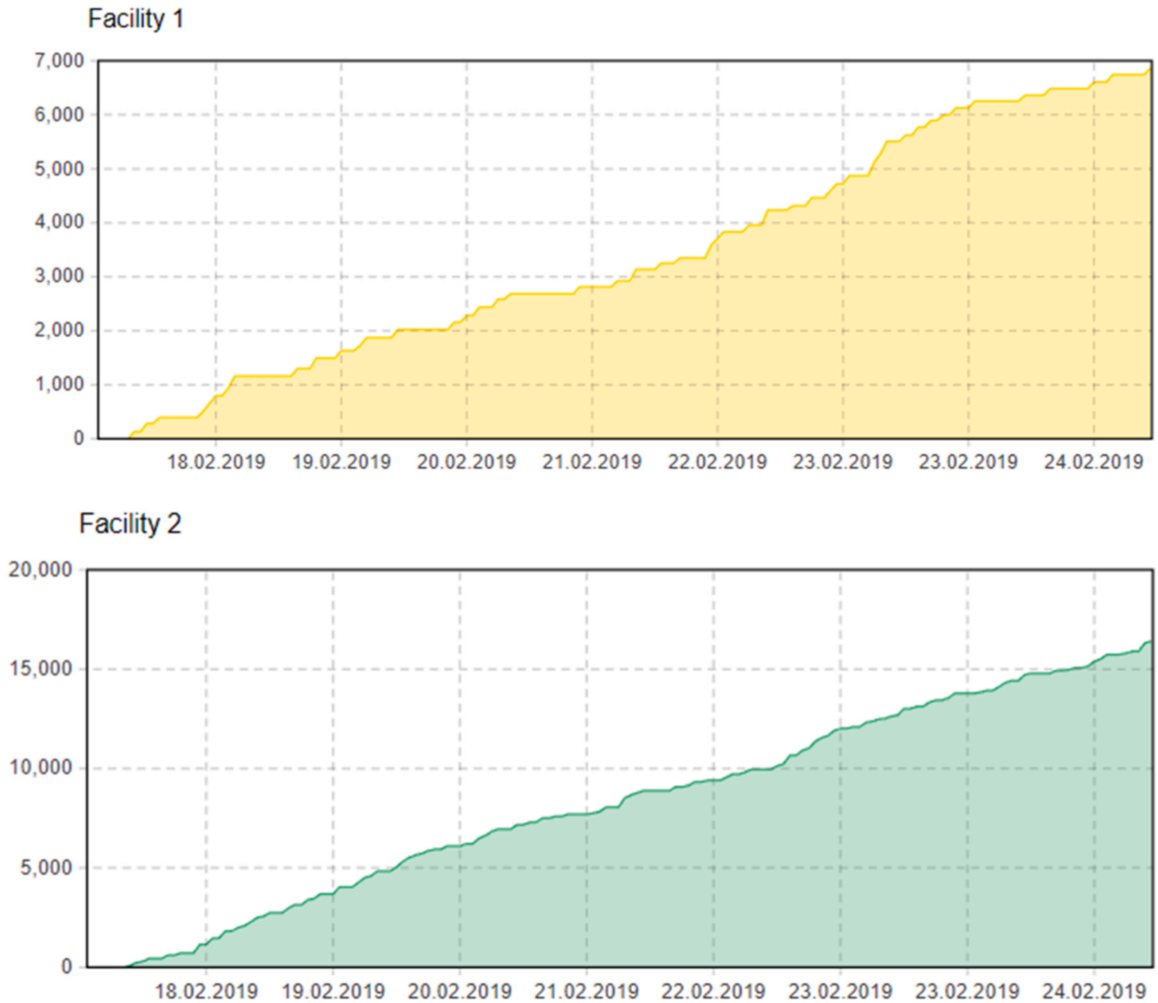

Fig. 6. The total travel distance (km) cumulatively for both collection areas.

collection point facility. The problem constraint is deemed as the average time between a tree log pick-up request and truck assignment should be less than time period of sixty minutes, Eq. (4). The objective function is to minimize the total cost subject to time requirement.

$$TD = \sum Kij \tag{1}$$

$$TW = 160 + 0{\cdot}89 \times DW \tag{2}$$

$$TC = (FC \times NT) + (DC \times TD) + RC \tag{3}$$

$$\sum (TPkj - TAkj) / TN <= 60 \tag{4}$$

where.
TCTotal transportation cost (Euro).
TDTotal truck driven distance in kilometer within a time period.
TWTrain cost per wagon (Euro).
FCTruck fixed cost (Euro).
NTNumber of trucks assigned to a facility.
DCTruck driving cost per kilometer (Euro).
RCTrain transportation cost of five wagons (Euro).
KijDriving distance between facility i and tree pickup location j.
TPkjPickup request time for pickup request k and tree log location j.
TAkjFleet assignment time to pickup request k at location j.
TNTotal number of trips in each simulation run.
DWTotal train driven distance in kilometers.

The optimization problem is then solved by using AnyLogic optimization engine, which is using metaheuristic search to find a suitable configuration solution for collection point facility locations which then would determine the number of transportation fleet required. Metaheuristic approach does not guarantee an optimal solution but in time less than a minute a suitable solution can be achieved with a sample data.

4. Results

The truck number is a major factor in transportation costs. In this paper, the truck number transporting tree logs is presented by a chart (Fig. 4). In addition, the number of trucks is illustrated based on weekdays and separated by each collection point facility. This detailed information assists managers to plan comprehensively for the company's logistics operation. The charts below represent only scenario one execution, but the same indicators exist for scenario two.

Inventory level is another key performance indicator to evaluate the process efficiency, inventory cost or storage restrictions. When the pickup and delivery processes to a facility are completed, the inventory level is updated instantly (Fig. 5). Additionally, when the train transports logs from facilities and delivers them to the factory, the inventory levels at facilities are deducted. The fluctuation of inventory level is driven by operating schedules of trucks and trains.

Travel distance is another substantial factor in transportation costs. Therefore, the total cumulative kilometer driven for each facility based on real-world routes is computed and presented by a chart on a daily basis (Fig. 6).

The location of facilities and the number of fleet units allocated to each facility have a significant impact on the logistics costs. The number

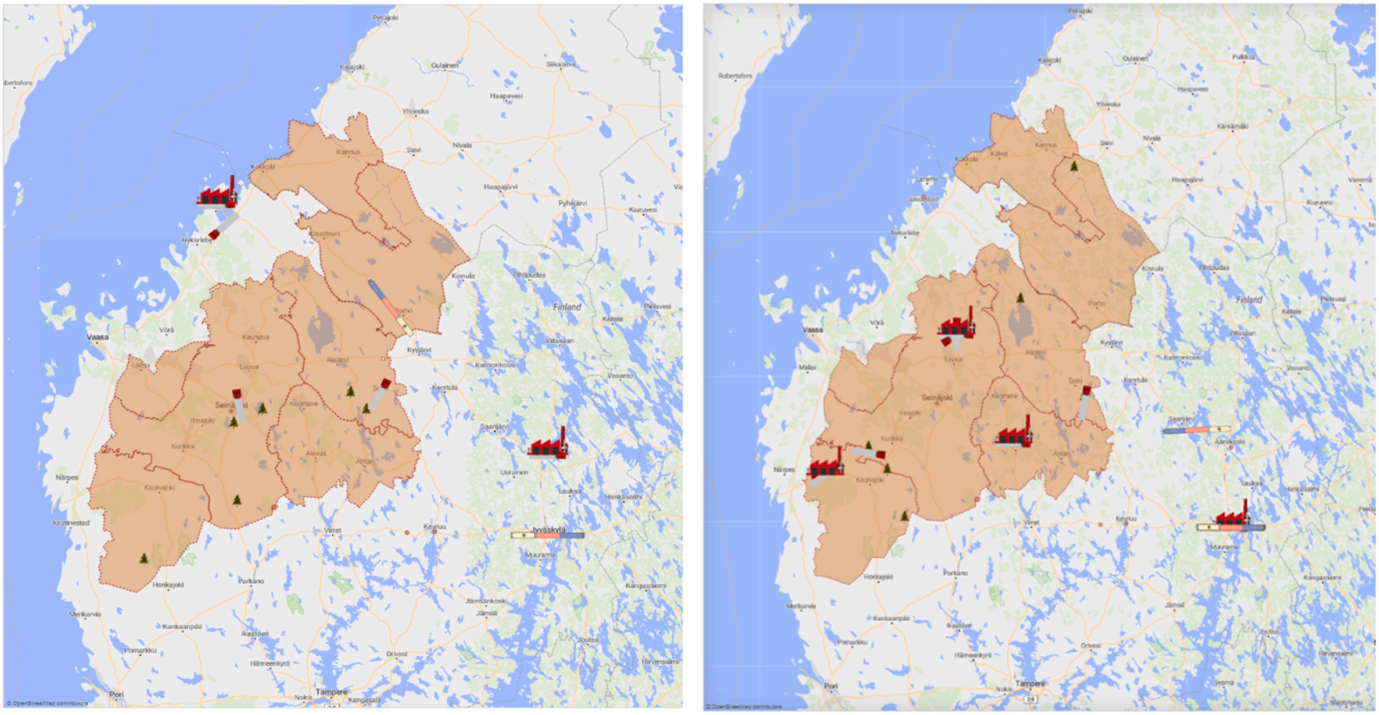

Fig. 7. Scenario 1 and 2 - GIS map and facilities location solutions proposed by the optimization of collection points with direct structure and train connection.

of facilities and their locations differs between Scenario 1 and scenario 2 and GIS maps for both scenarios are demonstrated in Fig. 7. The optimization seeks to determine the minimum transportation cost by altering the fleet size assigned to each facility and by comparing the total logistics cost of each simulation run. Simulation modelling is executed exclusively for both scenarios 1 and 2. Finally, the minimum transportation cost for scenarios 1 and 2 are compared to identify the best facility locations set up for the case company.

Each simulation version within a scenario runs for the time frame of two weeks with a different combination of truck numbers for every facility and each version is iterated within a defined number of times. The minimum and maximum number of trucks for each facility are set as 0 and 10 respectively and transportation costs with all generated scenarios are evaluated. The *Current* column in Fig. 8 presents the last run fleet assignment and transportation cost for each scenario and column *Best* represents the most optimal outcome of all simulation runs. The optimization outcome of scenario one, suggests that six trucks should be assigned to facility one and zero trucks to facility two with a transportation cost of 920,859 euros. Scenario two in which the potential facility locations are different from scenario one proposes that the company should assign five trucks to facility two and no truck to other locations. The transportation cost presented in Fig. 7 is 755,345 euros. It can be observed that the potential facility locations and the number of trucks in scenario two yield significant transportation cost savings within two weeks of operation. Additionally, the optimization parameters and input are presented in Table 1.

5. Discussion

Collection point location selection and fleet management require management to make strategic decisions since logistics cost optimization can lead to various economic prosperities. This paper targets both collection point locations and truck number allocation to minimize the transportation cost. The proposed ABM approach creates a transportation model based on potential facility locations and truck numbers and calculates the total logistics costs. In the optimization process, the simulation is executed for every possible combination of fleet allocation to each facility and geographical location of facilities, and subsequently, transportation costs of different scenarios are likened. In the illustrative example, the least transportation cost for scenario 1 is 920,859 euros with assigning six trucks to facility one and for scenario 2 is 755,345 euros with designating five trucks to facility two; the case company can decrease the logistics cost by choosing the scenario 2 setting. This illustrative example shows possible use of agent-based model combined with GIS system.

This paper has contributed to present and agent-based model which can operate as a decision support tool for the following collection problem: to determine the optimal facility location and fleet number based on transportation costs and uncertainty in demands' location and number. The proposed method has utilized case company data to present the outcome and analysis. The case company operates in the field of forest management and oversees tree log transportation and sought solutions for tactical level decision making how to organize the collection operations. The novelty of the presented approach is that by combining map information with simulation, one can build quite complex dynamic models and combine this with traditional optimization approach. Use of agent-based simulation is a very visual method and can be communicated easily with the actual decision-makers in such way that the proposed solutions are not just single point answers from a "black-box".

This study has show that several distinct components can impact the operational performance in complex supply chains, and therefore the broader factors should be taken into account to identify the best solution for supply chain problems. The proposed simulation method can incorporate various components into the modelling. In this paper, facility locations, their processes, transportation, inventories, and routing factors are included in the modelling and logistics cost minimization is sought under these parameters' integration.

This paper is about log transportation from forest to factories. The related problems presented in the literature are related to biomass in general. Previous studies in literature have shown examples of various decisions related to forest supply chain management. There are several different but intercoupled problems, such as location problems, inventory management, scheduling and routing problems, which have dependencies. Mathematical optimization is a suitable tool for finding

Fig. 8. Scenario 1 and 2 - transportation cost optimization demonstrating the solution total cost and development of the optimization in rounds.

Table 1
Optimization model parameters.

Optimization Parameter	Scenario 1	Scenario 2
Facility 1_Truck_Number	*Number of trucks assigned to collection point*1	*Number of trucks assigned to train station*1
Facility 2_Truck_Number	*Number of trucks assigned to collection point*2	*Number of trucks assigned to train station*2
Facility 3_Truck_Number	–	*Number of trucks assigned to train station*3
Factory	–	*Number of trucks assigned to factory*
Truck fixed cost (Fc)	150000Euro	150000Euro
Truck driving cost per kilometer (Dc)	1.56Euro	1.56Euro

solutions, but as pointed out by Ghasemi et al. [13] metaheuristic approach is enabling possibilities for complex models. Agent based modelling can enhance more complexity as agents can communicate with each other and the behavior can be dynamic and stochastic. Introduction of maps and topology in terms of geographical information systems can bring another level for visualization and communication with the decision makers.

The proposed ABM model in this paper can be utilized as a pragmatic tool for managers to identify the key operational factors and observe the possible outcome by changing their value in the modelling; for instance, key operational factors such as facility locations, fleet number, trucks driving speed, routing methods, trip time, the order assigning policy, number of pickups per region and loading and unloading amount can be adjusted by managers and the derived outcome is instantly presented through different key performance indicators. In addition, the proposed modelling offers an efficient approach to plan for companies' prospective developments. If a company plans to build a new facility or terminate one, the possible scenarios, and their impact on the company's operational performance can be assessed with the ABM method. The ABM simulation can be also employed for optimization purposes. Logistics simulations can be executed for any time period with different values for targeted parameters and the most optimized values for those parameters can be determined based on the objective function.

The ABM approach, contrary to other modelling methods, is flexible and can be adjusted to supply a variety of required information; for instance, ABM modelling utilized in this paper can contribute to planning logistics operations by providing fleet sizing information in hourly, daily, weekly or monthly basis, and by merging different transportation types such as train and trucks carrying the tree logs delivery between facilities and pickup locations. In addition, the proposed ABM approach, merging discrete event and agent-based simulations, can link the transportation to facility operations; for instance, companies can monitor inventory levels for every facility during operating hours.

Furthermore, the ABM method provides a practical tool on how to model random pick-up points within a region for companies operating under similar conditions. The GIS feature utilized in ABM modelling is a powerful tool in transportation management. This feature analyzes the existing routes, computes the travelled distances, and pinpoints the closest facility from the demand or pickup point. Particularly, the travelled distance is a major factor to determine transportation cost and can be obtained from map data.

6. Conclusions

Facility location and fleet sizing optimization can lead to economical efficiency of transportation. The proposed ABM approach in this paper minimizes the logistics costs by selecting the optimal facility location and fleet size. The key concept of ABM modelling is built based on agents that can act autonomously, interact with other agents and the environment, and make decisions according to a set of goals. This feature of the ABM approach is utilized to model the transportation cost simulation and to incorporate broader components in the forest supply chain such as the geographical location of potential facilities, inventory levels, real-world vehicle and train route, tasks assigning policies, and fleet sizing to obtain a highly accurate solution.

The solution approach is described by using forestry company data. The case company plans to operate under one of the two potential scenarios to collect tree logs from different regions and deliver logs to potential facility locations; the logs are transported from regions to two fixed collection points in scenario one and to three train stations and a factory in the scenario two. The proposed modelling method is created with agents interacting with each other such as facility, factory, truck, train, order, and region. The Order agent represents the tree log pickup location and a truck from the nearest facility is dispatched to the order agent location to lade logs and transport them to the facility. The tree log pickup point is random within each region and the facility for delivering logs is selected according to the shortest route between the pickup point and facilities. The GIS embedded in modelling provides the existing route and trip time information between pickup points and facilities for trucks and trains.

The proposed ABM approach is a powerful tool for managers to observe how efficient a system is performing; the business operating effectiveness can be measured through key performance indicators based on different time scales such as hourly, daily, weekly or monthly; for instance, inventory levels, truck utilization and travelled distance indicators on the daily scale are provided in this paper. In addition, managers can observe how a system reacts to different system parameter values; for instance, location and number of facilities, number of pickups, loading and unloading time, vehicle driving speed, and routing methods parameters can be changed and derived outcomes can be evaluated. The use of agent-based simulation has also its limitations. Modelling is very flexible for various setups, but description of all behavior is not as transparent as in pure mathematical optimization based approaches. Also solving the problem is based on metaheuristics and there is no guarantee of optimality. Despite the limitations, we believe that agent-based modelling has good usability in complex inter-coupled modelling of transportation related problems in the wood collection and further work is needed in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. Ahmadvand, M. Khadivi, R. Arora, T. Sowlati, Bi-objective optimization of forest-based biomass supply chains for minimization of costs and deviations from safety stock, Energy Convers. Manag.: X 11 (2021), 100101.
[2] A. Babaeinesami, P. Ghasemi, A.P. Chobar, M.R. Sasouli, M. Lajevardi, A new wooden supply chain model for inventory management considering environmental pollution: a genetic algorithm, Found. Comput. Decis. Sci. 47 (4) (2022) 383–408.
[3] Michael O. Ball, B.L. Golden, A.A. Assad, L.D. Bodin, Planning for truck fleet size in the presence of a common-carrier option, Decis. Sci. 14 (1) (1983) 103–120.
[4] F. Basile, L. Pilotti, M. Ugolini, G. Lozza, G. Manzolini, Supply chain optimization and GHG emissions in biofuel production from forestry residues in Sweden, Renew. Energy 196 (2022) 405–421.
[5] Tolga Bektaş, Laporte Gilbert, Vigo Daniele, Integrated vehicle routing problems, Comput. Oper. Res. 55 (2015) 126, https://doi.org/10.1016/j.cor.2014.08.008.
[6] Eric Bonabeau, Agent-based modeling: Methods and techniques for simulating human systems, Proc. Natl. Acad. Sci. 99 (suppl 3) (2002) 7280–7287.
[7] Ann Melissa Campbell, Jill R. Hardin, Vehicle minimization for periodic deliveries, Eur. J. Oper. Res. 165 (3) (2005) 668–684, https://doi.org/10.1016/j.ejor.2003.09.036.
[8] David Correll, Yoshinori Suzuki, Bobby J. Martens, Logistical supply chain design for bioeconomy applications, Biomass-.-. Bioenergy 66 (2014) 60–69.
[9] M. Dashtpeyma, R. Ghodsi, Forest biomass and bioenergy supply chain resilience: a conceptual decision-making model, Glob. J. Eng. Technol. Adv. 14 (03) (2023) 217–253.
[10] Marco Diana, Maged M. Dessouky, Nan Xia, A model for the fleet sizing of demand responsive transportation services with time windows, Transp. Res. Part B: Methodol. 40 (8) (2006) 651–666, https://doi.org/10.1016/j.trb.2005.09.005.
[11] Shuva Gautam, Luc LeBel, Marc-André Carle, Supply chain model to assess the feasibility of incorporating a terminal between forests and biorefineries, Appl. Energy 198 (2017) 377–384.
[12] S. Gazran, T. Boukherroub, M. Rönnqvist, M. Paquet, Optimizing truck platooning transportation planning: an application to forestry products supply chains, Can. J. For. Res. (2023).
[13] P. Ghasemi, K. Khalili-Damghani, A. Hafezolkotob, S. Raissi, A decentralized supply chain planning model: a case study of hardboard industry, Int. J. Adv. Manuf. Technol. 93 (2017) 3813–3836.
[14] Bruce Golden, Arjang Assad, Larry Levy, Filip Gheysens, The fleet size and mix vehicle routing problem, Comput. Oper. Res. 11 (1) (1984) 49–66.
[15] Petri Helo, Javad Rouzafzoon, Logistics information systems. International Encyclopedia of Transportation, edited by Roger Vickerman, Elsevier,, Oxford, 2021, pp. 76–84.
[16] Petri Helo, Javad Rouzafzoon, Angappa Gunasekaran, Service Supply Chain Design by Using Agent-Based Simulation, in: Kohtamäki Marko, Tim Baines, Rodrigo Rabetino, Ali Z. Bigdeli (Eds.), Practices and Tools for Servitization: Managing Service Transition, Springer International Publishing, Cham, 2018, pp. 387–403.
[17] Helo, Petri, Javad Rouzafzoon, Gisle Solvoll, Thor-Erik Sandberg Hanssen, Lars Westin, and Jonas Westin. 2018. "Distribution center location analysis for Nordic countries by using network optimization tools." In.: Vaasan yliopisto.
[18] T. Holzfeind, C. Kanzian, M. Gronalt, Challenging agent-based simulation for forest operations to optimize the European cable yarding and transport supply chain, Int. J. For. Eng. 32 (1) (2021) 77–90.
[19] Kalle Karttunen, Lauri Lättilä, Olli-Jussi Korpinen, Tapio Ranta, Cost-efficiency of intermodal container supply chain for forest chips, Silva Fenn. 47 (4) (2013) 24.
[20] K. Katsaliaki, P. Galetsi, S. Kumar, Supply chain disruptions and resilience: a major review and future research agenda, Ann. Oper. Res. (2021) 1–38.
[21] Tsuguki Kinoshita, Keisuke Inoue, Koki Iwao, Hiroshi Kagemoto, Yoshiki Yamagata, A spatial evaluation of forest biomass usage using GIS, Appl. Energy 86 (1) (2009) 1–8.
[22] John G. Klincewicz, Hanan Luss, Martha G. Pilcher, Fleet size planning when outside carrier services are available, Transp. Sci. 24 (3) (1990) 169–182.
[23] S.T. Klosterhalfen, J. Kallrath, G. Fischer, Rail car fleet design: optimization of structure and size, Int. J. Prod. Econ. 157 (2014) 112–119, https://doi.org/10.1016/j.ijpe.2013.05.008.
[24] K. Laasasenaho, A. Lensu, R. Lauhanen, J. Rintala, GIS-data related route optimization, hierarchical clustering, location optimization, and kernel density methods are useful for promoting distributed bioenergy plant planning in rural areas, Sustain. Energy Technol. Assess. 32 (2019) 47–57, https://doi.org/10.1016/j.seta.2019.01.006.
[25] Lesyna, William R. 1999. Sizing industrial rail car fleets using discrete-event simulation. Paper presented at the Simulation Conference Proceedings, 1999 Winter.
[26] Haibing Li, Andrew Lim, A metaheuristic for the pickup and delivery problem with time windows, Int. J. Artif. Intell. Tools 12 (02) (2003) 173–186.
[27] S.L.Y. Lo, B.S. How, W.D. Leong, S.Y. Teng, M.A. Rhamdhani, J. Sunarso, Techno-economic analysis for biomass supply chain: a state-of-the-art review, Renew. Sustain. Energy Rev. 135 (2021), 110164.
[28] J. Lohmer, N. Bugert, R. Lasch, Analysis of resilience strategies and ripple effect in blockchain-coordinated supply chains: an agent-based simulation study, Int. J. Prod. Econ. 228 (2020), 107882.
[29] Francesco Longo, Advances of modeling and simulation in supply chain and industry, SAGE Publications Sage, UK: London, England, 2011.
[30] Macal, Charles M., and Michael J. North. 2009. Agent-based modeling and simulation. Paper presented at the Winter simulation conference.

[31] L. Melchiori, G. Nasini, J.M. Montagna, G. Corsano, A mathematical modeling for simultaneous routing and scheduling of logging trucks in the forest supply chain, For. Policy Econ. 136 (2022), 102693.
[32] A. Mobtaker, M. Ouhimmou, J.F. Audy, M. Rönnqvist, A review on decision support systems for tactical logistics planning in the context of forest bioeconomy, Renew. Sustain. Energy Rev. 148 (2021), 111250.
[33] M. Molinaro, G. Orzes, From forest to finished products: the contribution of Industry 4.0 technologies to the wood sector, Comput. Ind. 138 (2022), 103637.
[34] Birger Raa, Fleet optimization for cyclic inventory routing problems, Int. J. Prod. Econ. 160 (2015) 172–181.
[35] Rouzafzoon, J., & Helo, P. (2018, September). Developing logistics and supply chain management by using agent-based simulation. In 2018 First International Conference on Artificial Intelligence for Industries (AI4I) (pp. 35–38). IEEE.
[36] Javad Rouzafzoon, Petri Helo, Developing service supply chains by using agent based simulation (null), Ind. Manag. Data Syst. 116 (2) (2016), https://doi.org/10.1108/IMDS-05-2015-0220.
[37] Takanori Sakai, André Romano Alho, B.K. Bhavathrathan, Giacomo Dalla Chiara, Raja Gopalakrishnan, Peiyu Jing, Tetsuro Hyodo, Lynette Cheah, Moshe Ben-Akiva, Simmobility freight: an agent-based urban freight simulator for evaluating logistics solutions, Transp. Res. Part E: Logist. Transp. Rev. 141 (2020), 102017, https://doi.org/10.1016/j.tre.2020.102017.
[38] Meng Sha, Rajagopalan Srinivasan, Fleet sizing in chemical supply chains using agent-based simulation, Comput. Chem. Eng. 84 (2016) 180–198.
[39] J. She, W. Chung, H. Vergara, Multiobjective record-to-record travel metaheuristic method for solving forest supply chain management problems with economic and environmental objectives, Nat. Resour. Model. 34 (1) (2021), e12256.
[40] Wen Shi, Jennifer Shang, Zhixue Liu, Xiaolu Zuo, Optimal design of the auto parts supply chain for JIT operations: Sequential bifurcation factor screening and multi-response surface methodology, Eur. J. Oper. Res. 236 (2) (2014) 664–676, https://doi.org/10.1016/j.ejor.2013.11.015.
[41] Timo Tahvanainen, Perttu Anttila, Supply chain cost analysis of long-distance transportation of energy wood in Finland, Biomass-.-. Bioenergy 35 (8) (2011) 3360–3375.
[42] Caroline Thierry, Jacques Lamothe, Didier Gourc, A review of Vendor Managed Inventory (VMI): from concept to processes AU - Marquès, Guillaume, Prod. Plan. Control 21 (6) (2010) 547–561, https://doi.org/10.1080/09537287.2010.488937.
[43] Koen H. van Dam, Arief Adhitya, Rajagopalan Srinivasan, Zofia Lukszo, Critical evaluation of paradigms for modelling integrated supply chains, Comput. Chem. Eng. 33 (10) (2009) 1711–1726.
[44] Yong Wang, Shouguo Peng, Xuesong Zhou, Monirehalsadat Mahmoudi, Lu Zhen, Green logistics location-routing problem with eco-packages, Transp. Res. Part E: Logist. Transp. Rev. 143 (2020), 102118, https://doi.org/10.1016/j.tre.2020.102118.
[45] Peiling Wu, Joseph C. Hartman, George R. Wilson, An integrated model and solution approach for fleet sizing with heterogeneous assets, Transp. Sci. 39 (1) (2005) 87–103, https://doi.org/10.1287/trsc.1030.0050.
[46] Hongde Yu, Qinhui Wang, Klein E. Ileleji, Chunjiang Yu, Zhongyang Luo, Kefa Cen, J. Gore, Design and analysis of geographic distribution of biomass power plant and satellite storages in China. Part 2: Road delivery, Biomass-.-. Bioenergy 46 (2012) 785–792, https://doi.org/10.1016/j.biombioe.2012.06.028.
[47] Fengli Zhang, Dana M. Johnson, Jinjiang Wang, Integrating multimodal transport into forest-delivered biofuel supply chain design, Renew. Energy 93 (2016) 58–67.
[48] K. Zhao, Z. Zuo, J.V. Blackhurst, Modelling supply chain adaptation for disruptions: an empirically grounded complex adaptive systems approach, J. Oper. Manag. 65 (2) (2019) 190–212.