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Integrated Routing of Heavy Electrical and Diesel Trucks in Forest Transports

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Abstract. Fossil free forestry transports are important to reach climate goals. In Sweden, road transports account for around 50% of the industry's CO2 emissions and almost 20% of the road freight volumes. Previous studies have shown that electrification is a cost-effective way for carbon abatement, while at the same time the requirements for flexibility in routing makes electrification of forestry transport challenging. The current trend is to introduce more electrical vehicles in different sectors. However, there are challenges for the forest industry including long distances, heavy weights, multiple shifts and lack of recharging stations. We propose an analytical decision tool that solves an integrated vehicle routing problem. This model includes detailed energy consumption and recharging requirements for each route generated. The solution method consists of phases where we first identify full truckloads and then generate a set of generic routes. These are later used to construct routes for individual trucks. The coordination to find the best route for each truck is found by solving a mixed integer programming model. We use a case study to analyze the impact of increasing proportion of electrical trucks.

Keywords: Electrical trucks, CO2 emission, energy consumption, routing

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Introduction

Fossil free forestry transports are important to reach climate goals. In Sweden, road transports account for around 50% of the industry's CO2 emissions and almost 20% of the road freight volumes. Forest industry accounts for 36% of business road transportation work, which uses roughly 250 million liters of diesel (skogsindustrierna.se). The current trend in transport sectors for smaller trucks is to introduce more electrical vehicles. However, there are special challenges for the forest industry. The forest vehicles are heavily laden, with a gross weight of up to 74 tonnes, and are often driven on poor quality roads, usually in multiple shifts. The need for flexibility is great: the transports go from about 200,000 different locations in the forest, which vary over time, to just over 1,000 receiving locations (industries and terminals). Forestry operates all over the country and uses the entire road network, transports usually start in the most peripheral parts of the road network to end at industries and terminals that are more centrally located. Due to the geographically dispersed operations, access to charging can be a challenge. Another challenge is that the transport system is complex, developed over a long period of time. The system consists of several actors and is affected by both external factors (e.g. weather and the fluctuating needs of the industry) and internal factors (e.g. information flows between actors and combination of vehicle types in the fleet).

Several forest companies in Sweden have been early in trying out new technologies for electric vehicles and have taken the first steps towards electrification: The world's first electric logging truck used by the company SCA is rolling on Swedish roads. The company Södra Skogsägarna has presented far-reaching ambitions for electrification, and the company Stora Enso in collaboration with its transport suppliers ordered electric heavy trucks for wood chip transport. Now the industry is asking itself: how do we scale up the electrification of forestry transport in a cost-effective way? The ambition and desire to convert to electric operation in the industry is great, but the uncertainties are also great.

There are many practical questions arising when introducing electrical trucks. An important practical question is where to locate infrastructure to recharge the trucks. The hauliers' questions concern whether it is profitable to drive electrically, or what is required for it to be profitable: Where do charging stations need to be, and what do electricity prices need to be? What proportion of the fleet should be electric? How does electrification affect the logistics setup and the drivers' working day? Electricity producers and actors who offer charging infrastructure are also interested parties with questions about how big the demand for electricity output will be at different locations, and where charging infrastructure should be located. Other stakeholders also include municipalities, regions, and the state, which partly depends on a competitive forestry industry to reach climate and business policy goals, and partly needs to understand the effect of possible financial support.

There exists a rich literature on forest transportation. Audy et al. (2023) provides a recent review on transportation and route planning in forestry. More detailed studies of routing of forest trucks are found in Andersson et al. (2008) and Flisberg et al. (2009). Previous research on the electrification of heavy forest transport is however very sparse. In previous literature, calculations of costs for electrification have been made, but these are either at a very general level (based on average value calculation) (Olsson et al. (2021)), at driveline level (i.e. without consideration of transport tasks) (Cunanan et al. (2021)) or made for completely different types of applications, e.g. for transport to and from ports (Giuliano et al. (2021)) or for road transport (Mauler et al. (2022)). Overall, these studies identify battery electric heavy-duty vehicles as economically competitive and with great potential to reduce CO2 emissions, although there are challenges linked to range and planning (see e.g. Mauler et al. (2022) and Inkinen & Hamalainen (2020) for reviews). There are still only a few studies that study the effects of different electrification strategies on logistics and flows. However, these are typically of a more qualitative nature, see e.g. Gillström et al. (2022).

The logistics questions that we want to answer in this article are: Which routes are cost-effective to electrify, and where should other fossil-free fuels be used? What percentage of the fleet can/should be electric? How does electrification affect the logistics structure and flows? What will be the demand for electricity and power at different points, given different strategies for charging? What does the interaction look like between electrification and heavier transport, 74 tons and above? We have proposed and developed an advanced analysis tool to answer such questions. The tool compares the routing solutions and performance for a mixed fleet of diesel and electrical trucks. An important part is to compute detailed energy consumptions for different road profiles and temperatures for diesel and electrical trucks. We have detailed information on the fuel consumption for diesel trucks from an empirical model. A physical based energy model is then used to identify when it is possible to regenerate energy to the batteries. These models are combined to identify the relative energy consumption for the two truck types. An inventory routing model over one week with daily time periods that finds the optimal routes for the fleet of trucks is then developed. This uses a tactical destination planning solution which finds the best combinations of loaded and empty transports. These solutions are used to explicitly generate many routes. An optimization model based on a generalized set-partitioning model is then used to select routes that cover all required transports. The trucks used are typically two-shifts trucks which require a detailed description of the battery energy status when the trucks changes shifts. There are three main research contributions. The first is the solution approach to enable the integrated routing of diesel and fully electrical trucks. This includes detailed routes including recharging for the electrical trucks and special consideration of connection of two shifts as the status of battery for the second shifts depends on the status of charge of the battery from the first shift. The second is the proposed energy consumption model for electrical trucks that is based om a combination of detailed diesel truck consumption and a relative compensation based on well-known physical models for energy consumption. This also include the possibility to recharge batteries while braking. The third is the detailed analysis of a large cases study where many aspects are considered and analyzed.

The case study originates from a Swedish forest company with 14 industries, 219 harvest areas and about 40 available truck shifts are used for what-if scenarios. As the electrical trucks have less capacity (time) for driving and that purchase price is high, the diesel trucks have today a lower overall cost. Moreover, a sensitivity analysis on diesel price is performed. If the diesel price is doubled; the electrical trucks are more competitive. In a mixed fleet, it is optimal to plan for high utilization rate for the electric trucks to compensate for their higher purchase price. Also, electrical trucks are used more often on shorter trips where the proportion of loading and unloading time versus loaded driving time can be increased. The structure of the remaining part is as follows. In Section 2, we provide the various models and methods used to develop the tool and provide all necessary data. Section 3 describes the case study and Section 4 provides the results. Concluding remarks is given in Section 5.

Materials and methods

National road database NVDB and SNVDB

NVDB (Swedish national road database) is a collaboration between the Swedish Transport Administration (Trafikverket), Sweden's municipalities and regions, the forestry industry, the Swedish Transport Agency (Transportstyrelsen) and Land Survey (Lantmäteriet). The Swedish Transport Administration is the principal of NVDB. Sweden's municipalities and regions - all 290 municipalities in Sweden deliver data on the municipal road network and on individual road networks within designated areas. The forestry industry delivers data on the individual road network that is of interest to the forestry industry. The Land Survey (Lantmäteriet) delivers data on the other individual road network. The Swedish Transport Agency delivers traffic rules (for example speeds, prohibited direction of travel or overtaking prohibitions) from all decision-making authorities. NVDB uses a relational database model, with tables and fields that store information about various road-related attributes. It contains extensive geographic information, including coordinates, geometries, and topological data, which allow precise mapping and spatial analysis of the road network. The data from NVDB is often integrated into geographic information systems (GIS) and other transportation planning and management software for analysis and visualization. The database is regularly updated to reflect changes in the road network, ensuring that the information remains current and accurate. SNVDB is the forestry-specific counterpart of NVDB, focusing on forest-related data and information. SNVDB contains the information from NVDB but is complemented with detailed information about forestry-related attributes, such as turning options in the forest, hilliness, curvature, specific forest roads for high volume, and road accessibility in different seasons.

Calibrated Route Finder

The Calibrated route finder (CRF) online system (Rönnqvist et al., 2017) managed by Biometria (biometria.se) which is a logistic hub in Swedish forestry. CRF relies on a set of servers to provide real-time information about individual routes between two points and their characteristics. This information includes details such as distance, objectives, and utilized links. On a typical day, approximately 20,000 server requests are processed. The base servers manage a network composed of arcs and nodes, where arcs represent different road segments and nodes signify intersections or changes in attributes (such as speed limits). Many road features are categorized into subclasses. For instance, road features include functional road classes and speed limits. In Sweden, roads are classified from RC0 to RC9, with RC0 indicating European motorways and RC9 representing lower-quality forest roads. RC7-9 specifically categorizes private forest roads. Similarly, speed limits range from 20 to 120 km/h, encompassing 12 different limits. To determine the optimal route, a scalar weight is assigned to each attribute to balance them, as they cannot be directly converted into a common unit (e.g., monetary values). These weights are then used to compute an aggregated arc cost. Finding the shortest or minimum cost route is efficiently accomplished using variations of Dijkstra’s algorithm. The network model in CRF uses an expanded network. This network includes turns and crossings with respect to possibility and permissibility to turn. With the information from SNVDB, it is possible to define an augmented network. This can consider behaviour and rules in crossings.

SkogforskCalc and Energy consumption

SkogforskCalc (SFCalc) is a system developed by Skogforsk, the Forestry Research Institute of Sweden, designed to estimate the total execution cost of specific transportation modes. The includes a detailed estimation of fuel consumption and route time. SFCalc estimates running costs using a statistical model that predicts time and fuel consumption. The route is divided into short segments with constant road features (e.g., speed limits and curvature). Time and fuel consumption for each segment are determined using a lookup table that was created based on statistical analysis of driving patterns from timber trucks. The data was collected from the CAN bus of 21 vehicles during a period of one year. The vehicles were of varying configuration with respect to engine power, number of axles (7, 8 and 9) for different weight configurations (64, 70 and 74 tonnes), tire types and loader arrangement. The combination is spread of Sweden and reflect the standard logging trucks used. In total, over 700,000 km of driving was recorded. CAN data was recorded with 1 Hz using a logger (Owasys 450) and a contactless CAN-bus reader installed in each vehicle. The logger also contains a GNSS receiver for positioning. This data was matched with road features from the SNVDB for binning purposes. Given that some road feature combinations are rare, a large amount of driving data is needed for a comprehensive and statistically significant database. When data for rare combinations is unavailable, a smoothing approach is used, employing adjacent bins to complete the lookup table. The overall lookup table is divided into three distinct sub-tables:

1. Arc Table: This table includes lookup entries for various road features such as road class, curviness, hilliness, surface, load status, speed, and whether the route is intra- or extra-urban.
2. Crossing and Node Behavior Table: This table covers all possible crossing scenarios. Key factors include the road class approaching the crossing, the highest road class at the crossing, and the type of maneuver (e.g., left or right turns, through traffic). Factors such as speed limits and road class changes at the crossing are also considered.
3. Speed Limit Change Table: This table details the impact of speed limit changes on fuel consumption. When the speed limit increases, fuel consumption temporarily rises before stabilizing; conversely, fuel consumption decreases when the speed limit drops.

Energy consumption of electrical trucks

The battery capacity of a logging truck is limited, and it is necessary to recharge the battery one or several times during a shift. We consider two different cases. The first case is to charge the battery at a given charging location (industries or public charging locations). The status of charge of the battery during a route is described in Figure 1 (top) where the truck performs three loaded transports during a shift. In the example, the truck is recharged after the second unloading and on the way to the third pickup location. It is also interesting to study if it is possible to charge the battery while unloading as is illustrated in Figure 1 (bottom).

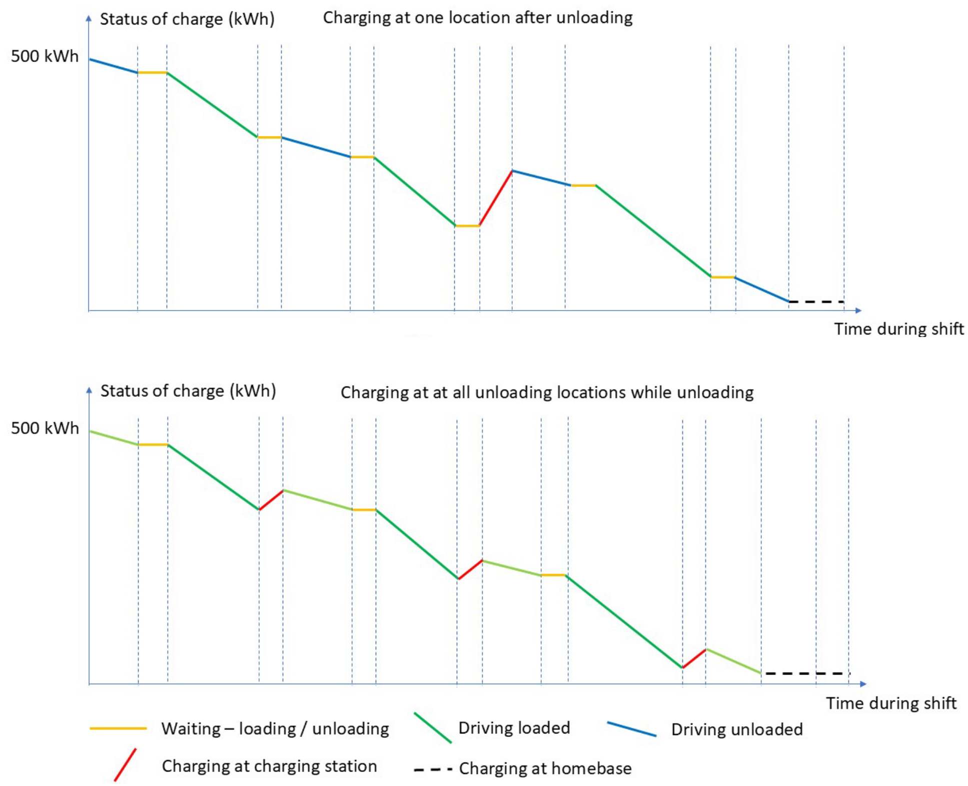

Figure 1. Illustration of the battery status (energy level) during a shift where three transports are done. Top - The recharging is done at an external recharging station. Bottom - The recharging is done while unloading at a demand point.

It is difficult to estimate the energy consumption of an electrical truck as few data is available. Our approach is to use a physics-based energy model, which considers the fundamental physical principles that affect energy usage in transportation. These models can be quite complex, but there are four main parts, i.e.,

Fuel Consumption (in liters per kilometer) =
(Rolling Resistance + Aerodynamic Drag + Gravitational Effects) / Engine Efficiency

The *rolling resistance* is the force required to overcome the rolling resistance of the tires on the road. This resistance depends on the type of road surface, tire properties, and the weight of the vehicle. The *aerodynamic drag* is the resistance to motion caused by air friction. It depends on the vehicle's shape, speed, and the density of the air. *Gravitational effects*; in hilly or mountainous terrain, gravitational forces play a role in fuel consumption. Climbing uphill requires more energy, and descending consumes less. The *engine efficiency* of the engine in converting fuel into mechanical work affects fuel consumption. Modern engines are designed to be more fuel-efficient but varies among different trucks. Each of these factors would have more detailed equations that consider variables such as road grade, vehicle speed, load weight, and engine characteristics. In our approach, we make use of the following model.

$$F = (m_{eff}av + mgvsin\alpha + C_r mgv + C_d A\frac{\rho v^3}{2}) / e_{eff}$$

Here, m_{eff} is the effective mass (actual weight plus the rotational mass), a the acceleration, v the truck speed, α the road gradient, g the gravitational force, C_d the coefficient for air drag, C_r the coefficient for rolling resistance, ρ the air density, and e_{eff} the engine efficiency in converting diesel to energy. The accuracy of the model depends on the information available on the coefficients, speed and slope estimates. When the speed is assumed is constant, the acceleration is 0 and the first term disappears. When accelerating after, e.g., a crossing the speed changes and there is a need to integrate the equation over time until the assumed speed is obtained. In our use of the model, we make use of the hilliness index which provides an average slope for each arc in the network. For the constant speed, we make use of an estimated speed for a combination of speed limit and functional road class. The model above makes it possible to include the effect of regenerative breaking to recharge the battery while braking going downwards in a slope. As we use the system SFCalc to estimate the energy and fuel consumption for the diesel truck, we make several assumptions to ensure the models are coordinated. We compute the energy consumption using the physics model with and without regenerative braking. Next, we compute a proportionality factor between them and adapt the arc table used in SFCalc. Essentially, we use the arc table for determining the energy consumption on the arcs where the electrical consumption is adjusted with the factor, the energy consumption on nodes is assumed to be equal for electrical and diesel trucks.

Solution approach

The routing problem is an integrated inventory and routing problem (Audy et al., 2023) as it covers multiple days. An additional complication with many standard routing problems is that there is not a determined allocation between supply and demand points. There exist several different solution methods. The problem is of large scale and hence it is necessary to use a heuristic approach to enable high quality solution within limited solution time. Our proposed solution method follows the following main steps as illustrated in Figure 1. Below, we provide a general description and in the next section the detailed mathematical models are described.

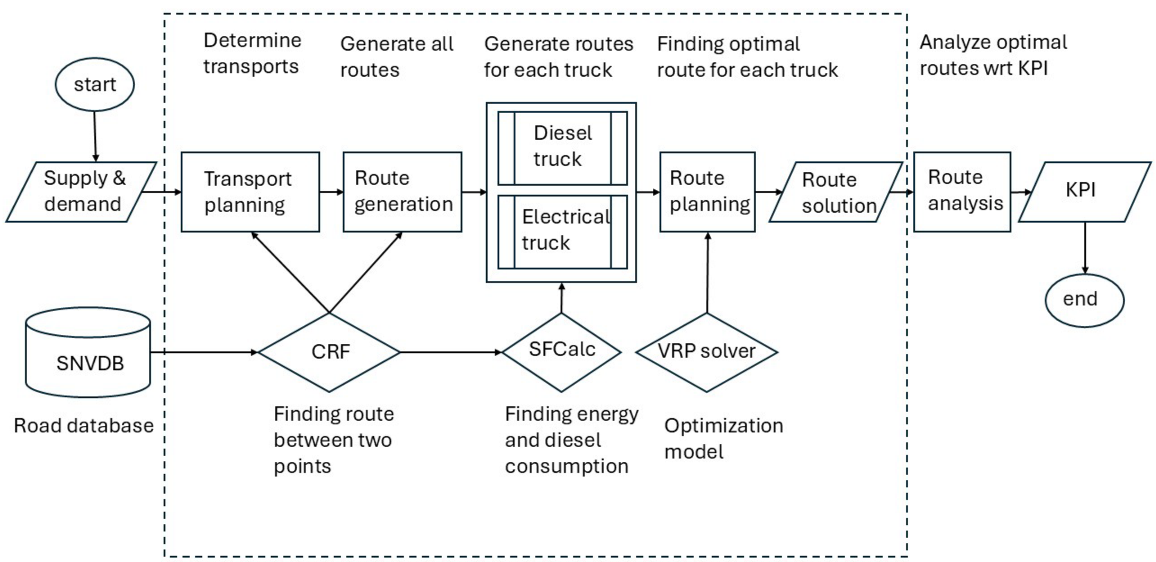

Figure 1. Illustration of the overall solution approach and data sources in the developed analytics decision tool. The activities within the box with broken lines refer the decomposed solution method to find the routes

Step 1: Transport planning

First, we determine the flow between supply and demand nodes for all time periods. This can be formulated as a transportation problem (Audy et al, 2023) where the decision variables are the flow between supply and demand nodes in each time period and for each assortment. The constraints are inventory balancing constraints for each supply node, demand node, time period, and assortment. There are also constraints that balances the transportation work (expressed in ton*km) over all days. Given a flow solution, we then determine a set of full transports for each day. This can be done by a rounding heuristic using the LP solution. The solution is a set of full transport for each of the days. As a second part, we also determine the "empty" truck flow from demand to supply nodes. This is to provide a solution to indicate where trucks should go once they are unloaded to better avoid empty driving. This is also formulated as a transportation problem, but where all assortments are aggregated as we want to identify the empty transports that balances the loaded transports. This will be used later in the route generation to focus on generating efficient routes, i.e., reduce empty driving.

Step 2: Generic route generation

Here all generic routes for each day is generated given the full truck loads. A generic route is a route that starts at a supply point and end at a demand point. This is done by an enumeration process where the routes are built based on the full truckload and information on the best combination of empty truck loads. The latter reduces considerably the number of routes. To find distances and route times, we us the CRF system.

Step 3: Specific route generation

Given the generic routes, we next generate routes for each truck. As each truck has a unique home base, we need to add the driving from home base to first supply point and the driving back home from the last demand point. Due to this additional time, not all routes can be used by all trucks. Also, for the electrical truck, we need to analyze the SoC and add time for recharging. In the generation, we look for the lowest cost alternative for recharging location and how much to recharge. An important aspect is also to compute the SoC at the end of the shift. As the charging takes time, the number of routes possible for each electrical truck is lower (or equal) to a diesel truck if operated from the same home base. The energy consumption for both types of trucks is found by SFCalc and physical energy model. In the route generation, we also ensure that the routes are within the shift time limits and any required rest time.

Step 4: Route planning

The last step is to select one route for each combination of truck and shift. This is modeled as a mixed integer programming model. It has structure of a generalized set partitioning model with some additional side constraints. These additional constraints are needed to make sure compatibility between the first and second shift for each electrical truck. If the second route needs a certain SoC level, the first needs to meet this level. This problem is solved with a commercial mixed integer programming solver.

Route analysis

Once we have a full route solution, we can analyze a set pf KPIs including total cost, energy consumption, use of charging locations, driving times, and charging times.

Models and route generation in solution approach

Transportation planning – loaded transports

To formulate the transportation problem, the following notation (sets, coefficients and decision variables) are defined:

Sets

I : set of supply points (harvest areas or terminals)

J : set of demand points (industries)

A : set of assortments

G : set of assortment groups

T : set of time periods (weeks)

A_g : assortments that assortment group g can use

G_a : assortment groups that assortment a can be used for

Parameters

s_{iat} : supply (truck loads) at supply point i of assortment a during period t

d_{jat} : demand (truck loads) at demand point j of assortment group g during period t

c_{ijat}^{truck} : unit cost of truck transportation flow from node i to node j of assortment a during time period t

c_{nat}^{node} : unit inventory cost at node n of assortment a during time period t

h_{nt}^{node} : maximum inventory level at node n during time period t

d_{ij} : distance between supply point i and demand point j

M : large penalty value

Decision variables

x_{ijagt}^{truck} = flow (truck loads) from node i to node j of assortment a to assortment group g during time period t

$l_{nat}^{node,a}$ = inventory level (truck loads) at node n of assortment a in period t

$l_{ngt}^{node,g}$ = inventory level (truck loads) at node n of assortment group g in period t

w = target transport work for all periods

u_t^-, u_t^+ = deviation from target (under -, over +) in period t

The model can now be formulated as

$$[M1]\ \min z_1 = \sum_{i\in I}\sum_{j\in J}\sum_{a\in A}\sum_{g\in G_a}\sum_{t\in T} c_{ijat}^{truck} x_{ijagt}^{truck} + \sum_{n\in I\cup J}\sum_{a\in A}\sum_{t\in T} c_{nat}^{node} l_{nat}^{node} + \sum_{t\in T} M(u_t^- + u_t^+)$$

subject to

$$l_{ia,t-1}^{node,a} + s_{iat} - \sum_{j\in J}\sum_{g\in G_a} x_{ijagt}^{truck} = l_{iat}^{node,a}, \forall i\in I, a\in A, t\in T \quad (1)$$

$$l_{jg,t-1}^{node,g} - d_{jgt} + \sum_{i\in I}\sum_{a\in A_g} x_{ijagt}^{truck} = l_{jgt}^{node,g}, \forall j\in J, g\in G, t\in T \quad (2)$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{a\in A}\sum_{g\in G_a} d_{ij} x_{ijagt}^{truck} = w - u_t^+ + u_t^-, \forall t\in T \quad (3)$$

$$x_{ijagt}^{truck} \ge 0, \quad \forall i\in I, j\in J, a\in A, g\in G_a, t\in T \quad (4)$$

$$l_{nat}^{node,a},\ l_{nat}^{node,g} \ge 0, \quad \forall n\in I\cup J, a\in A, g\in G, t\in T \quad (5)$$

$$u_t^-, u_t^+ \ge 0, \quad \forall t\in T \quad (6)$$

$$w \ge 0 \quad (7)$$

The objective function (0) minimizes transportation and inventory costs and the penalty for balancing transport work. Constraint sets (1) – (2) states the inventory balancing constraints at supply points and demand points, respectively. Constraint (3) balances the transport work over all time periods. Constraints (4) – (7) gives non-negativity constraints on the continuous variables.

The problem is a linear programming (LP) model. Given the solution from this model, we heuristically generate a solution with full truck loads. The supply and demand are provided in full truck loads. Hence, the solution is often given in integer numbers of full truck loads. If the flows are decimals, we use a simple rounding heuristic that provides a set of transports (full truck loads) for each day.

Transportation planning – empty transports

Once the full transports are determined, we identify the best empty flows for each time period. The motivation is to reduce empty driving alternatives in the later route generation. If we can identify the best combination for the empty driving, it is possible to reduce the number of generic routes generated. The problem can be modelled as follows given the full transports and the following parameters and decision variables.

Parameters

s_{it}^2 : number of loaded transports leaving supply point i in period t

d_{jt}^2 : number of loaded transports arriving at demand point j in period t

c_{ji}^{empty} : unit cost of empty truck t from node j to node i

Decision variables

y_{jit} = number of empty transports from demand node j to supply node i in period t

The model is as follows.

$$[\text{M2}] \quad \min z_2 = \sum_{j \in J} \sum_{i \in I} \sum_{t \in T} c_{ji}^{empty} y_{jit}$$

$$\text{subject to} \quad \sum_{j \in J} y_{jit} = s_{it}^2, \forall i \in I, t \in T \qquad (8)$$

$$\sum_{i \in I} y_{jit} = d_{jt}^2, \forall j \in J, t \in T \qquad (9)$$

$$y_{jit} \geq 0, \quad \forall i \in I, j \in Jt \in T \qquad (10)$$

This model is much smaller as there is no need to include assortments. The objective function is to minimize the total cost of empty driving. Constraint (8) states the number of empty loads arriving to supply points, and constraint (9) states the number of empty loads leaving the demand points. Constraint (10) states the nonnegativity restrictions on the continuous variables. As all supply and demand constraints are given in integer and this is equivalent to a network model, solutions are integer. The solution may give rise to disjunctive set of nodes where transports are done. In order to limit this, we also add additional empty flows from each demand node to supply nodes that do not provide full truck loads to the demand node. This will increase the number of routes but at the same time ensure that potential routes are generated.

Route generation

The solutions above provides us with information useful for generating generic routes for each day. It is important to note that this enumeration does not consider individual trucks as these are associated with a particular home base where a truck would start and end a shift. In a generic route, we ignore the start and end home base. We have for each supply points, a list of transports to demand points. For each demand point, we have a list of empty transports to supply points. Also, we have the route time for each transport provided by the CRF system. Next, we make an enumeration of all possible generic routes that are possible to complete within the shift length. A generic route is a combination of a set of loaded and empty transports. For example, the simplest would be only one loaded transport from a supply to a demand point. It would be as many of theses as there are transports during the day. Next, we have routes that are one loaded followed by an empty transport from the unload location to a second supply point, and then a second loaded transport. We then continue to build all possible routes with more loaded and empty transports. Clearly, the number of potential routes increases fast as we include more transports. As we generate all possible routes based on the actual full truck loads, the number of generic routes is much smaller than if we allow any combinations. For example, suppose there are m supply points. If our empty transports only use a fraction of these going from a specific demand point, we can greatly reduce the enumeration.

In the next phase, we generate a set of routes for each combination of shift and truck. This generation is based on the generic routes. Each truck has a home location where the truck starts and ends. This additional time will reduce the number of routes as some will exceed the shift time limit. Also, for each truck, we ensure that the resting time requirement of 45 minutes after each 4.5 hours of active driving is satisfied. For the electrical truck, we apply additional checks. We ensure that we include required recharging locations so that the SoC of battery does not go too low. As recharging requires additional time, the number of explicit routes for electrical is less or equal to the diesel truck routes. As different recharging alternatives result in different SoC, we generate multiple versions of the same generic route. An important information for each route generated is the remaining energy at the end of shift 1 or what is needed to operate shift 2.

Route planning

From the route generation, each truck has many potential routes. In the synchronization, we need to select one route for each truck and shift. At the same time, we need to cover all full-load transports for each day with minimum cost. This problem can be formulated with the following sets, parameters and decision variables.

Sets :

V : set of vehicles (V^D – diesel trucks, V^E – electrical trucks)

V_1^D – diesel trucks shift 1, V_1^D – diesel trucks shift 2

V_1^E – electrical trucks shift 1, V_1^E – electrical trucks shift 2

R_v : all possible routes for truck v

K : all full truckload transports

Parameters :

c_j: cost of route j for vehicle v

b_v : vehicle in shift 2 related to vehicle v in shift 1

e_{vj}^1: energy left in battery of route j for electrical vehicle v ($v \in V_1^E$)

e_{vj}^2: energy required in battery at start of route j for electrical vehicle v ($v \in V_2^E$)

$$a_{ir} : \begin{cases} 1, \text{ if transport } i \text{ is done in route } r \\ 0, \text{ otherwise} \end{cases}$$

Decision variables :

$$x_{rv} = \begin{cases} 1, \text{ if vehicle } v \text{ is using route } r \\ 0, \text{ otherwise} \end{cases}$$

The model can be formulated as

$$[M3] \quad \min z_3 = \sum_{v \in V} \sum_{r \in R_v} c_{vr} x_{vr}$$

$$\text{subject to} \quad \sum_{r \in R_v} x_{vr} = 1, \quad v \in V \tag{11}$$

$$\sum_{v \in V} \sum_{r \in R_v} a_{ir} x_{vr} = 1, \quad i \in K \tag{12}$$

$$\sum_{r \in R_v} e_{vr}^1 x_{vr} - \sum_{r \in R_{b_v}} e_{b_v r}^2 x_{b_v r} \geq 0, \quad v \in V_1^E \tag{13}$$

$$x_{vr} \in \{0,1\}, \quad v \in V, r \in R_v \tag{14}$$

Constraint (11) states that each truck is allocated to one route. We note that we have two sets of trucks, one for each shift and that there is a direct relation which trucks are equivalent in the two sets. Constraint (12) is to ensure that each loaded transport is done. Constraint (13) ensure that electrical trucks have enough ending battery capacity from the first shift to operate the second shift route. Constraint (14) is the binary restriction on each variable. This model is a mixed integer programming model. It is an extension of a set-partitioning problem in a similar fashion as done in Bredström and Rönnqvist (2005) where the synchronization is done for ensuring a time synchronization rather than a energy synchronization.

Case study

The case study is based on data from a large Swedish forest company. The data comprises transport data from 147 harvest areas to 15 industries for 10 different assortments (mix of species and log dimensions). There are 20 existing diesel trucks with individual home bases working in 2-shifts of 11 hour each. As electrical truck has less capacity, we have introduced 20 equivalents, but also two additional for better comparison. Hence, we have a capacity of 40 diesel and 44 working shifts for diesel and electrical trucks, respectively. The planning period covers 5 days. Loading time for each truck is 45 min and unloading time 20 min. In practice, there is a limited number of full transports for each truck, and we use a maximum of four. The geographical distribution of harvest areas and mills is visualized in Figure 3. The aim is to study the impact when a proportion of the diesel trucks are replaced by electrical trucks. We assume the same home bases for the electrical trucks as for the corresponding diesel trucks. The additional four are copies of the first four. Charging is assumed to take place at home between shifts (or during nights) or at the 5 largest industries and 24 public charging stations for trucks.

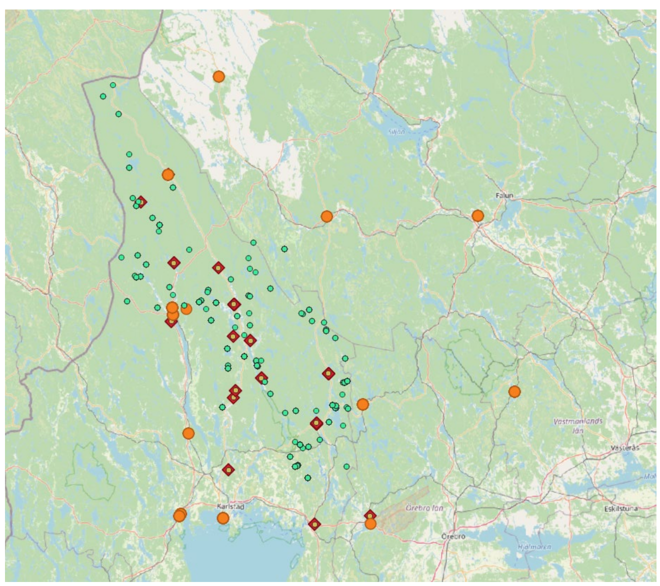

Figure 3. Geographical distribution of industries (orange circles), home bases (red diamonds) and harvest areas (green circles).

The key information about costs and capacities used is given in Table 1. All costs are given in SEK (Swedish krona, 10 SEK is equivalent of 1.0 USD). The reason for the higher fixed daily cost per shift for electrical truck is based on the higher purchase price. Also, an important rule in the routing is a required (law) 45 min break for any 4.5 hours driving.

Table 1. Information used in the case study.

Aspect	Capacity	Cost	Cost
Battery	500 kWh		
Shift diesel trucks	11 hours	3940 SEK/shift	330 SEK/h
Shift electrical trucks	11 hours	5940 SEK/shift	330 SEK/h
Charging (home base)	100 kWh	0.70 SEK/kWh	
Charging (industry & public)	350 kWh	3.00 SEK/kWh	
Diesel		14 SEK/l	

The 13 instances we consider is described in Table 2. We want to analyze how the proportion of electrical trucks impact the overall solution. Hence, we test ranges between 0 and 100% proportion of electrical trucks (instances I1-I5). Instance I6 is to allow for charging while unloading. Instance I7 is to allow for a dual battery system at home which can be charged slowly during the shift followed with a fast recharging of the truck battery once it returns home. Instances I8-I13 test different levels of diesel price (80-300% of base price).

Table 2. Instances used in the case study.

Instance	Description
I1	Using 100% diesel trucks
I2	Using 20% electrical and 80% diesel trucks
I3	Using 50% electrical and 50% diesel trucks
I4	Using 100% electrical trucks
I5	Possibility of 100% diesel or electrical trucks
I6	I5 with charging during unloading
I7	I5 with possibility of dual battery system at home base
I8 - I13	I5 with 80%, 120%, 150%, 200%, 250%, and 300% diesel price

Results

Optimization approach

The transportation problems, which are formulated as linear programming problem are easy to solve. The LP models are solved using the commercial Woodflow decision support system (creativeoptimization.se). The routing problems are MIP models and much harder. Here the commercial MIP solver CPLEX (version 16?) (www.cplex.com) is used. All computations are done on a standard laptop with 64 GB RAM and AMD Ryzen 9 with 3.79 GHz processor.

The first LP problem (loaded flows) has 6,886 variables and 3,089 constraints. The second LP problem (empty flows per day) is solved per day. The problem for Monday has 2,685 variables and 345 constraints, and the other days have models of similar size. The LP problems can be solved close to optimality in short solution time. Table 3 gives the number of generic and detailed routes generated for each of the five days. This is based in the instance I5 when there are maximum number of diesel and electrical trucks available. The proposed approach to identify the best empty transports reduces considerably, multiple hundred of times, the number of generic routes.

Table 3. Number of generic and detailed routes generated for each of the five days.

Aspect	Monday	Tuesday	Wednesday	Thursday	Friday
Number of transports	87	87	82	85	80
Number of generic routes	6,954	82,470	17,906	12,381	12,306
Potential No. of generic routes	5.858,925	7.711,658	4.044,606	4.106,969	2.752,614
No. of diesel truck routes	67,535	789 807	197 113	109 858	105 550
No. electrical truck routes	67,299	643 466	194 558	104 972	88 226
Total number of routes	134,834	1,433 273	391,671	214,830	193,776

The number of variables for the routing problem [M3] for each of the daily routing problem ranges between about 134 thousand and 1.43 million variables. The number of constraints depends on the number of shifts and trucks, and the number of transports done each day. For example, on Monday the number of constraints is 219. Even though the number of variables is high, it is solved to optimality (cplex mip gap of 0.1%) within a number of minutes.

Analysis of instances

The main results of costs and energy use of the instances I1-I7 are given in Table 4. When electrical trucks are used, there is a need of using more shifts. The main reason is the reduced time driving because of required charging time. When we use only diesel trucks, there is a need of 31.4 shifts while we need 43.6 shifts with only electrical trucks. When we use 100% electrical trucks, we increased to 22 trucks as the overall capacity is lower for electrical and we want to do all transports. The energy cost is cheaper with electrical trucks, but the fixed shift cost makes the electrical trucks less competitive. In instance I5 when we let the trucks compete, it is optimal to use in practical only diesel trucks.

Table 4. Results from the instances regarding number of shifts and costs.

Instance	I1	I2	I3	I4	I5	I6	I7
# diesel trucks available	20	16	10	0	20	0	0
# electrical trucks available	0	4	10	22	22	22	22
# used electrical shift	0.0	2.4	21.6	43.6	0.4	40.2	40.2
# used diesel shift	31.4	29.4	16.0	0.0	31.0	0.0	0.0
# total used shift	31.4	31.8	37.6	43.6	31.4	40.2	40.2
working cost (h) kSEK	495	498	509	524	494	516	513
shift cost (kSEK)	316	383	545	847	318	732	855
fuel cost (kSEK)	555	532	305	0	551	0	0
charging cost (electricity) (kSEK)	0	26	317	729	4	747	617
charging cost (time) kSEK)	0	1	22	52	0.2	20	37
total cost (kSEK)	1366	1440	1699	2152	1367	2016	2023

The results from changing the diesel price are given in Table 5. When the diesel price increases to between 150% and 200%, the electrical trucks become more competitive.

Table 5. Results from varying the diesel price.

Instance	I5	I8	I9	I10	I11	I12	I13
% of base diesel price	100%	80%	120%	150%	200%	250%	300%
# diesel shift available	20	20	20	20	20	20	20
# electrical shift available	22	22	22	22	22	22	22
# used electrical shift	0.4	0.0	0.4	2.8	24.8	32.0	32.4
# used diesel shift	31.0	31.4	31.0	29.2	14.8	10.0	9.6
# total used shift	31.4	31.4	31.4	32.0	39.6	42.0	42.0
Working cost (h) kSEK	494	495	494	494	450	507	508
Fixed shift cost	318	316	318	330	514	574	582
Fuel cost (diesel) kSEK	551	444	661	789	559	465	525
Charging cost kSEK	4	0	4	25	295	441	457
Charging cost (time) kSEK	0.2	0	0.2	1	18	29	31
Total cost (kSEK)	1367	1255	1477	1639	1885	2016	2103

Table 6 provides more detailed information on times and distances. There is a total of 421 transports to do during the five days. We can note that using only electrical trucks, there are three long transports that cannot be done due to transport capacity. The reason is that there is no possibility to charge the battery for these transports and they are too long for one battery charge. If there would be additional charging station, we would be able to make all transports. The energy used per km varies between 2.37 and 2.68 kWh per kilometer. The diesel consumption is 5.5 kWh per km. It is important to note that these values are before any losses in the systems. For example, a diesel truck is assumed to have a 33% efficiency rate when converting diesel to energy. The distance driven per shift is higher for the diesel trucks (438-479 km) as compared to the electrical trucks (168-360 km). At the same time, we see that the working hours to drive is higher for diesel trucks. This is because of the reduced time due to recharging of the batteries for the electrical trucks. As we have charging time for electrical, there is less need to enforce the rule of 45 min rest for every 4.5 hours. This is because charging time is counted as rest time.

Table 6. Results from the instances regarding details about times and distances.

Instance	I1	I2	I3	I4	I5	I6	I7
# failed Transports	0	0	0	3	0	0	0
# transports electricity	0	17	202	418	7	421	421
# transports diesel	421	404	219	0	414	0	0
used shifts total	31.4	31.8	37.6	43.6	31.4	40.2	40.2
total energy (MWh)	396	388	304	190	394	187	186
# used shifts electrical	0	2.4	21.6	43.6	0.4	40.2	40.2
energy (kWh) / km electrical	-	2.37	2.44	2.40	2.68	2.42	2.43
# transports electrical	-	1.42	1.87	1.92	3.50	2.09	2.09
work time electrical (h)	-	5.74	6.74	7.28	6.83	7.78	7.74
rest time electrical (h)	-	0.00	0.12	0.19	0.00	0.28	0.34
charging time away (h)	-	0.36	0.61	0.72	0.36	0.31	0.56
charging time home (h)	-	4.42	3.38	3.25	2.64	3.00	5.14
distance electrical per shift (km)	-	278	308	343	168	363	360
distance loaded electrical (km)	-	121	143	153	80	168	168
# used shifts diesel	31.4	29.4	16.0	0	31.0	0	0
energy (kWh) / km	5.5	5.5	5.4	-	5.5	-	-
# transports diesel	2.68	2.75	2.74	-	2.67	-	-
work time diesel (h)	9.55	9.79	10.20	-	9.57	-	-
rest time diesel (h)	0.49	0.50	0.50	-	0.49	-	-
distance diesel per shift (km)	438	449	479	-	441	-	-
distance loaded diesel (km)	212	216	226	-	213	-	-

Concluding remarks

Road transport of timber and forest material from the forest to industries (sometimes via terminals) is a necessary part of the forestry industry. At the same time, road transport contributes about 50 percent of forestry's CO2 emissions, so there is a great incentive for the industry to change these to fossil-free to reach its climate goals. An important next step towards reducing emissions now is electrification. We have developed an analytical tool that can be used to analyze how electrical trucks best can be introduced and how to best balance the transport assignments between electrical and diesel trucks. The tool is based on detailed information from multiple big data sources. The proposed solution approach can efficiently solve the large-scale vehicle routing problem. This can be used as an important tool for more detailed analysis in how to include electrical trucks or deciding on where charging locations are best suited. It is a heuristic approach and there is no guarantee of optimal solutions. However, as electrical and diesel trucks face the same condition, the analysis on the trade off between the different trucks are fair.

The results shows that we need additional electrical trucks as compared to diesel as the electrical truck have less (time) capacity. As the charging capacity and battery capacity increases, the gap will decrease. Also, the higher purchasing cost of electrical trucks makes the overall cost higher with electrical trucks. However, this is also expected to be lower with increased production of electrical trucks. Forestry's transport makes up just under 20 percent of Sweden's transport and has an average distance of approximately 90 km from forest to industry.

In 2022, approx. 6.6 million tonne km of transports were carried out, which with the Swedish average for emissions from heavy vehicles of 0.12 kg CO2 equivalents per tonne km gives approximately 790,000 tonnes of CO2 equivalents per year. Considering forestry's relatively short average distance, we can assume that 70 percent of transport can be electrified with technology available within the next five years. An estimate of the potential for reduced emissions with electrification of forestry transport is therefore around 550,000 tonnes of CO2 equivalents per year. The introduction of electrical trucks will increase as more transporters are interested and the number of high-capacity charging stations increases.

It is interesting to study case studies from different parts of the country with different geographical condition, for example, hilliness, availability of charging locations, geographical spread of supply and demand points. It is also interesting to further develop the energy consumption for electrical trucks. The generation of routes for the routing problem can also be further developed. It would be interesting to also add routes for the electrical trucks that have different strategies to increase the SOC of the battery before the shift ends. For example, it is possible to stop at a recharging station with higher capacity to charge more before moving to the home base for slower charging. Also, the generation of generic routes is a heuristic approach, and it would be interesting if the propose approach using empty transports can be further developed and analyzed.

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