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An Agent-Based Simulation of Truck Fleet Operations to Supply a Biorefinery Year-Round

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Abstract

Background: The cost to operate a truck fleet to haul feedstock from satellite storage locations (SSLs) to a biorefinery is typically more than 30% of the logistics cost. The use of central control can minimize truck wait times and maximize truck productivity (Mg hauled per day). *Methods:* An agent-based model, developed in Python 3.12.7, simulated truck hauling operations and SSL loading operations at a 1 min time step for each day in a six-day workweek over a 48-week hauling season for a theoretical biorefinery centered in Gretna, VA, USA. Several truck and SSL operational parameters included stochastic components to allow for random variability (e.g., drive speed and loading rate). *Results:* The theoretical minimum fleet, assuming no unproductive time, was 6 trucks. Assuming realistic delays, a fleet of 13 trucks could supply the biorefinery with one unloading operation, but unproductive time was over 50% of the hauling day. *Conclusions:* By adding a second unloading operation at the biorefinery, average truck idle time was reduced, and a fleet of 8 trucks could achieve the same average truck productivity with total unproductive time reduced to about 20% of the total truck fleet operating time.

Keywords: simulations; agent-based models; herbaceous feedstock; biomass logistics; load-out operations; truck hauling; truck productivity; satellite storage locations; biorefineries; supply chains

1. Introduction

Biomass is naturally a distributed resource. When accumulating this resource at a processing facility (e.g., a biorefinery), a key issue is the average cost of delivery. The feedstock density, defined as the biomass produced per unit area within a given radius of the biorefinery, is an important parameter. Any region with a high density of feedstock in the production area around the biorefinery, and a high-yielding feedstock crop, will have an advantage. Another significant component is the efficiency of the delivery operation, i.e., the logistical processes required to transport feedstock from the production fields to the biorefinery. In 2023, 20.1 billion tons of goods were transported by freight through various means, of which truck transportation using the road network was the most dominant, accounting for 64.5% of all goods [1]. Trucks have been found to be optimal for short-distance transportation, accounting for 75% of transportation within 161 km and ideal for same-day round trips less than 400 km [1]. Truck transportation is critical to biomass supply chains; however, there are still gaps in the literature on this topic.

A common feedstock delivery strategy is to use satellite storage locations (SSLs), representing intermediate sites between the land where the biomass is harvested and the

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biorefinery where the biomass is processed [2]. Feedstock is stored at SSLs in units, such as bales, and picked up by trucks to be transported. This approach has been used for many different feedstocks. Zamora-Cristales et al. [3] studied the delivery of forest residue by truck trailers in Oregon, USA. An [4] optimized the delivery of corn stover bales from 48 SSLs to a biorefinery in Ontario, Canada. Resop et al. [5] created a database of 199 SSLs with switchgrass feedstock for a theoretical biorefinery in Virginia, USA. Feedstock bales at SSLs are loaded onto trailer sets by a load-out operation and picked up by trucks to be hauled to the biorefinery [6]. Resop et al. [6] advocated for the industry to be organized in such a way to provide for central control of the delivery operation. The biorefinery takes ownership of the biomass at the SSLs and schedules the two main processes: (1) the load-out operations at the SSLs, and (2) the hauling operations by a truck fleet. Central control of the delivery operation means there are multiple load-out crews working at several SSLs being unloaded simultaneously. A fleet of trucks located at the biorefinery are dispatched by a "Feedstock Manager", such that a truck arrives at an SSL when a load of biomass is ready when the truck arrives.

The truck fleet can be optimized when truck cycle time (i.e., a round trip from biorefinery to SSL) is minimized. Doing so allows for maximum productivity per truck over the annual operating season. Truck cycle time has three components: travel time between the biorefinery and SSL, load time at the SSL, and unload time at the biorefinery. Travel time is set by highway regulations, but traffic conditions make it highly variable. Cundiff and Grisso [7] proposed technology that minimizes both load time and unload time, thus providing an opportunity to maximize average productivity of each truck in the truck fleet. Ultimately, optimization is a complex balance between components, such as the number of trucks in the fleet, as well as the amount of idle or waiting time at various steps in the cycle, such as loading equipment waiting for a truck to arrive with an empty set of trailers at the SSL [3].

The transportation of feedstock has been modeled by several approaches, including traditional mathematical methods, like computer simulation and agent-based modeling (ABM), and more recent artificial intelligence (AI) advances, like machine learning (ML) and digital twins (DT) [1]. In the rail industry, simulations like Rail Traffic Controller (RTC) have been used to optimize the dispatching and scheduling of trains based on real-life parameters [8]. The supply chain model, Arena Simulation Software, has been used to simulate biomass feedstock [9]. The Integrated Biomass Supply Analysis and Logistics (IBSAL) model has been used to simulate the harvest, storage, and transportation of different biomass feedstock, such as corn stover or switchgrass, to a biorefinery [10–12]. The IBSAL model is a highly detailed model of the feedstock supply chain, including parameters for trucks, labor, fuel, equipment, and weather.

Machine learning using supervised classification or regression, such as random forests (RF) or neural networks (NN), has been used to optimize biomass supply chains [1]. For example, identifying suitable harvesting sites and selecting optimal storage locations [13]. Machine learning has the potential to forecast demand in complex, non-linear supply chains, allowing modelers to optimize inventories [14]. While ML tools are powerful, they require high-quality observed data for model training [1]. In the realm of biomass supply chains, ML has been generally used for static problems, like feedstock supply estimation and site suitability, and not for dynamic problems, like truck scheduling.

For dynamic problems, digital twins have improved the efficiency in supply chains, such as those involving multi-modal transportation [1]. In a digital twin, real-life objects are connected through technologies, such as the internet of things (IoT) and cloud computing [15]. Components of the supply chain, from suppliers to ships to trucks to destinations, are in continuous communication with a digital computer system that mimics the real-life

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system [16]. While digital twin technology has the potential to optimize supply chains in real time, it requires the installation and integration of a significant amount of computing infrastructure to be fully utilized [1].

When simulating dynamic systems with multiple moving components, an accepted strategy is agent-based modeling. Agent-based models (ABM) allow supply chains to represent different components, such as suppliers, manufacturers, and distribution centers, as separate agent objects in a dynamic, decentralized logistic system [17]. Agent-based simulations allow the modeler to define stochastic parameters, such as truck travel time, loading time, and unloading time, to allow for random variability to replicate the uncertainty of real-life processes [3]. Stochastic simulations like these can estimate critical supply chain metrics, such as truck waiting time [3].

Many studies have utilized ABM for forest biomass supply chains. Helo et al. [18] used ABM to simulate tree log collection in a region of Finland. They created agents to represent different components of the supply chain, such as trucks and facilities. Geographic information systems (GIS) were used to determine routing between log pickup locations and facility locations. The use of ABM was noted as a valuable tool for optimizing facility locations and the size of the truck fleet. Pinho et al. [19] created an ABM in Python, called SimPy, to simulate forest biomass supply chains in Finland, representing trucks and depots as agents. Zahraee et al. [20] used ABM to simulate wood chips delivered to biomass boilers in Victoria, Australia. Truck agents varied between states, such as idle, traveling, loading, and unloading. Routing was calculated using GIS, and uncertainty was represented using stochastic parameters, such as biomass availability and travel time. It was noted that ABM could be used as a precursor for a digital twin framework. These studies demonstrate the potential for ABM for forest biomass supply chains and reveal the lack of research performed so far on systems involving herbaceous feedstock, such as those with switchgrass bales stored in a set of SSLs and in regions like the Southeast, USA.

The objective of this study was to develop a model to simulate central control to maximize the productivity of both the SSL load-out operations and the truck hauling operations for a given production area in the Piedmont province supplying a potential biorefinery located in Gretna, VA, USA. Due to the theoretical nature of the SSLs and biorefinery used for this study, an ABM approach was appropriate due to the lack of real-life supply data for training a machine learning model and the lack of real-time truck data for implementing a digital twin. Productivity was estimated using an ABM that simulated each truck, SSL, and load-out operation for every minute in a 48-week hauling season. Several strategies to minimize truck wait time were explored, based on scenarios varying the number of trucks and the number of unloading operations at the biorefinery.

Constraints with the potential to reduce the truck productivity include:

1. The Feedstock Manager might not be able to schedule a truck to arrive at an SSL when a load is ready, resulting in reduced productivity of the load-out operation.
2. The average travel velocity for each truck cycle is a random variable, expected to be different for each load, depending on traffic and road network factors.
3. The average load time at an SSL and unload time at the biorefinery are random variables, expected to be different for each load, depending on various external factors.
4. One or more trucks might arrive at the biorefinery while a previous truck was being unloaded, resulting in idle time for trucks that must wait in a queue.
5. There might not be enough time for a truck to complete a cycle by the end of the hauling day, resulting in the cancellation of the trip and reduced productivity of the truck.

All constraints on truck productivity also have an impact on load-out productivity.

2. Materials and Methods

2.1. Study Area

The study area was a 48 km radius around Gretna, VA, USA (Figure 1). The potential switchgrass production for a theoretical biorefinery at the center of this area was defined by Resop et al. [5], who created a database of 199 satellite storage locations (SSLs) representing switchgrass grown in local fields and stored on site for eventual transport by trucks using two 20-bale trailers in tandem [6]. The Gretna database has been the subject of multiple feedstock hauling logistics studies, which explored the use of central control [6] and optimized the load and unload technology [7]. A constant switchgrass yield of 6.7 Mg/ha was used, based on the average expected yield for this region [21]. This expected yield was used to estimate production from the potential harvest area, which was derived from the National Land Cover Dataset (NLCD), assuming scrubland and grassland were most likely to be converted to switchgrass production for a biorefinery [5].

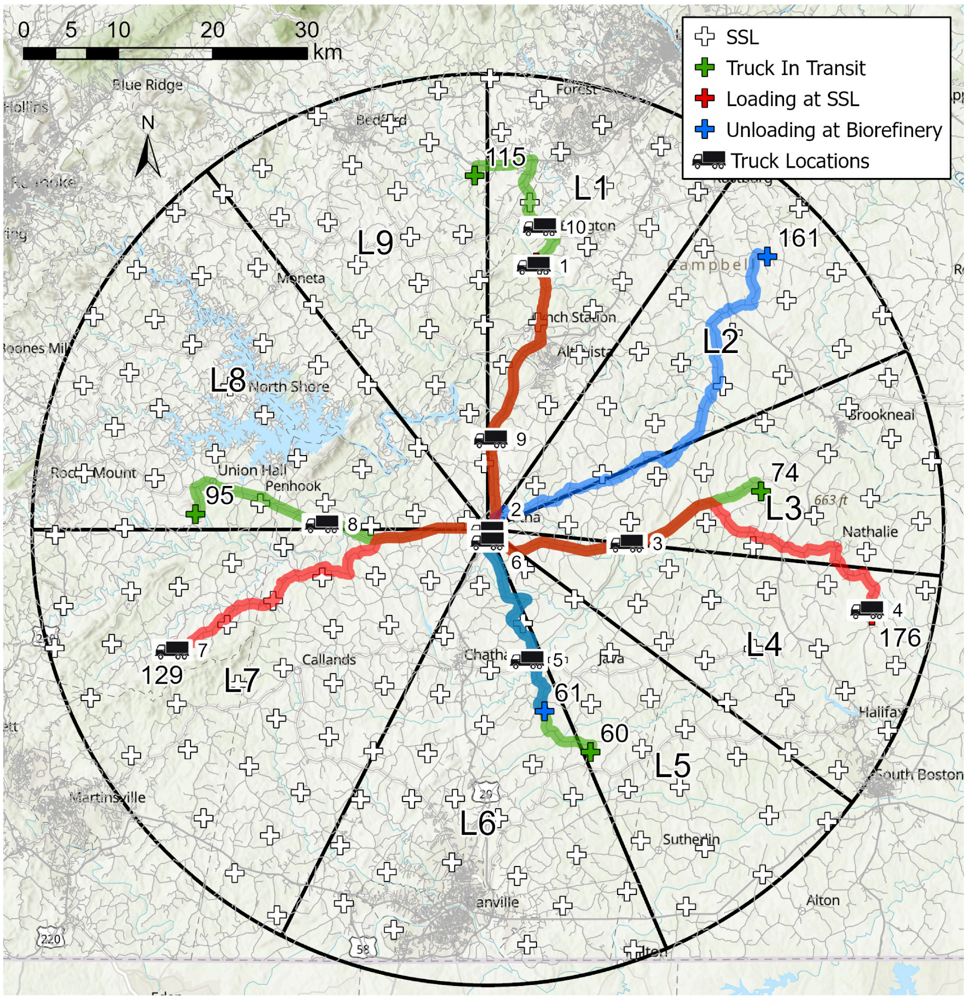

Figure 1. The theoretical biorefinery in Gretna, VA showing the satellite storage locations (SSLs) and truck locations for nine load-out operations (LOOs) on a given day in the 48-week hauling season.

2.2. Load-Out Operations

To organize delivery of feedstock from the SSLs to a biorefinery, a set of load-out operations (LOOs) was created. A load-out operation was defined as the processes that occur at an SSL to prepare feedstock for delivery to the biorefinery. A load-out operation consists of loading round bales stored at the SSL onto a set of two 20-bale rack trailers in tandem to be picked up by trucks for hauling [6]. Assuming 0.4 Mg/bale, each truck hauls an average load of 16 Mg biomass. Resop et al. [6] found that nine LOOs, which were derived by dividing the overall production area into subareas with approximately equal production, resulted in an optimized annual delivery cost for the Gretna database. The sequence of SSLs to be processed by load-out operations was defined as either starting from the one closest to the biorefinery and moving out ("in-to-out") or the one farthest from the biorefinery and moving in ("out-to-in") as defined by Resop et al. [6]. This set of nine LOOs with their associated sequences of SSLs was used as the basis for this study (Figure 1). The sequence for each LOO was selected arbitrarily; no analysis was performed here to optimize them. The SSL sequence was not expected to have a significant impact, but this should be explored more in future research. Load-out operations were assumed to operate ten hours a day and six days a week over a 48-week hauling season.

2.3. Truck Hauling

Each round trip of a truck to deliver feedstock from an SSL to the biorefinery consisted of the following steps, defined as the "hauling cycle" (Figure 2). The key processes are summarized in Table 1. The trucks start each day waiting at the biorefinery. A truck leaves the biorefinery and starts driving to an SSL if either of the following conditions are true: (1) the LOO at that SSL has finished loading their trailers with 40 bales (i.e., a load of 16 Mg biomass) or (2) the central control system calculates that the load-out operation at an SSL will finish loading their trailers before the truck arrives, based on the SSL loading speed and the truck driving speed. In either case, it is assumed that an SSL will have a set of trailers loaded and ready to be picked up once a truck arrives. When a truck arrives at an SSL, it unhooks its set of empty trailers and hooks the full trailers. Once loaded, a truck drives back to the biorefinery. When a truck arrives at the biorefinery, assuming no other trucks are being processed, it unloads the set of full trailers. If other trucks are currently being unloaded, then the truck enters an "unloading queue" to wait. Once a truck has unloaded and has a set of empty trailers, the truck waits at the biorefinery until it is dispatched, and the hauling cycle starts again. A truck ends operations for the day once it determines it can no longer complete a cycle before the end of the hauling day, which was defined to be twelve hours a day and six days a week over the 48-week hauling season.

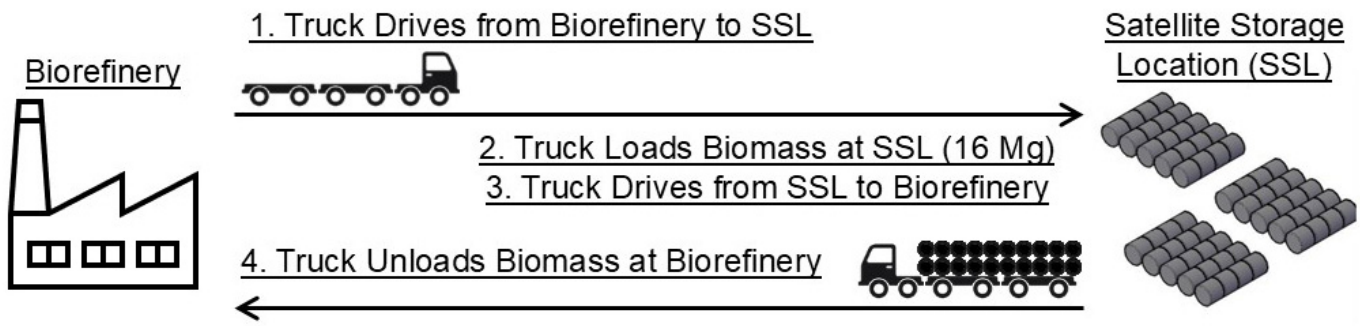

Figure 2. The hauling cycle used by the simulation represents a round trip of a truck to drive to an SSL, load trailers of biomass at the SSL, return to the biorefinery, and unload the biomass.

Once an SSL has depleted its supply of feedstock, defined as having less biomass than necessary for a full load (i.e., 16 Mg), then the LOO moves to the next SSL in its sequence. This process was defined as a "move between SSLs" and, for simplicity, was assumed to require a half day, or six hours, to complete [6]. This means that once a LOO completes loading operations at an SSL, it will take six hours before it can start loading operations at the next SSL in the sequence. A "move between SSLs" requires a change to the hauling cycle defined above. During a normal cycle, a truck travels from the biorefinery to an SSL and back. During a "move between SSLs", a truck first travels from the biorefinery to the next SSL in the load-out sequence to drop off the set of empty trailers (so it is ready to start load-out operations), then travels to the current SSL and hooks to the set of full trailers, and then travels back to the biorefinery to unload.

Table 1. Definitions of possible truck states in the agent-based model simulation.

Truck State	Definition
Waiting at Biorefinery	Truck is waiting to be dispatched to an SSL.
Driving to SSL	Truck is driving from biorefinery to SSL to pick up load.
Loading at SSL	Truck is at SSL, leaving empty trailers and picking up full ones.
Driving to Biorefinery	Truck is driving from SSL to biorefinery to deliver the load.
Waiting in Queue	Truck is at biorefinery waiting in a queue to unload trailers.
Unloading at Biorefinery	Truck is leaving full trailers and picking up empty ones.
End of Operations	Truck does not have enough time in the day to start a new cycle.

2.4. Network Analysis

The theoretical biorefinery was located at the center of the production area around Gretna, VA. Network analysis was implemented using ArcGIS Pro 3.4 (ESRI, Redlands, CA, USA). A road network feature class derived from the 2020 US Census was utilized. A subset consisting of primary and secondary roads, assumed to be the roads available for truck transport, was used to create the network dataset. The Origin Destination Cost Matrix tool was used twice to calculate the shortest path travel distance (km) between locations using the road network. First, between each of the SSLs and the biorefinery (199 $\times$ 1) and second, between each of the SSLs and each other (199 $\times$ 199). These distance matrices were exported as databases and imported into the model.

2.5. Agent-Based Model

An agent-based model simulation was created using Python 3.12.7 and object-oriented language concepts to design custom classes representing the types of agents. Additional Python packages (e.g., NumPy 1.26.4, Matplotlib 3.10.6, Pandas 2.2.2, Seaborn 0.13.2) were used for data management and visualization. Three different classes represented the agents in the simulation: Trucks, SSLs, and LOOs. Table 2 defines the properties of each agent class. Truck agents represented each individual truck that travels between the biorefinery and the SSLs. The number of truck agents was allowed to vary per simulation. Satellite storage locations (SSLs) represented stationary locations with biomass stored in bales awaiting delivery to the biorefinery and were defined as j = 199 SSLs. Load-out operations (LOOs) represented the process of loading bales into trailers at SSLs for delivery, moving from one SSL to another in a sequence, and were defined as k = 9 LOOs. All time-based parameters were represented with respect to minutes since the model used a 1 min time step.

Table 2. Class attributes defining the properties of each type of agent in the simulation.

Property Name	Property Definition
	Truck Class
Truck ID	Truck identifier (i = 1 to n, where n = number of Trucks in simulation)
SSL ID	Current SSL assigned to Truck (Set to None if no SSL is assigned)
Truck State	Current state of the Truck (see list of states in Table 1)
Distance	Distance (km) from the Truck to the Biorefinery (0 = At Biorefinery)
Driving Speed	Current driving speed (km per minute) of the Truck on the road network
Number of Loads	Total loads the Truck has delivered to the Biorefinery (16 Mg each)
Load Time	Current time required (minutes) to load Truck at SSL
Unload Time	Current time required (minutes) to unload Truck at Biorefinery

Table 2. *Cont.*

Property Name	Property Definition
	Satellite Storage Location (SSL) Class
SSL ID	Satellite Storage Location (SSL) identifier (j = 1 to 199 SSLs)
Truck ID	Current Truck assigned to SSL (Set to None if no Truck is assigned)
LOO ID	Load-out Operation (LOO) assigned to the SSL
Distance	Distance (km) from the SSL to the Biorefinery based on road network
Biomass	Amount of biomass (Mg) stored at SSL based on annual production
Number of Loads	Total loads from the SSL that have been delivered (16 Mg each)
Trailer State	Number of bales in the trailer set at the SSL (0 = Empty; 40 = Full)
Loading Rate	Current trailer loading rate (bales per minute) by the LOO at the SSL
Move Flag	Set to True if a "move between SSLs" is in progress by the LOO
	Load-out Operation (LOO) Class
LOO ID	Load-out Operation (LOO) identifier (k = 1 to 9 LOOs)
SSL ID	Current Satellite Storage Location (SSL) being processed by the LOO
SSL Sequence	List of SSLs processed by the LOO over the 48-week hauling season

2.5.1. Random Parameters

To represent the inherent uncertainty of the system, several model parameters were allowed to vary randomly based on pre-defined distributions. The chosen random parameters were truck driving speed (km per minute or kpm), SSL trailer loading rate (bales per minute or bpm), truck load time at an SSL (minutes), and truck unload time at the biorefinery (minutes) (Table 3). The random distributions represented the variability of real-life events, such as the randomness of a truck's driving speed as impacted by factors like traffic or weather (Figure 3). The Python NumPy module was used to generate all random values for the simulation.

Table 3. Random parameters used in the simulation to represent the uncertainty of real-life events, including their expected values and 95% confidence intervals (CIs).

Parameter Name	Expected Value	95% CI
Truck Driving Speed (km per minute or kpm)	0.84	0.72 to 1.00
SSL Trailer Loading Rate (bales per minute or bpm)	0.62	0.44 to 0.89
Truck Load Time at an SSL (minutes)	17.54	12.50 to 22.50
Truck Unload Time at the Biorefinery (minutes)	25.45	20.00 to 40.00

The truck driving speed random parameter was based on the variability of road travel due to unexpected delays when traveling. Resop et al. [6] assumed an "ideal" travel velocity of 70 kph; however, a "traffic factor" was incorporated here to represent anticipated delays. This traffic factor was defined as a random normal distribution with a mean of 1.4 and constrained to the range 1.0 to 1.8 (Figure 3). The ideal velocity was divided by a random traffic factor to estimate the real-life velocity (e.g., 70 kph/1.4 = 50 kph). The truck driving speed was stored as kpm instead of kph due to the 1 min time step of the simulation. A random driving speed was generated for each truck before each new hauling cycle (i.e., a round trip to an SSL).

The SSL trailer loading rate random parameter represented the speed of load-out operations at an SSL to load an empty set of trailers with 40 switchgrass bales. The "ideal" time to load a trailer set was assumed to be 45 min [7]. To represent the real-life variability, a random non-uniform distribution was defined, such that 10% of the load-out operations loaded in the ideal time (45 min), 10% loaded in twice the ideal time (90 min), and the remaining 80% used a random sample from a uniform distribution ranging from 45 to

90 min. A random load time was generated before each new SSL loading operation and converted to a rate in terms of bpm (Figure 3).

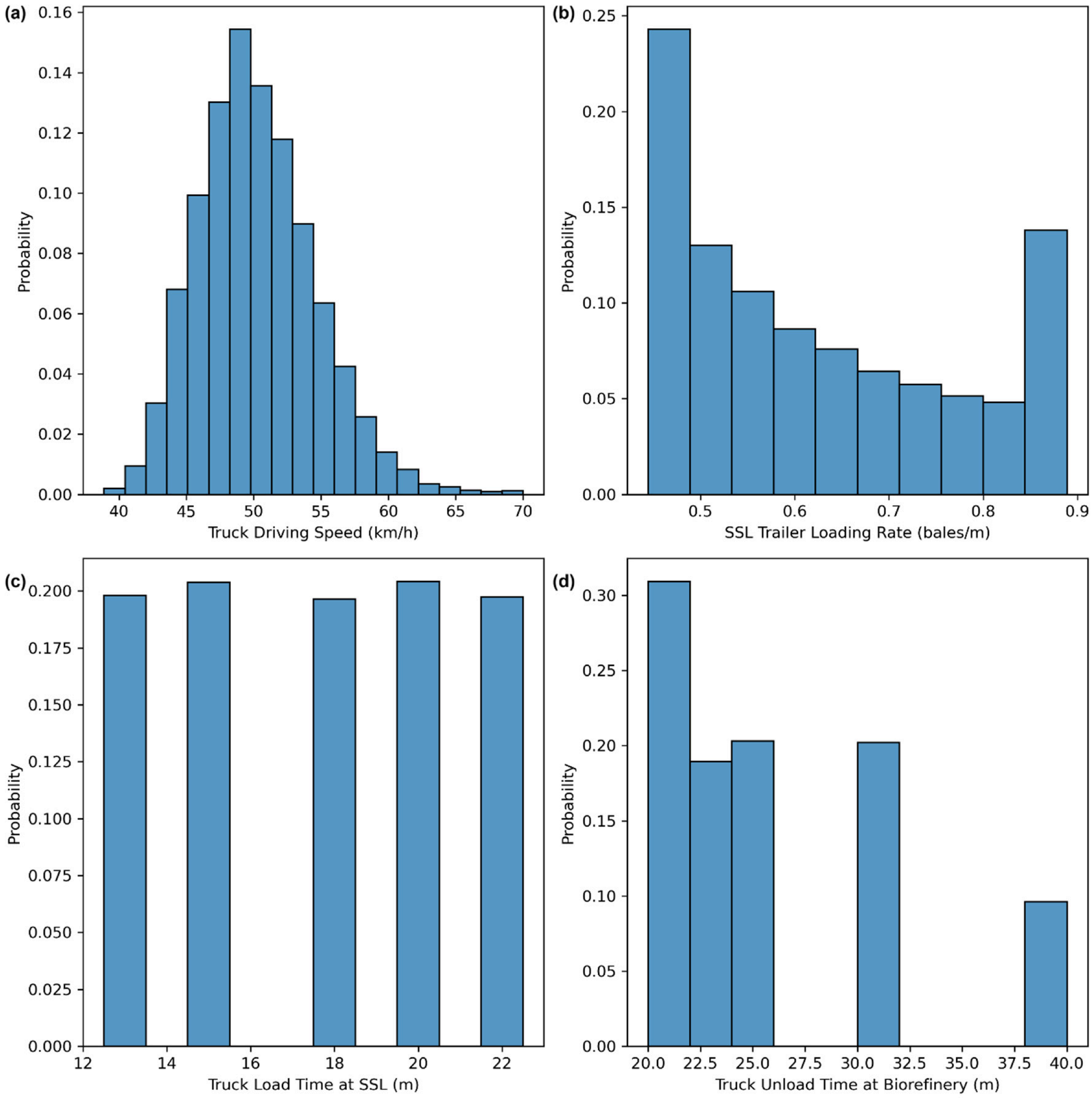

Figure 3. Histograms representing the random parameter distributions used in the simulation: (**a**) truck driving speed, (**b**) SSL trailer loading rate, (**c**) truck load time, and (**d**) truck unload time.

The truck load time at the SSL was defined as the time required for a truck to arrive at an SSL, drop off a set of empty trailers, and hook the set of full trailers. This process was assumed to have an "ideal" time of 15 min [6]. However, to account for the uncertainty in real-life load times, a random uniform distribution was used to estimate the load time before each loading operation at an SSL, such that load times of 12.5, 15, 17.5, 20, and 22.5 min each had a 20% likelihood of being randomly selected (Figure 3).

The truck unload time at the biorefinery was defined as the time required for a truck to arrive at the biorefinery, weigh the trailers, verify the biomass quality, unload the full trailers, load the empty trailers, and weigh out. This process was assumed to have an "ideal" time of 20 min [6]. Once again, a random distribution was used to estimate the unload time before every unloading operation. The distribution was non-uniform, such that an unload time of 20 min had a 30% likelihood, times of 22.5, 25, and 30 min each had a 20% likelihood, and 40 min had a 10% likelihood (Figure 3).

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2.5.2. Initial Conditions

The simulation began by creating agent objects. The number of trucks could vary, depending on the scenario. Each truck object was initialized as waiting at the biorefinery and not having an assigned SSL. A total of 199 SSL objects were created and initialized. The properties of each SSL, such as the amount of biomass stored (Mg) and the road distance to the biorefinery (km), were imported from databases based on the results of the previously defined spatial and network analyses performed in ArcGIS. Nine LOO objects were created using the SSL sequences defined for each (i.e., "in-to-out" or "out-to-in"). The initial SSL for each LOO, representing the start of load-out operations, was set as the first SSL in each LOO sequence.

2.5.3. Daily Simulation

Load-out operations at the SSLs, the process of loading bales into trailers, were assumed to occur ten hours a day. The daily start time was defined as 0600, so the standard workday for load-out operations was 0600 to 1600. The start time of truck hauling was assumed to start one hour later than load-out operations to give the LOOs time to complete their loading and have full trailers available for pickup. An extra 30 min was allowed at the end of the twelve-hour hauling day to allow trucks mid-route to complete their delivery. As a result, the standard workday for truck hauling was 0700 to 1930. Based on these times, the daily simulation was designed to run at 1 min time steps from 0600 to 1930, or 810 min.

Load-out operations occurred each day from 0600 to 1600 at each SSL currently being processed by the nine LOOs. During load-out operations, if the set of trailers at an SSL has less than a full load (i.e., 40 bales), then the trailers are loaded based on the SSL's current trailer loading rate (in bpm). Once the set of trailers reaches a full state, then the load-out operations at that SSL pause while they wait for a truck to arrive. When the truck completes loading at the SSL (i.e., picks up the full trailers and drops off a set of empty trailers), then the load-out operations at the SSL start again with the empty trailers. Once the biomass stored at an SSL is less than the amount needed for a full load (i.e., 16 Mg), then the SSL has reached "end of operations" and the LOO starts the process of a "move between SSLs". This process involves the LOO moving equipment from the SSL just emptied to a new SSL. For simplicity, the "move between SSLs" process was assumed to be six hours or 360 min. If there is not enough time in the simulated day to complete the "move between SSLs", then it occurs the following day. The new SSL cannot start load-out operations until the "move between SSLs" is completed. When a truck makes the final trip to an SSL that ended operations, it will drive to the new SSL to drop off an empty trailer set (so it will be ready to start load-out operations) before driving to the old SSL to pick up the full trailer set.

Hauling operations occurred each day from 0700 to 1930 for each truck. For each minute of the hauling day, each truck checks its current state to determine its action (Table 1). If the state is "waiting at biorefinery", then the truck will check the trailer state of each SSL. If an SSL completes loading operations before the truck arrives (based on the current loading rate of the SSL and assuming this loading rate stays constant), and the truck can complete the round trip before the end of the hauling day, then the truck will begin driving to the SSL. If the state is "driving to SSL", then the truck's distance (km) to the biorefinery will increase by the truck's current speed (in kpm). Once the truck's distance has exceeded the SSL's distance to the biorefinery (i.e., it has arrived at the SSL), then the truck will begin loading. If the state is "loading at SSL", then the truck will load the trailers at the SSL based on its current load time (in minutes). Once the truck has finished loading, it will start driving back to the biorefinery. If the state is "driving to biorefinery", then the truck's distance (km) to the biorefinery will decrease by the truck's current speed (in kpm). Once the truck's distance is less than zero (i.e., it has arrived at the biorefinery), then the truck will enter the "unloading queue". The number of unloading operations that can occur simultaneously at the biorefinery could vary, depending on the scenario. If the state is "waiting in queue", then the truck will wait until it is at the front of the queue to begin unloading. If the state is "unloading at biorefinery", then the truck will unload the trailers based on its current unload time (in minutes). Once the truck has finished unloading, it returns to the "waiting at biorefinery" state to wait for another SSL to be ready. This cycle continues for each truck until the end of the hauling day.

For any trucks that remain in the "unloading queue" at the biorefinery at the end of the hauling day, they will be unloaded at the end of the day during "nighttime" operations. This process is to ensure the trailers are empty and ready for a new truck cycle at the start of the next day. Once the end of the hauling day has been reached by the simulation, each truck should be in the state of "waiting at biorefinery" with an empty set of trailers and no assigned SSL. Similarly, each SSL currently being processed by a LOO should be waiting to start loading operations the next day.

Internal verification of the model was performed on the daily simulation at the minute level through extensive inspection of important object attributes, such as truck states, and model outputs, such as biomass delivered, to ensure that all agents were following the rules defined by the model design. For example, during a "move between SSLs" event, verification was done to ensure a truck first traveled to the new SSL before traveling to the old SSL. Once it was verified that the daily simulation was accurately simulating a single hauling day, the model was expanded to simulate each day in the hauling season.

2.5.4. Annual Simulation

To simulate the annual 48-week hauling season, the daily simulation was automated with a loop to replicate the same processes every day in the season. Assuming the truck hauling and load-out operations both operate over a six-day workweek, this means there are (48 weeks) × (6 days per week) = 288 days of operation in an annual hauling season. At the start of each day, each truck is assigned an initial SSL based on those currently being processed by LOOs. Each truck proceeds with its hauling cycle when ready and is automatically assigned new SSLs as they become available. Each SSL being processed by a LOO loads trailers as they arrive and awaits trucks for hauling. Each LOO moves from SSL to SSL when they finish processing the biomass from the current SSL. At the end of each day, the truck hauling and load-out operations pause, with the trucks waiting at the biorefinery, and operations continue the next day in a seamless manner. At the end of the annual simulation, a mass balance check was performed to verify that the amount of biomass that left the SSLs over the hauling season was equal to the amount that was delivered to the biorefinery.

Two simulation parameters were varied to evaluate different scenarios: (1) the number of trucks (n) used by central control and (2) the number of unloading operations (m) at the biorefinery. To account for the stochastic variability of the random parameters, each scenario was replicated for ten trials. The goal was to find the optimal combination of these parameters, the number of trucks (n) and the number of unloading operations (m), that could deliver all the biomass stored at the SSLs over the 48-week (288-day) hauling season in the most efficient manner. Too few trucks might be unable to deliver all the biomass in the time required, and too many trucks would result in wasted time waiting at the biorefinery. As an optimization problem, what is the fewest number of trucks needed to haul all the biomass in the required time? The number of unloading operations was added as an additional parameter to adjust for optimization. The optimization problem then becomes: what is the minimal number of trucks and unloading operations needed to complete the delivery of biomass in the required time?

3. Results and Discussion

The total truck operating hours required to haul all loads from all SSLs was calculated using the following constants: 57.8 kph truck speed, 17.5 min load time, and 25.5 min unload time (Table 3). Assuming no travel delays and no waiting time for loading and unloading, the required total was 19,590 h per year. The annual truck operating hours were defined as (12 h per day) × (6 days per week) × (48 weeks per year) = 3456 h per year per truck. The required truck operating hours of 19,590 h per year divided by 3456 h per year per truck gives a theoretical minimum fleet of 5.7 or 6 trucks. The question becomes, how close to this minimum fleet can be achieved with realistic operating parameters using the agent-based simulation? The 48-week (288-day) simulation was run for the following scenarios: with m = 1 unloading operation for n = 10, 11, 12, and 13 trucks and with m = 2 and 3 unloading operations for n = 7, 8, 9, and 10 trucks. The hauling productivity was summarized (mean and standard deviation) over ten trials per scenario (Table 4). Overall, the model output demonstrated little variability over each scenario across the ten replications. This is likely due to the model simulating an entire hauling year (288 days). The stochastic variability of the parameters tended to average out over time, akin to the law of large numbers.

Table 4. Annual biomass delivered over the hauling season for each scenario, summarized as the mean ± standard deviation over ten simulation trials per scenario.

Number of Trucks	Annual Biomass Delivered (% of Total Storage)	Average Biomass Delivered (Mg per Day)	Number of Hauling Days
One Unloading Operation			
10	90.6 ± 0.21	479.9 ± 1.14	288 ± 0.00
11	93.7 ± 0.28	496.3 ± 1.42	288 ± 0.00
12	96.8 ± 0.20	512.4 ± 1.04	288 ± 0.00
13	98.9 ± 0.07	523.8 ± 0.32	288 ± 0.00
Two Unloading Operations			
7	93.4 ± 0.21	494.5 ± 1.10	288 ± 0.00
8	98.9 ± 0.11	524.5 ± 1.86	288 ± 0.84
9	99.0 ± 0.00	567.2 ± 2.38	266 ± 1.10
10	99.0 ± 0.00	605.0 ± 1.89	250 ± 0.71
Three Unloading Operations			
7	94.6 ± 0.21	500.8 ± 0.95	288 ± 0.00
8	99.0 ± 0.07	528.9 ± 6.78	285 ± 3.53
9	99.0 ± 0.00	578.5 ± 4.05	261 ± 1.83
10	99.0 ± 0.00	622.4 ± 2.17	243 ± 0.84

The maximum annual biomass delivered from these simulations was 150,976 Mg or 99.0% of the total biomass stored in the SSLs. This is because each SSL has biomass remaining in storage at the end of the simulation since less than a full load (16 Mg) was not shipped. This biomass was assumed to be managed by a “clean-up” operation, which would collect the leftover biomass at each SSL and deliver it to the biorefinery. This cleanup operation was not part of this study; however, the impact of the “clean-up” operations on overall truck productivity and fleet size should be studied in future research. For these simulations, delivery of 99.0% of the total biomass stored in the SSLs was defined as a successful completion of the hauling season.

With one unloading operation, none of the scenarios (n = 10, 11, 12, or 13 trucks) were able to successfully complete the delivery of biomass stored in the SSLs over the 48-week hauling season. The closest result was obtained by the scenario with 13 trucks, which delivered 98.9% of the total biomass. Each additional truck resulted in only a modest increase in productivity, ranging from 479.9 Mg delivered per day for 10 trucks to 523.8 Mg delivered per day for 13 trucks. Figure 4 shows an example snapshot of the truck states and distance to biorefinery for the scenario with 10 trucks in Week 14 of the 48-week hauling season. Figure 4a shows the 9 SSLs currently being unloaded by LOOs at the start of an example day, with their distance to the biorefinery represented by a polar plot. Figure 4b–f show the states of the 10 trucks and their current location every three hours of the example day as they drive back and forth between the biorefinery and the SSLs. It was observed that, with only one unloading operation, much of the time for each truck was spent "waiting in queue" at the biorefinery to unload.

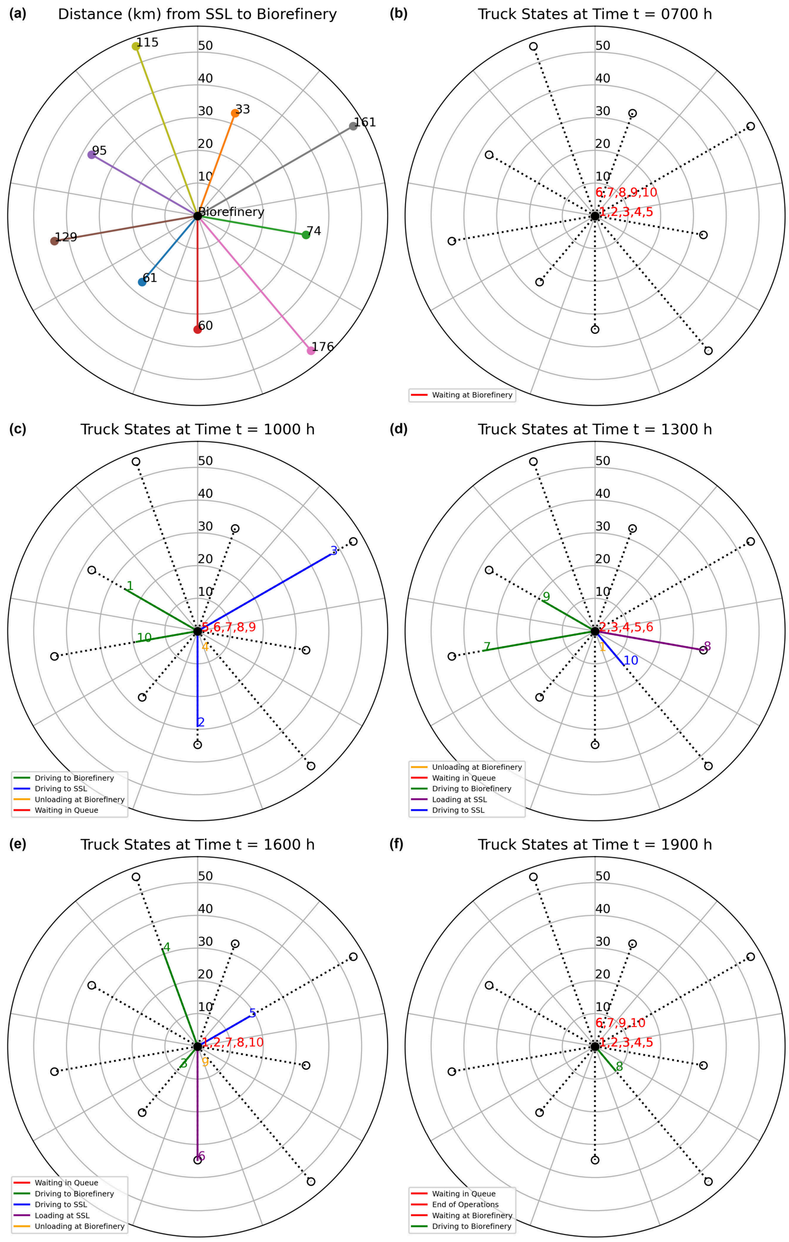

Figure 4. An example snapshot of a daily simulation with n = 10 trucks and m = 1 unloading operation: (**a**) the SSL IDs being processed by the nine load-out operations in a given day of the 48-week hauling season with their distance to the biorefinery represented by a straight line on a polar plot and (**b**–**f**) the truck IDs and their states every three hours in one twelve-and-a-half hour hauling day (starting at 0700 h), showing the trucks drive back and forth between the biorefinery and SSLs.

There was a significant increase in truck productivity with a second unloading operation. Two scenarios (n = 9 and 10 trucks) completed the delivery within the 48-week hauling season, with time to spare. With 7 trucks, only 93.4% of the biomass was delivered; however, 8 trucks were close to completion at 98.9%. It is important to note that the estimated productivity with 8 trucks and two unloading operations (524.5 Mg delivered per day) was approximately equal to the estimated productivity with 13 trucks and one unloading operation (523.8 Mg delivered per day). Thus, by adding a second unloading operation, the truck fleet could be reduced by 5 trucks.

Each simulation kept track of each truck's state for each minute of each day. Table 5 summarizes the average time a truck spends in each state in a twelve-and-a-half-hour hauling day (i.e., 750 min per day) over the 48-week hauling season (i.e., 288 days per year). With one unloading operation, the average time spent waiting in the queue to be unloaded ranged from 264 to 318 min (35 to 43% of the hauling day), going from 10 to 13 trucks. Obviously, this is a concern and necessitates additional unloading operations. Adding a second unloading operation, the time spent waiting in queue ranged from 20 to 31 min (3 to 4%), going from 7 to 10 trucks. As a direct comparison (keeping the number of trucks constant), with 10 trucks, the time waiting in queue was reduced from 264 to 31 min going from one to two unloading operations.

Table 5. The minutes per day per truck spent in each state averaged over the hauling season for each scenario, summarized as the mean ± standard deviation over ten simulation trials per scenario.

Number of Trucks	Waiting at Bio.	Driving to SSL	Loading at SSL	Driving to Bio.	Waiting in Queue	Unloading at Bio.	End of Ops.
One Unloading Operation							
10	15 ± 0.5	154 ± 0.5	53 ± 0.1	153 ± 0.5	264 ± 1.3	65 ± 0.1	46 ± 0.5
11	21 ± 0.7	144 ± 0.5	50 ± 0.2	143 ± 0.5	288 ± 1.3	59 ± 0.1	45 ± 0.4
12	28 ± 0.8	136 ± 0.3	47 ± 0.1	135 ± 0.3	306 ± 1.2	54 ± 0.0	43 ± 0.6
13	41 ± 1.4	127 ± 0.1	45 ± 0.1	126 ± 0.1	318 ± 1.5	50 ± 0.1	43 ± 0.6
Two Unloading Operations							
7	5 ± 0.3	226 ± 0.4	79 ± 0.3	224 ± 0.4	20 ± 0.5	112 ± 0.3	84 ± 0.7
8	36 ± 1.3	207 ± 0.3	73 ± 0.1	205 ± 0.3	26 ± 0.7	104 ± 0.2	100 ± 1.1
9	88 ± 1.4	184 ± 0.1	65 ± 0.1	182 ± 0.1	29 ± 0.5	93 ± 0.3	108 ± 1.4
10	133 ± 1.5	166 ± 0.1	58 ± 0.1	164 ± 0.1	31 ± 0.4	84 ± 0.3	113 ± 1.5
Three Unloading Operations							
7	5 ± 0.3	228 ± 0.6	80 ± 0.3	226 ± 0.6	4 ± 0.2	113 ± 0.4	93 ± 1.3
8	47 ± 1.7	207 ± 0.2	73 ± 0.2	205 ± 0.2	6 ± 0.2	104 ± 0.2	108 ± 1.3
9	103 ± 1.3	184 ± 0.2	65 ± 0.1	182 ± 0.2	8 ± 0.3	93 ± 0.2	115 ± 1.6
10	151 ± 1.5	166 ± 0.1	58 ± 0.1	164 ± 0.1	8 ± 0.2	84 ± 0.2	119 ± 1.6

The average time spent unloading at the biorefinery was higher for the m = 2 simulation, 84 to 112 min, as compared to 50 to 65 min for the m = 1 simulation. As a direct comparison, with 10 trucks, the time spent unloading increased from 65 to 84 min going from one to two unloading operations. This is counterintuitive, but is explained by the fact that each truck hauls more loads per year in the m = 2 simulation. For example, 7 trucks hauled on average 1259 loads per truck in the m = 2 simulation as compared to 855 loads per truck for 10 trucks in the m = 1 simulation. More loads per truck explains why the driving time totals (to SSL and to biorefinery) were higher for the m = 2 simulation. The goal is to "keep the wheels of the trucks turning".

The total "unproductive time" for a truck was defined as the time a truck spends during a hauling day in a state not actively driving, loading, or unloading (i.e., "waiting at biorefinery", "waiting in queue", or "end of operations"). The total unproductive time was calculated for each scenario based on the average minutes per day per truck in these states (Table 5). The total unproductive time was expressed as a percentage of the total hauling day (i.e., 750 min) and summarized over each scenario (Figure 5). With one unloading operation, the unproductive time was greater than 40% for all truck scenarios and increased with each additional truck, with a maximum over 50% with 13 trucks, meaning that trucks were spending over half of their time in an idle state.

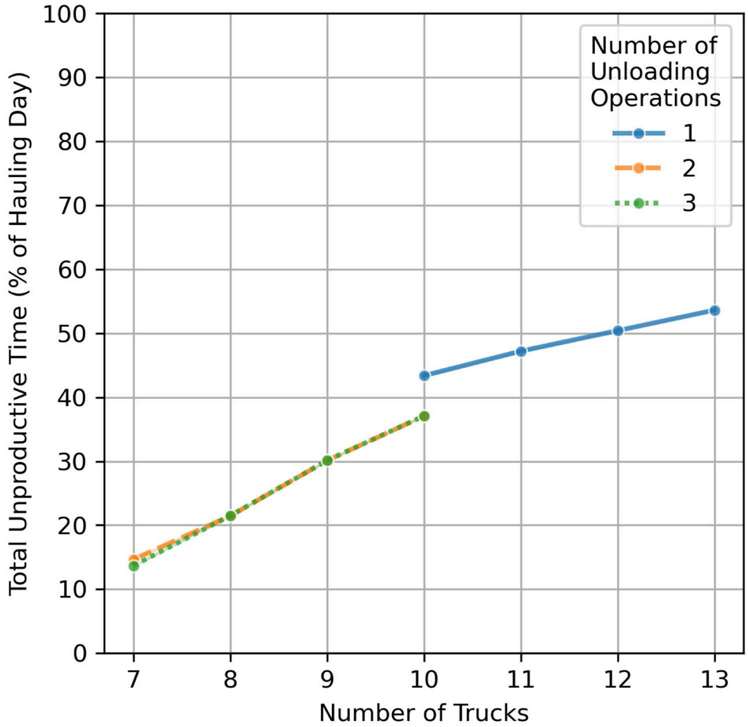

Figure 5. The total unproductive time that a truck spends waiting at the biorefinery on average per day (as a percentage of the total hauling day) for each scenario.

With a second unloading operation, the unproductive time decreased significantly (Figure 5). For $n = 8$ trucks in the $m = 2$ simulation, the total unproductive time was about 20%. As previously stated, the theoretical minimum truck fleet, assuming no unproductive time, was about 6 trucks. It may be possible for a production operation to achieve the 20% unproductive time target, but it is not likely; there are too many uncertainties. A 9-truck fleet with 30% total unproductive time is likely more realistic. In the scenarios with three unloading operations ($m = 3$), the total unproductive time did not improve over the $m = 2$ scenario. With three unloading operations, trucks spent less time waiting in the unloading queue, but more time waiting at the biorefinery for an available SSL (Table 5).

4. Conclusions

It is imperative to organize a biorefinery supply chain in a way to maximize truck productivity (Mg per day) and thus minimize truck fleet size. This is done by minimizing unproductive time (load time, unload time, waiting in a queue, waiting to be dispatched). Central control, where the truck fleet is under the control of a feedstock manager at the biorefinery, is the key to efficient hauling. The agent-based simulation developed for this study used open-source programming tools and could easily be adapted to another study area. The primary requirement for a given production area is a database of potential feedstock, which can be estimated from common land cover datasets such as the NLCD, organized into a set of SSLs, and divided into a set of LOOs. The results demonstrate that for the study area centered in Gretna, VA, USA with 199 SSLs, trucks can be dispatched to one of nine LOOs operating simultaneously such that a truck arrives at an SSL when a load is ready, thus minimizing load time. Two unloading operations at the biorefinery significantly reduced the time trucks waited in the queue and thus reduced the total idle time. It was found that utilizing two unloading operations and 8 trucks could achieve the same productivity, with less truck idle time, as one unloading operation and 13 trucks.

There were some limitations and uncertainties with the current simulation design that are important to note and could be improved with future research. For example, the model used a single stochastic parameter to represent traffic delays. However, these delays could be caused by several sources in addition to traffic, such as adverse weather conditions, which would vary seasonally and would not be constant over the 48-week hauling season. In addition, the model assumed the same truck speeds going to the SSLs (without a load) and going back to the biorefinery (with a load), and this difference in load would likely have an impact on the average truck speed each way in the trip cycle. Also, the road screening rules of the network analysis only considered primary and secondary roads as available for trucks. Future studies should consider additional rules, such as vehicle class filters due to weight restrictions as well as directionality and turn restrictions.

Future research should also conduct a cost–benefit analysis to better compare the scenario outcomes. The current study only addresses costs in relative terms. For example, if the required truck fleet is reduced from 10 to 8, then the truck ownership and labor costs are reduced by 20%. However, a more formal analysis should compare the cost of adding one unloading operation with the benefit of reducing the truck fleet by 5 trucks.

The minimum truck fleet required to deliver all loads from 199 SSLs distributed over a 48 km radius surrounding the biorefinery over a 48-week hauling season was 6 trucks, assuming no delays. When assuming reasonable delays in a real-life production setting, this simulation study predicted that a fleet of 8 trucks could haul these loads by utilizing two unloading operations; total unproductive time was 20% of the total operating time. A fleet of 9 trucks, which might better account for the uncertainty, could haul the loads with a total unproductive time of 30%.

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