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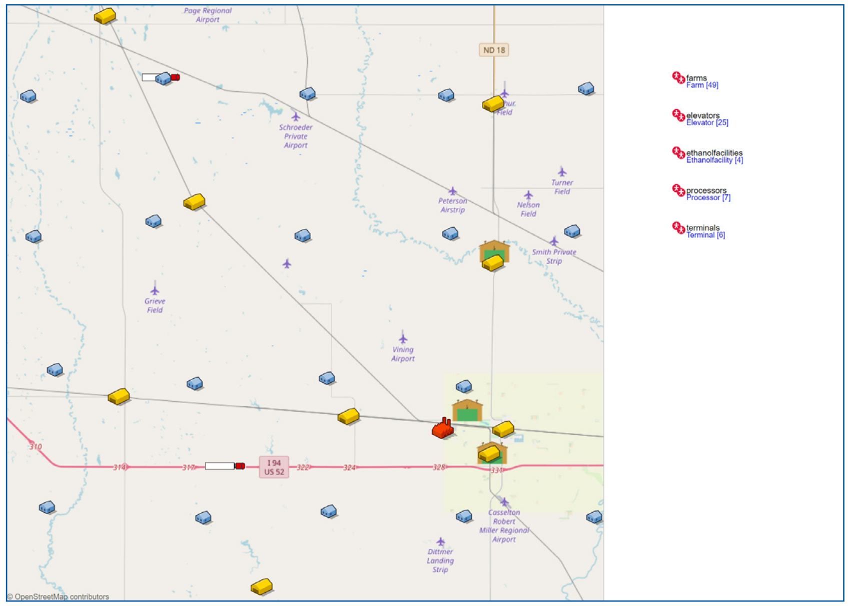
## Application of a Multi-Agent System with the Large-Scale Agent-Based Model for Freight Demand Modeling

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# APPLICATION OF A MULTI-AGENT SYSTEM WITH THE LARGE-SCALE AGENT-BASED MODEL FOR FREIGHT DEMAND MODELING

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## ABSTRACT

To support agricultural logistics and energy development, road and bridge infrastructure has been in North Dakota due to the recent oil boom and the long-term importance of the agricultural industry. With the advance of simulation and data mining, the agent-based model (ABM) has emerged as a solution. Agent-based modeling techniques reflect a high level of detail for travel patterns in a region or state.

This research will review state-of-the-art ABM in transportation, determine an agent's travel behavior in rural and small urban freight movement, design a multi-agent system, and investigate applicability of the agent's travel behavior to statewide freight demand mode.

This paper outlines an agent-based freight transportation model of the grain upstream supply chain for Cass County in North Dakota. The objective is to develop a model incorporating stochastic variables to capture the uncertainties each entity faces, and consequently the effects of variables and strategies on traffic flows. This model simulates a robust level of the decision-making process at a granular level to assess the impact of cargo policy at local, state, regional, and national scales.

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# 1. INTRODUCTION

To support agricultural logistics and energy development, road and bridge infrastructure is critical in North Dakota due to the recent oil boom and the long-term importance of the agricultural industry. Due to the nature of infrastructure investment, transportation planning should require long-term projection and large investment using public finance. Thus, statewide freight demand modeling is a great tool to ensure a plan and to enhance effective and efficient investment. However, sources of traffic on the infrastructure are various and dynamic, depending on time, weather, geographic characteristics, and travelers' behavior and activities. We assume that a group of travelers or agents would provide a variety of driving patterns. Predicting travelers' behavior has been a cumbersome task in transportation planning because of the wide variation of behavior among travelers.

Conventional transportation planning is not sensitive to the changes of information and technologies due to limited effects (Wang and Mohamed Wahba 2010). Thus, a learning-based algorithm needed over time for advancing the transportation assignment model (TAM). For example, mode choice and time-dependent problems in the traditional four-step process are not adequately addressed (Rieser, Grether and Nagel 2009). The conventional models produce origin-destination (O-D) matrices for the assignment step in the downstream end of the four-step model and ignore the behavior from the upstream, which generates demand (Rieser, Grether and Nagel 2009). Furthermore, the traditional approach does not represent such small-scale effects as local accessibility (Rieser, Grether and Nagel 2009). For these reasons, micro-level of behavior demand models are required to support large-scale scenarios, as well as micro level of transportation operations management (Otani, Sugiki and Miyamoto 2011).

Hensher and Figliozzi argued that current freight models and public policy tools cannot catch up with the rapid changes in the supply chain structures, logistics, and technological advancements. In such a fast-paced environment, the conventional four-step approach, originally developed for passengers, are not able to address the complexity of the decision-making process in any geographic location (Hensher & Figliozzi, 2007). Amir Samimi, in line with many other researchers, believes that complexity of the decision-making process, lack of an acceptable freight modeling framework, and freight data scarcity are the major obstacles for freight forecasting tools. A successful freight forecasting tool must be able to address these problems either by adopting the traditional methodologies or introducing an entirely new framework of freight demand forecasting tools (Southworth, 2003).

With the advance of simulation and data mining, the agent-based model (ABM) has emerged as a solution. The agent-based modeling technique would reflect a high level of detail for travel patterns in a region or state. The ABM includes three elements: agents, agent relationship, and agent's environment (Macal and North 2009). The individual known as an agent is an entity for decision-making. ABM was applied to the Canadian grain handling and transportation systems (Lawrence, Nolan and Schoney 2016).

When an agent uses a vehicle, ABM is also called as a vehicle agent. The ABM using the vehicle agent is called vehicle-based modeling. Agents interact with each other and react to transportation infrastructures and policies. The agent-based freight demand modeling has been emerging as a critical component in transportation planning to represent realistic travel activities throughout road networks and among facilities. ABM allows aggregations and disaggregation of agent characteristics, behaviors, and interactions under the freight demand context (Harper, et al., 2011).

However, agents should interact in long-term environments, such as mid- and long-range transportation plans. By simulating the agents, it is possible to aggregate the freight movement in a large network to provide important information about statewide freight demand without losing details. In large-scale road networks, a variety of agents interact over space and with time in response to information about transportation infrastructure, logistics facilities, and policies. Thus, the multi-agent system is designed for the statewide micro level in this study. For modeling purposes, agents are grouped; the groups interact with other agent groups, and each agent in a group interacts with other agents in the group. Thus, the behavior (i.e., principal decision rules and response rules) of an agent group, and each agent in the group can be simulated under different transportation operations and planning scenarios. The multi-agent system includes decision-making rules, such as destination choice, departure and arrival time, mode choice, route choice, and sensitivity to travel impedance.

This research will review state-of-the-art agent-based modeling in transportation, determine agent's travel behavior in rural and small urban freight movement, design a multi-agent system, and investigate applicability of the agent's travel behavior to statewide freight demand mode.

This paper outlines an agent-based freight transportation model of the grain upstream supply chain for Cass County in North Dakota. The objective is to develop a model incorporating stochastic variables capturing the uncertainties each entity is facing, and consequently the effects of various variables and strategies on traffic flows. This model simulates a robust level of decision-making process at a granular level to assess the impact of cargo policy at local, state, regional, and national scales.

The approach is unique in the focus on the application of agent-based modeling for grain transportation in that the freight goods and vehicle movements are modeled as derived demand arising from the needs and behaviors of the individual organization. The proposed model is a microscopic type, which is a modification of the traditional four-step approach. The model reproduces each entity involved in the upstream supply chain of grain products, such as farms, elevators, processors, and ethanol facilities. This model is built on the main idea that shipments are simulated for supplier-consumer relations with the intermediaries. Each is represented by an agent entity. The diversity of freight transportation is another important factor in analyzing freight modeling. Transport-related choices may be influenced, for example, by the geographical locations of supplier and consumers and by commodity types. The model structure consists of four main stages, including:

- Production
- Distribution
- Conversion of commodity flows to trucks flows and train flows
- Traffic assignment

The objectives of this study are threefold:

1. To review state-of-the-art transportation planning models adopting micro-simulation of the agent-based model in freight modeling
2. To test the feasibility of ABM in large-scale agricultural transportation planning
3. To provide a research framework to use ABM in agricultural transportation demand modeling

This paper is structured as follows. In Section 2, a brief overview of recent freight transportation models is presented. Data sources and related assumptions are explained in Section 3. In Section 4, the proposed ABM is introduced and the logic for each agent is described. The findings and results of a model application for Cass County and model validation are presented in Section 5. Finally, the last sections present the conclusions and direction for future work.

# 2. LITERATURE REVIEW

This paper reviews the models of flow factoring method, origin-destination factoring method, a hybrid model, economic activity model, supply chain logistics model, tour-based model, and activity-based model in brief. In addition to the traditional model, the study also reviews the ABM, which has attracted transportation planners in recent years.

## 2.1 Definition of the Key Terms

Before reviewing further literature, here is a summary of several terms being used for the travel demand model, so they can be referred to throughout the paper (Figure 2.1).

An **agent** is an autonomous agent, including individuals or a set of entities (e.g., passenger, driver, households, organizations, and groups). The entity should be discrete and active with its own goals and behaviors (Macal and North 2006). An autonomous agent carries a capability to adapt and modify its behavior. For example, a commuter will drive from home to a workplace on a local highway to avoid a toll; however, the commuter running late after dropping off a child at school is willing to pay a toll by taking an interstate highway. The driver is a discrete and autonomous entity with the capability to adopt a couple of different highway systems.

An **activity** is a continuous interaction with the physical environment, a service or person, within the same socio-spatial environment relevant to the sample/observation unit. It includes any pure idle times before or during the activity, such as waiting at a doctor's office (Ortuzar and Willumsen 2012). From the perspective of an agent, it means traveling to reach a workplace for socio-economic activity. The agent's associates will have the same activity goals, but the time and space might be different for each person.

A **stage** is a continuous movement using a mode of transport or, more precisely, one vehicle. It includes any pure waiting (idle) times immediately before or during that movement (e.g., waiting for a bus, searching for a parking space, and making parking maneuvers) (Ortuzar and Willumsen 2012)

A **trip** is a continuous sequence of stages between two activities (a trip can have only one stage, such as a car trip, or more as in a multi-mode trip) (Ortuzar and Willumsen 2012)

A **tour** is a sequence of trips starting and ending at the same location. A trip chain is the same as a tour, but it may not end at the same location.  (Ortuzar and Willumsen 2012). Tours may be classified by length of the trips and by their most relevant activity.

Each trip has one or more purposes. However, a trip purpose is defined by the most important activity undertaken at one end of the trip (Ortuzar and Willumsen 2012). Individual passengers may make different choices as part of planning process. The planning process considers how experiences and information from the learning process inherited from previous periods, and present situations influencing the choice on the upcoming tour (Wang and Mohamed Wahba 2010).

**A plan** contains the itinerary and activities the agent (traveler) wants to include during a period. The plan includes trip legs the agent must travel between activities (Rieser, Grether and Nagel 2009).

In summary, an agent travels to achieve a trip purpose with a tour, which starts in one place and ends in another via one or more stages with multiple trips or directly between origin and destination. The frequency and sequence of the activities and paths to take depend on the agent's behavior over time and space limitations.

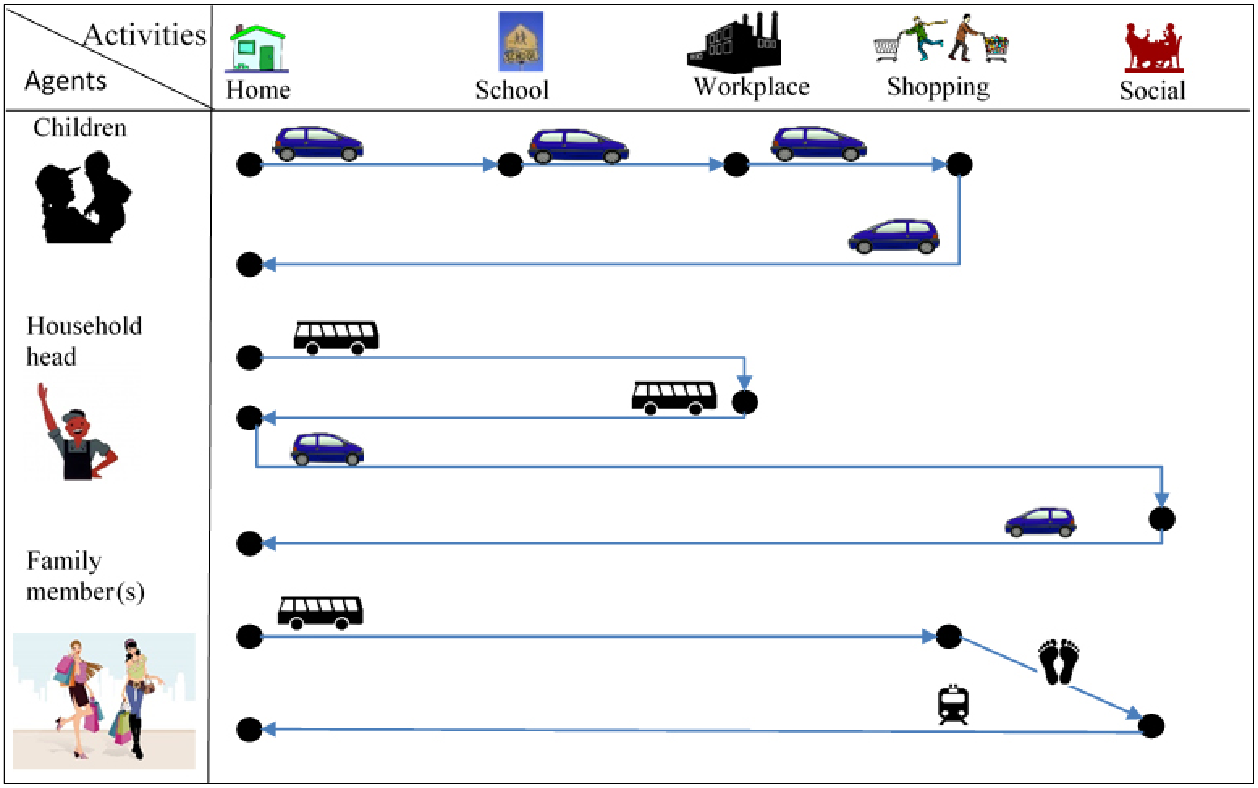



**Figure 2.1** Agents, daily activities, tours, trips, and purposes (reconfigured from Ortuzar & Willumsen, 2012, pg. 475).

## 2.2 Simulation and Other Travel Demand Modeling

In the context of simulation, agent-based modeling and simulation may be compared to discrete-event system modeling, which simulates a system where a state variable changes only at a discrete set of points in time (Banks and John S. Carson II 1996). All entities and locations are objects in a system, and those objects interact with each other based on rules and policies. The rules and polices emulate behavior of the objects. Similarly, agent-based modeling and simulation model the behavior of agents and define their behaviors and interactions with other agents. All of the agents and entities for the simulation models are associated with object-oriented programming (OOP). In the OOP language environment, the behavior and procedures are encapsulated in objects (i.e., entities and agents). An entity, or an agent, is an instance of a class in OOP.

Activity-based models have received extensive interest as a new generation of travel demand models. Travel demand models forecast the usage volume of changes, both in the attributes of the transportation systems and in predicting user behaviors. Traffic volume, as a result of transportation systems use, is based on the characteristics of various entities, including travelers, land-use policy, and facility locations. Thus, the activity-based model treats travel as being derived from the demand for social and economic activities

### 2.2.1 Flow Factoring Method

Federal Highway Administration (FHWA) describes a simple growth factor method as the simplest and most direct method to forecast future freight demand. It simply factors existing freight demand to forecast future freight demand either based on historical traffic trends or forecasts of economic activity. This method is widely used by DOTs and MPOs, and other planning agencies for the short-term forecast of freight volumes on transportation systems. The State of Minnesota used an economic factoring method to forecast truck flows on its Truck Highway (TH) system for the TH 10 segment through Sherburne, Anoka, and Ramsey counties. In a similar approach, Florida DOT, with the University of Florida, developed the Heavy Truck Freight Model for Florida Ports (Barker, Brown, Director, Deborah Butler, & Clark, 2008).

### 2.2.2 Origin-Destination Factoring Method

In a similar approach, a growth factor can be applied to just two additional components of mode split and traffic assignment on the base year O–D table. Unlike the previous method, this explicitly considers the O–D travel patterns of commercial vehicles. Ohio developed an interim freight model to provide a clear picture of current and future freight movements on important highway corridors. Base-year truck trip tables for long-haul movements are well characterized in commodity flow data sets, such as the Commodity Flow Survey and the Reebie TRANSEARCH database. The Ohio Interim Freight Model was designed to assess freight trends and impacts on Ohio's roadways. The project found that O-D tonnage table could convert to daily trucks and mapped to Ohio's roadways (Barker, et al. 2008).

### 2.2.3 Hybrid Model

A hybrid model combines two features of the commodity-based (long-haul approach) and truck (three-step models/short haul approach) model. The truck model (three-step truck model) uses traditional trip generation, trip distribution, and traffic assignment methods. It cannot capture shifts between modes; hence, they are part of a comprehensive model using the simultaneous assignment of the truck vehicle trips. The New Jersey Truck Model developed highway freight truck flows by assigning an O-D table of freight truck flows to highway networks. In this model, the O-D table was produced by applying truck trip generation and distribution steps to existing and forecasted employment and other variables of economic activities for transportation analysis zones (TAZ).

The traditional four-step traveling demand model includes trip generation, trip distribution, mode choice, and trip assignment. It was developed for a passenger model; however, it has evolved for a freight model and applied widely. The model forecasts goods movement in traditional urban transportation planning models, state transportation planning models, and in site planning. The Indiana Commodity Transport Model, for example, is based on the model. The Florida Intermodal Statewide Highway Freight Model (FISHFM) is also a four-step commodity forecasting model. FISHFM estimates total truck trips on major highways based on a forecast of total employment and then assigns total truck and auto trips on the highways. An existing four-step model for passenger auto and total truck traffic provides the state zone structure, highway network, and employment data that serve as the structure for developing the commodity model. The Wisconsin Freight Model applied a four-step freight forecasting model. The latest effort in Wisconsin's freight forecasting was meant to determine the impact of new rail/truck intermodal facilities on highway truck volume and railroad tonnage.

### 2.2.4 Economic Activity Model

The economic activity model assumes a freight equivalent to combined economic activity, land use, and transportation used in passenger travel demand modeling. The economic activity model has two key sub-models: an economic/land use model and a freight transportation demand model. The Oregon Department of Transportation (ODOT) developed the interactive Transportation and Land Use Model Integration Program (TLUMIP), which includes a commercial travel model. It is an integration of economic, land use, and transportation models. Passenger and highway freight movements are integrated to simulate land use and travel behaviors with a variety of data sources (Barker, et al. 2008).

### 2.2.5 Supply Chain Logistics Model

State-of-the-art models have been developed to apply analytical methods that simulate logistics choices throughout supply chains for specific industries. Numerous attempts have been made to apply these concepts, borrowed largely from industry practices, to public decision support systems (DSS). For example, SMILE, one of the DSSs, is a strategic model for a large number of products and transportation modes. A three-constituent model incorporating production, inventory, and multimodal transportation forecasts freight flows in supply chain networks under different scenarios up to 25 years ahead (Tavasszy and Smeenk 1998). It can visualize the impacts of different policies on freight flows.

Azevedo et al. developed an integrated microscopic mobility simulator called SimMobility Short-Term (ST) (Azeved, et al. 2017). SimMobility is a multi-scale agent and activity-based simulator. It considers land use, transportation, and mobility-sensitive behavioral models, which simulate a high-resolution movement of agents (i.e., traffic, transit, pedestrians, and goods), as well as the operations of various mobility services and control and information systems. The simulator focused on impacts of innovative transportation services on transportation networks and the level of mobility. It was successfully calibrated using external data in Singapore. In a similar work, Boerkamps et al. used the GoodTrip model, a demand-driven, commodity-based urban freight movement model, to predict goods and vehicle flows in Tokyo, Japan. The model examined three types of urban distribution systems and the impacts of corresponding changes in infrastructure needs and usage, logistical performance, emissions, and energy use (Boerkamps, van Binsbergen and Bovy 2007).

### 2.2.6 Tour-based Model

A tour is a travel event starting from and returning to one location. The tour will have one or more trips to achieve a trip purpose. Activity-based models are tour-based, but not always the reverse. A tour-based model (TBM) addresses limitations of existing traditional freight forecasting models. The difference between a TBM and a supply chain logistics model (SCLM) is from a unit of analysis. A unit of analysis is a commodity/shipment for SCLM and a vehicle for TBM. Thus, a TBM is more concerned about tour characteristics of a vehicle trip and less concerned about what is being carried. This implies that the model could not be truly multimodal. Hunt and Stefan developed a tour-based microsimulation model for the city of Calgary in Canada using information from roughly 37,000 routes and 185,000 trips (within these tours) made in 2001 (Hunt & Stefan, 2007). Gliebe et al. extended this tour-based microsimulation approach enhancing a treatment of a temporal dimension and integrating the dimension with activity and location choices. The model presented an activity-based model of commercial vehicle and person movements, as part of the Ohio statewide model project (Gliebe, Cohen and Hunt 2007).

### 2.2.7 Summary

Most of the existing models lack behavioral content where various activities, such as manufacturing, inventory holding, and transportation, are expressed. This approach usually leads to loss of precision because of ignoring a decision maker's behavior and shipment attributes. This also applies to a vehicle-based or commodity-based four-step structure, which focuses on very specific aspects of freight movement and ignoring actors and freight markets. In addition to the aggregate nature of the model, the existing model lacks logistics components, such as intermediate handling facilities, multimodality, and shipment volume/size. However, transport companies have developed and used a wide variety of disaggregate logistics models for supply chain optimization models.

From a general point of view, four-step models focus on aggregate travel behaviors and ignore individual decision-making behavior and interaction between steps. During the 1970s, activity-based models were introduced to overcome these issues. The main objective of the activity-based model is to predict activities and related travel choices subject to time and space constraints. This approach has the potential to bridge the gap between macroscopic travel demand and the individual decision-making process, but it requires solving many optimization problems simultaneously.

## 2.3 Agent-Based Modeling

Agent-based modeling and simulation have gained increasing attention over the last two decades in defense, geography, and sociology. The reasons for such attention may be rooted in highly complex and interdependent systems in which conventional modeling may not be as applicable as before. Traditional approaches have difficulties in modeling whole aspects of today's complex transportation and logistics systems. Data are being collected at very fine levels of granularity to enable individual-based simulations with high computational power (Macal and North 2009). Julka et al. proposed an ABM for supply chain DSSs. It can evaluate the effect of changing internal policies of the refinery across various departments (Julka, Karimi and Srinivasan, Agent-based Supply Chain Management-2: A Refinery Application 2002). Freeman et al. investigated the role of ABM to examine the evolution of farm size and financial structure in Canadian prairie agriculture (Freeman, Nolan and Schoney 2009). In a recent study, Pourabdollahi et al. developed a freight demand model based on behavioral ABM for Chicago Metropolitan Area. The model used disaggregate and behavioral approaches for evaluating freight policy at the national and regional scale (Pourabdollahi, et al. 2016).

Since 2000, ABM has shown an increase of maturity and popularity in transportation, but mostly in intermodal and road transportation management (Davidsson, et al. 2005). A strategic approach with a long-term time horizon had not been done in the domains of transport and traffic.

Roozmand et al. proposed an ABM for a consumer decision-making process based on culture, personality, and human needs (Roozmanda, et al. 2011). This model sought the answer to why and when consumers decide to buy products. The primary part of the model is a utility function to evaluate the value of each product considering social status, social responsibility, and price. Ying developed an ABM for a microscopic simulation system of urban traffic. For the major elements of traffic, the study considered multiple-lane roads, intersections, traffic light control agents, and vehicles (Li, et al. 2003). The study used a Q-learning algorithm as a reinforcement learning method for a control agent to improve its control ability. It works by learning the action-value function (1) as follows:

$$\hat{Q} = f[(G, D, F, W, P), a, \theta] \tag{1}$$

Where, ($G$, $D$, $F$, $W$, $P$) = input state

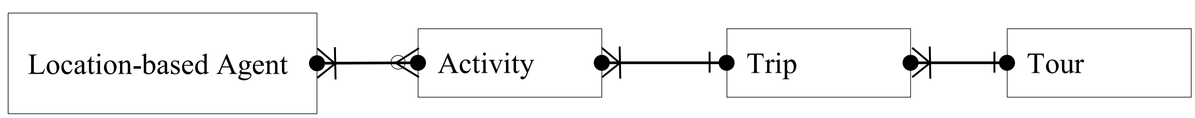
- $G$ = code of green phase
- $D$ = duration of the green light
- $F$ = traffic flow of the green phase
- $W$ = number of the waiting vehicles in red phase
- $P$ = prediction of traffic flow of the next 5 minutes
- $a$ = chosen action
- $\theta$ = the weight

The function shows the expected value of the utility of taking a chosen action $a$, given input state ($G$, $D$, $F$, $W$, $P$), and weight $\theta$. From a reinforcement learning perspective, the environment evaluates the decision and gives a reward to the agent. The reward of the control agent is setting the ratio of the number of passing vehicles of the green phase to the additional vehicle waiting time of the red phase during the decision interval.

Khouja et al. used ABM to determine optimal price and rebate value. The study considered two types of agents: consumers and sellers (Khouja, Hadzikadic and Zaffar 2008). Sellers will find the best price-rebate scheme in response to consumers' behavior over repeated lifecycles of products. A fitness function (performance measuring function) determines seller's actions. It defines the seller's profit over the product's lifecycle. On the other hand, a consumer's purchase history with rebates and redemption behaviors influence the learning process.

Boussier et al. developed a behavioral model describing the relationship between drivers' choices and the following tangible and intangible variables (Boussier, Sarramia and Estraillier 2008): distance, cost, weather, and accessibility. They considered an activity-based model and multi-agent architecture and a set of such variables, such as socio-demographics, traffic and urban variables, to build a multimodal traffic simulator. The study formulated a mathematical form to define the agent's behaviors from a survey. The primary part of the formulation is to make the driver's (i.e., agent's) heuristic decisions. The decisions are to classify and make a choice between similar conditions, and to make a choice between different alternatives. They tested the model with a car park choice scenario in which a driver agent selects the location, then, arriving at a destination, must park its car to carry out an activity.

Each location as an agent may have one or more activities or may not generate any activities, while one activity may belong to one or more locations (Figure 2.2). Each activity will belong to a trip, while one trip will explain one or more activities. One trip will belong to a tour, while one tour will include single or multiple trips. These relationships between entities (agents) can be depicted using an entity-relationship diagram (ERD) (Figure 2.2).




Legends: –|– one, ––|<– one or many, ––o<– zero or many

**Figure 1.2** Simplified entity relationship diagram (ERD).

## 2.4 Summary

An ABM offers a computational toolkit for a behavioral transportation model. The model provides a sophisticated and disaggregate model, which demonstrates how transportation agents interact and patterns of behavior will be emulated. By understanding deeper and precise interactions and behavior of transportation agents, transportation planners and modelers, as well as public users, can understand the systems better.

# 3. MODEL DEVELOPMENT

An agent is an individual or a set of entities that are discrete and autonomous. Thus, an ABM carries an agent or a set of agents, their relationship, and a framework for simulating agent behaviors and their interactions (Macal and North 2009). Required agents and their relationship should be defined by a modeler, while an AMB toolkit, such as Anylogic® and NetLogo, provide a platform. The major difference between discrete-event simulation and agent-based modeling and simulation is a view of interpretation. ABM is discussed with the agent's perspectives, while the discrete-event simulation discusses steps of the processes.

## 3.1 Adaptation and Suitability

Statewide travel demand modeling is a good place to apply agent-based modeling and simulation (ABMS). ABMS is usually guided to apply in the situations (Table 3.1) (Argonne, 2007).

Davidsson, et al. (2005) adopted Parunak's (1999) lists for an ideal application of agent technology. The list includes four attributes of modular, decentralized, changeable, and complex. Modular requires that the agent be well defined with a set of state variables. The variables should be clearly identified. The model becomes complex since the system for modeling illustrates a variety of behaviors, and the agents interact with other agents in the system's environment precisely. The application should be changeable. It should be easy to change the application's structure and toolkit. Due to the complexity of the system, the application requires significant capability. Thus, the application should be decomposed into stand-alone processes, therefore performing useful tasks without interruption. With Parunak's characteristics, Anylogic® is recommended for this study since it has geospatial modules incorporated with Google Map API, and it represents a realistic path for an agent's tour. Agent-based modeling can be done in many ways. Anylogic® is proprietary simulation software with agent-based modeling capability. Anylogic® is used to build the freight transportation model in which agents are being created in Geographic Information System topology (Merkuryeva and Bolshakovs 2010). Java programming language is periodically used to build the decision-making process.

**Table 3.1** Checklist of application of AMB to agricultural freight modeling

| ABM (Argonne, 2007) | Agricultural Transportation |
|---|---|
| When there is a natural representation as agents | In agricultural transportation, farm land, transporters, and facilities represents natural agents, which follow the simple rules observed from their practices. |
| When there are decision and behaviors that can be defined discretely (with boundaries) | Agents are spatially constrained as demand coverage. The farmlands are continuous but will discretely separate. Elevators and other facilities are discrete and carry decision rules. |
| When it is important that agents adapt and change their behavior | Farmers will change destination to avoid congestion while minimizing travel time and travel cost. |
| When it is important that agents learn and engage in dynamic strategic behavior | Farmers will choose agricultural facilities to maximize and will develop a long-term relationship and contracts. |
| When it is important that agents have a dynamic relationship with other agents, and agent relationships form and dissolve | Larger elevators will develop a dynamic relationship, so local smaller elevators will transfer grains to larger grains. |

| | |
|---|---|
| When it is important that agents form organizations and adaptation and learning are important at the organization level | Within a certain region, farmers will be assumed to homogeneous and shows the same behavior. A modeler can define the organization. |
| When it is important that agents have a spatial component to their behaviors and interactions | Agent's trips occur over a space. |
| When the past is no predictor of the future | Farmers travel paths and traffic on networks are not available for predicting the future traffic on specific segments. |
| When scale-up to arbitrary levels is important | Agent's travel paths will be aggregated over a period for planning purpose. |
| When process structural change needs to be a result of the model, rather an input to the model | Usage of farmland will have an impact on transportation network. |

## 3.2 Modeling Framework

This study consists of the following steps:

1. Define agents: physical agents (fixed agents and movable agents) and virtual agents, which are not physically seen
2. Understand the characteristics of agents, including behavior
3. Identify interaction factors and rules, which are tertiary, intermediary agents between two agent groups
4. Run the model
5. Validate the model
6. Collect outputs

Agent-based modeling can be explained by three major characteristics: types of application, time horizon, and agents (Davidsson, Henesey, Ramstedt, Törnquist, & Wernstedt, 2005). Agent-based modeling may be either a decision support system (DSS) or an automation system (Figure 3.1). Depending on the time horizon of the modeling, it will be explained as strategical modeling for a long-term horizon, tactical modeling for a medium-term horizon, or operational modeling for a short-term horizon. Individual agents can be modeled, as can multi-agents. Multi-agents will explain the interaction between or among agents, which might be competitive or cooperative due to attitude. Coordination structure can be predetermined static or dynamic to explain agents. The agents might be centralized or decentralized.

This study will focus on a strategical decision support system, which is dynamic with multi-agents. The agent will be competitive and decentralized. The agents are dynamic to change their decision within a level of threshold.

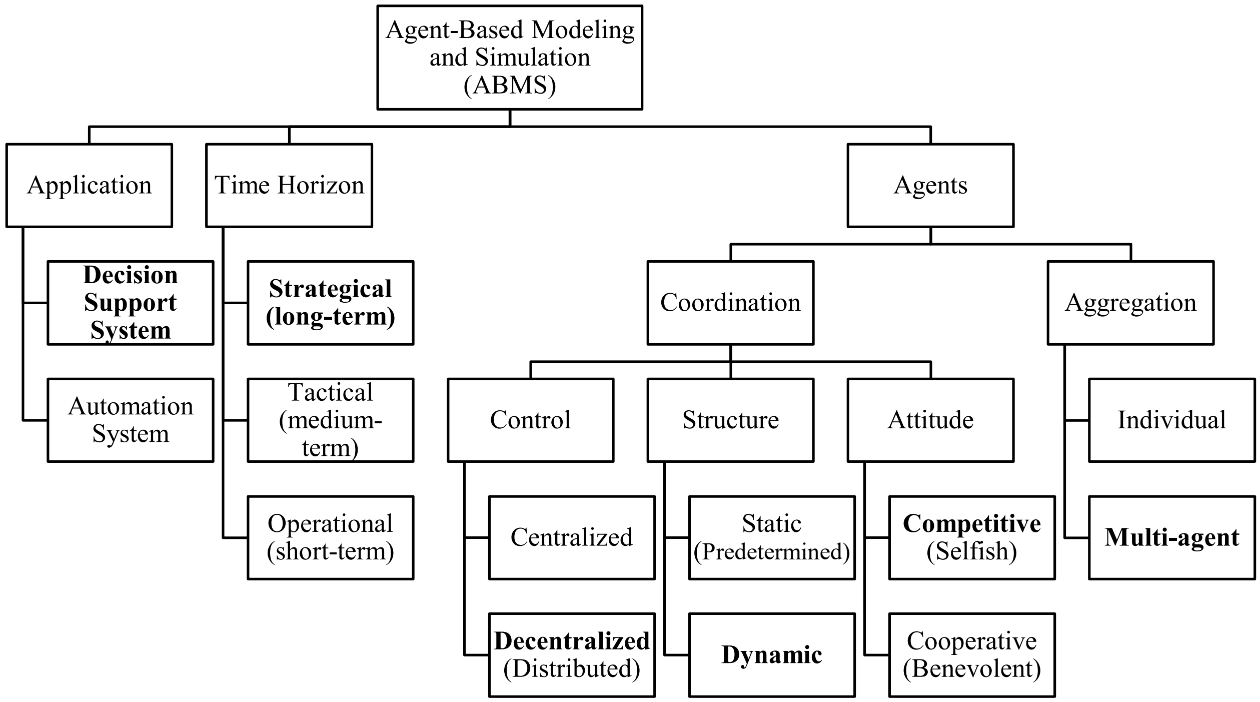



**Figure 2.1** Applications, time horizon, usage, and coordination of ABM (Davidsson et al., 2005).

A supply chain is generally defined as a network of suppliers, factories, warehouses, distribution centers, and retailers through which raw materials are acquired, transformed, and delivered to customers (Julka, Karimi and Srinivasan, Agent-based Supply Chain Management: A Refinery Application 2002). Logistics as part of a supply chain refers to "the process of planning, implementing, and controlling procedures for the efficient and effective transportation and storage of goods including services, and related information from the point of origin to the point of consumption for the purpose of conforming to customer requirements" (Council of Supply Chain Professionals 2017). In this study, we focus on logistics in the upstream supply chain of the grain industry. However, the model has great potential for further extension downstream to the end customer. The problem can be described as modeling grain in an upstream supply chain that includes farms, grain elevators, and intermediate markets.

### 3.2.1 Defining Agents

We categorize the agents into four groups: organization, people, objects, and non-material. Individual agents can participate in a group voluntarily or naturally (Ashforth and Mael 1989). A group is defined as two or more individuals (i.e., agents), interacting and interdependent, who congregate to achieve its goals. The groups can be formal or informal. A formal group is defined by the group's structure, particular assignments and tasks, and goals; while informal groups, such as alliances, are neither formally structured nor organizationally determined.

Agent (source: Argonne National Laboratory)

- What is agent?
  - A discrete entity with its own goals and behaviors
  - Autonomous, with a capability to adapt and modify its behaviors

- Assumptions for agent?
    - Some key aspect of behaviors can be described.
    - Mechanisms by which agents interact can be described.
    - Complex social processes and a system can be built "from the bottom up."
- Examples: Diverse and heterogeneous
    - People, groups, organizations
    - Social insects, swarms
    - Robots, systems of collaborating robots
- How does it work?
    - Function → (memory) → Object → (autonomy) → Agent
    - Cellular automata have agents interacting in local "neighborhoods"
    - Agents can be connected by networks of various types and be static or dynamic
    - Agents can move over tiles in Geographical Information Systems (GIS)
    - Sometimes spatial interactions are not important ("Soup" Model)

The agents can create a group based on their interests and goals. So, when an agent carries multiple interests or multiple contracts, the agent can participate in one or more groups. Thus, the groups the agents participate in have conflicts; therefore, the agent should determine its group autonomously. The group can be spatial boundaries (i.e., discrete definition of continuous space) or social boundaries (i.e., discrete). The spatial boundaries are often being presented as tiles or a traffic analysis zone (TAZ). The agent groups interact to achieve their goals as well. Thus, we can define each group as an agent for macro level of analysis. Based on the social identity theory (Ellemers 2018), the individual agents can be developed through relational identification and collective identification. Within a group, agents can relate to others because of the agents' roles through relational identification. Collective identification explains that the agents can be connected with the aggregated characteristics of a group.

The attributes of a group include roles, norms, status, size, and cohesiveness. It is assumed that a group generates better information and knowledge than an individual agent. A group will show a collectivist culture with strong cohesiveness (Trubisky, Ting-Toomey, & Lin, 1991). Because a group requires and expects group member's roles, the individual behavior within the group is predictable, along with a set of expected behavior patterns. All groups have acceptable standards of behavior, or norms, which are shared by the group's agents. Status is a socially defined position or rank for the individual agents in a group by other groups or agents. Groups agree within themselves on status criteria in general, thus there is high concurrence in group rankings of individual agents in general. Based on this finding, the group can be categorized into subgroups that show homogeneous status. When an agent finds oneself in conflict, the agent moves to other groups with similar backgrounds and statuses.

Agents interact with each other in local "neighborhoods," which are within a group (Figure 3.2). In other words, the agents within a group can be connected by social, economic, and transportation networks, which are static or dynamic. Organization runs under groups of people with norms and standards. The agents also include people, objects, and non-material. Organization, objects, and non-material are examples of non-living agents, which determines passive decision-making processes; people and some non-materials are considered active thinkers, which can show learning capability, and apply knowledge based on its rationality.

An individual agent's behavior or emotion influences its group's behavior and emotion and vice versa (Ashforth and Mael 1989).

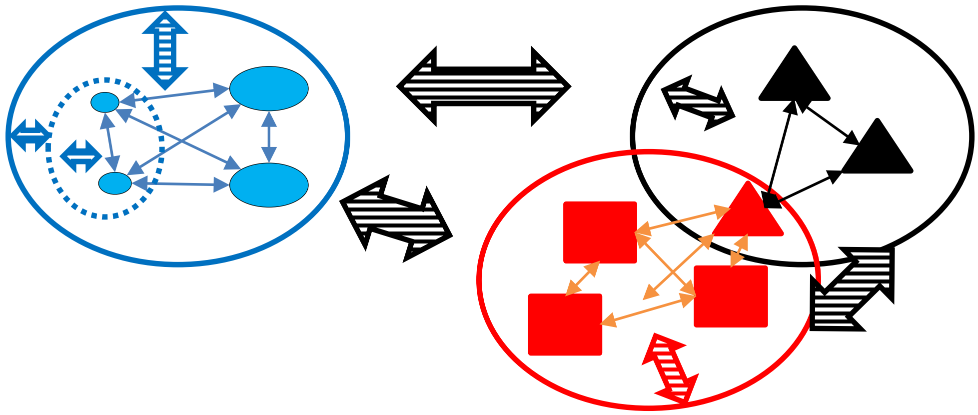


**Figure 3.2** Diagram of the interactions between agents within a group and between groups.

The agents are included to be active or passive (Table 3.2). Active agents will interact with other agents based on their own rules. The active agents will have a learning process to achieve their goals. Passive agents will be activated by a trigger with a command from other agents.

### Cellular Agents

A land or space, including square grid cells, can be an agent or cellular agent. Each cell is an individual that represents a collectivity of population behavior and economic activities on a piece of land (Shen, Martinez and Silva 2013). Many urban land-use transportation models are adopted for examining the dynamic and micro level of interactions (Shen, Martinez and Silva 2013, Wegner 2004). As a discrete agent updates its plan for each iteration, each cell updates its status once per iteration (Shen, Martinez and Silva 2013). The iteration will update its population, condition, and socioeconomic variables for every month or every year. For example, the yield rate of a crop on a cell will be updated according to the technology advancement or expected growth from the previous periods. Based on the land use of the cell, the crop yield rate and resource requirement will vary. The accessibility to the land parcel will also different depending on the distance to local roads, highways, and railroads and availability of the modes. It means the utility functions are based on the accessibility change by available modes (Shen, Martinez and Silva 2013). The cells can be converted into TAZs, and the centroid of TAZs can be converted into facilities (Zhang, et al. 2013). When a model generates O-D matrices, the centroid will be used for estimating them to represent each trip. The O-D matrix is disaggregated into individual trips. The cells carry coordinates and attributes.

**Table 3.2** Anylogic in three days (Grigoryev 2014)

| Types | Characteristics | Examples | |
|---|---|---|---|
| | | Active | Passive |
| Organization | The agent which other agents belong. | Firms, household | Companies, political parties, country |
| People | Autonomous and independently | Drivers, construction workers, model, planner | |
| Objects | Autonomous, dependent | Objects with people (airplane, ship, vehicles, trucks, locomotives) | Bridges, tolls, tunnels, highway segments, crossings |
| Non-material | Dependent, closely related to other types of agents | | Transportation plan, projects, ideas, investment |

## Aggregated Agents

As an example of agents (Figure 3.3), we will review the household and its members (Otani, Sugiki and Miyamoto 2011). The study considers the household as microdata. Although the household members are individual agents, the study reviewed the attributes of the household.

The propositions used in the study are as follows: 1) the household (organization agent) is a set of its members (people agents), and each has multivariate attributes such as age, gender, income, education, and car-ownership; 2) the household members and its head have relationships, such as a female child of a male head or a male child of a female head, and brothers, sisters, mother, father, and grandsons and granddaughters, etc. Other relationships are found in the National Travel Survey conducted by the U.S. Census Bureau (U.S. Department of Transportation 2018); 3) member and household attributes are continuous or discrete; 4) the agents are located in a discrete zone; 5) the types of households are characterized into various categories (see U.S. Census Bureau) for convenience. Thus, the attributes of the microdata of household are each member's gender, two sets of vectors of age ($a$) and housing type ($h$), three scalars of residential zone (r), the number of cars owned ($c$), and income ($m$). The above characteristics of the observed genuine population data set (2) can be denoted as B in the following equation:

$$B = \{[\vec{a}_i = a_{iA}, \vec{h}_i = h_{iH}, r_i, c_i, m_i] | 1 \leq i \leq N\} \tag{2}$$

where N is the sample size (the number of observed data)

$\vec{a}_i$: a vector data set representing ages of the household members of household $i$
$a_{iA}$: age of a member $A$ of a household $i$
$\vec{h}_i$: a vector data set representing a categorical value of housing type of household $i$
$h_{iH}$: housing type H of household $i$
$r_i$: residential zone of household $i$
$c_i$: number of cars owned of household $i$
$m_i$: income of household $i$

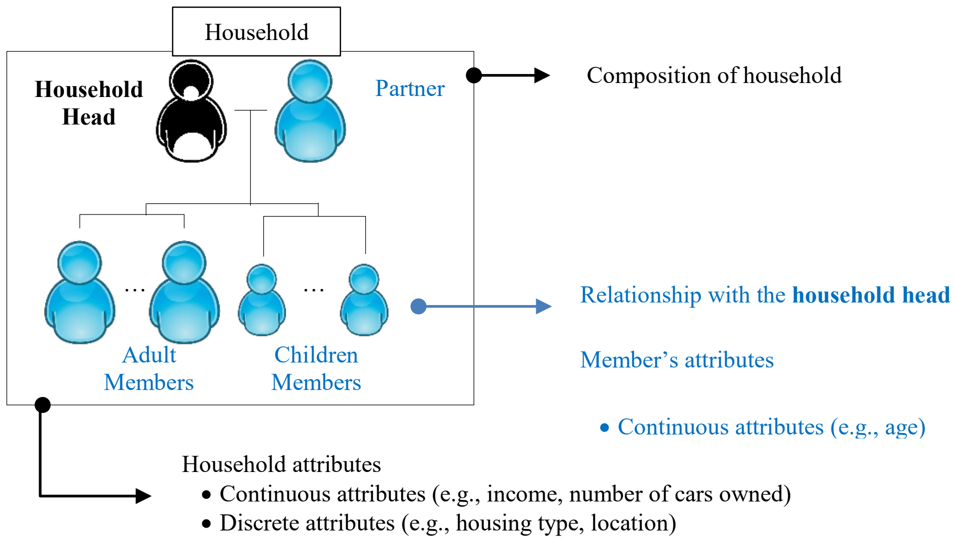



**Figure 3.3** General framework of household attributes (Otani, Sugiki and Miyamoto 2011).

Using the same number of data N of *j*th synthetic population (3), it is denoted as follows:

$$E_j = \{[\vec{a}_i^j = a_{iA}^j, \vec{h}_i^j = h_{iH}^j, r_i^j, c_i^j, m_i^j] | 1 \leq i \leq N'\} \tag{3}$$

where $N'$: the number of estimated data

$\vec{a}_i^j$: a vector data set representing ages of the household members of household i of the jth synthetic population

$a_{iA}^j$: age of a member *A* of a household *i* of the *j*th synthetic population

$\vec{h}_i^j$: a vector data set representing a categorical value of housing type of household *i* of the *j*th synthetic population

$h_{iH}^j$: housing type H of household *i* of the *j*th synthetic population

$r_i^j$: residential zone of household *i* of the *j*th synthetic population

$c_i^j$: number of cars owned of household *i* of the *j*th synthetic population

$m_i^j$: income of household *i* of the *j*th synthetic population

Further information can be found in (Otani, Sugiki and Miyamoto 2011).

### 3.2.2 Scoring Plans

Each agent has a plan, which contains the itinerary of activities. The activities will be performed by the agent during a day. The agent's plan includes detailed information of the order, type, location, duration, constraints of departing, arriving, and operating time for each activity, and the mode (Rieser, Grether and Nagel 2009). The plan consists of several modules, such as time and route, depending on the subject. The plan can be evaluated using the following approaches:

- Utility function
- Ranking
- Multi-criteria decision making

- Threshold
- Pass/fail tests

Suppose an agent generates new plans. Plans can be reused by the agent or other agents as an object can be reused in an oriented-object programming (OOP). If the best plan is selected for each agent, the selected plans will be executed for all agents at the same time on the transportation network, resulting in interaction among agents. The agents generate traffic flow, so the transportation network will be emulated as a queue on the network (Cetin, Burri and Nagel n.d., Rieser, Grether and Nagel 2009). This is the same approach in a discrete-event simulation for moving entities in a queue using the policy of first-in-first-out (FIFO). Thus, the queue has a capacity, thereby accommodating a limited number of agents in a certain period. The capacity of the queue (i.e., transportation link) will be determined by the free-flow speed and the number of lanes.

This study considers an agent's learning process from past experiences and given information. Each iteration performs a specific plan over a time slice; therefore, the agents will receive feedback from themselves and other multi-agents. The feedback will be fed into the next iteration. In this simulation, the term of iteration is differentiated from the term of "run" in general simulation, since a run is complete output of simulation for a simulation period. In other words, a run is a set of iterations. To reach a steady state of the simulation, the number of runs (N) will be determined based on the 95% confidence interval (4).

$$N = \left[\frac{z_{\alpha/2}\sigma}{E}\right]^2 \tag{4}$$

Where

E: margin of error
$\sigma$: standard deviation
$\alpha$: significance level (i.e., 1 – confidence level)
Z: standard normal

For the next iteration, the previous plan can be reused, copied, or modified by updating scores for new plans (Rieser, Grether and Nagel 2009). The probability for each plan to be selected can be noted as Equation 5.

$$P_k = \frac{e^{\beta \cdot s_k}}{\sum_{k=1}^{K} e^{\beta \cdot s_k}} \tag{5}$$

where $P_k$: probability for plan k to be selected
$s_k$ : a plan's current score
$\beta$: sensitivity parameter

Using a simple utility-based approach, the plans can be compared (Rieser, Grether and Nagel 2009, Zhang, et al. 2013). Let us assume an agent has *n* number of activities. The total utility (total score of a plan) is the sum of the following three utilities: utility earned for performing activity ($U_{perf, i}$), utility earned for arriving late to activity ($U_{late, i}$), and utility earned for traveling during trip I ($U_{trip, j}$) However, the utilities earned for traveling and arriving late are negative, thereby decreasing the positive utility earned for performing each activity (6). For the purpose of normalization, the utility value can be expressed in a monetary unit.

$$U_{total} = \sum_{i=1}^{n} U_{perf,i} + \sum_{i=1}^{n} U_{late,i} + \sum_{i=1}^{n} U_{trip,i} \tag{6}$$

Other disutility, such as waiting time for an activity, early leaving, and early arriving, can be added to punish, as shown in Equation 7.

$$U_{total} = \sum_{i=1}^{n} \left(U_{perf,i} + U_{late,i} + U_{trip,i} + U_{wait,i} + U_{early-leaving,i} + U_{early-arriving,i}\right) \tag{7}$$

where $U_{perf,\ i}$: utility earned for performing activity *i*

$U_{late,\ i}$: disutility earned for arriving late to activity *i*

$U_{trip,\ j}$: disutility earned for traveling for activity *i*

$U_{wait,\ i}$: disutility earned for waiting to perform activity *i*

$U_{early\text{-}leaving,\ j}$: disutility earned for early leaving for activity *i*

$U_{early\text{-}arriving,\ j}$: disutility earned for early arriving for activity *i*

### Performing an activity

Performing an activity *i* for performed duration *t* is positive utility in a logarithmic form (8).

$$U_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) \tag{8}$$

where $t_{perf,\ i}$: actual performed duration of activity *i*

$t_{*,\ i}$: typical performed duration of activity *i* (Rieser, Grether and Nagel 2009). In other words, it is an externally defined desired time budget of the agent for spending time on one or more activities of the same type activity *i* (Zhang, et al. 2013).

$\beta_{perf}$: marginal utility of an activity at its typical duration.

$t_{0,\ i}$: scaling parameter representing the minimum duration and the importance of an activity. This parameter has no impact on the model, while the plan does not drop the activity. It is proportional to t*, which is zero of the logarithmic function.

It is assumed that $\beta_{perf}$ is the same for all activities, because in equilibrium all activities at their typical duration need to have the same marginal utility.

### Disutility of being late

The disutility of being late is uniformly assumed, as noted in Equation 4, where $\beta_{late}$ is the marginal utility in dollars for being late to activity *i*, and $t_{late,i}$ is the number of hours late to activity *i*.

$$U_{late,i} = \beta_{late} \cdot t_{late,i} \tag{9}$$

$t_{late,i}$ is the difference between starting time of activity *i* ($t_{\text{start,i}}$) and the latest possible starting time for activity *i* ($t_{\text{lateest-start,i}}$) in the number of hours (Zhang, et al. 2013) (10).

$$U_{late,i} = \beta_{late} \cdot max\left[0, \left(t_{start,i} - t_{latest-start,i}\right)\right] \tag{10}$$

### Disutility for travel

The disutility for traveling is uniformly assumed, as shown in Equation 11, where $\beta_{travel}$ is the marginal utility in dollars for travel, and $t_{travel,i}$ is the number of hours spent traveling during trip from one activity *i*-1 to another activity *i*. This is typically in-vehicle travel time.

$$U_{travel,i} = \beta_{travel} \cdot t_{travel,i} \quad (11)$$

### Penalties

An agent may experience undesired time spent performing an activity. We will add penalties, disutility value, in the utility function. For example, if an agent planned to perform an activity of loading and unloading at a facility, the agent must spend "waiting time," which can be scored as follows (12):

$$U_{trwait,i} = \beta_{wait} \cdot t_{wait,i} \quad (12)$$

$B_{wait}$ is the marginal utility in dollars for waiting outside, and $t_{wait,i}$ is the number of hours spent waiting for activity *i*. This is typically in-vehicle travel time.

A supplier selection problem is one of the agent-based simulation applications. The supplier selection problem determines commodity flows between production and consumers in a market (Pourabdollahi, et al. 2016). The study introduced an algorithm using average importance weights for evaluating suppliers. The criteria include cost (price), reliability, delivery, and distance. The reliability was measured with annual production and supply capacity, while the delivery utilized the accessibility to different modes using travel time of different modes. All criteria show average weights. Based on the criteria, three steps were applied to the algorithm.

1. Each buyer calculates a score for each potential supplier and then ranks the suppliers. Suppose the buyers have a set of S potential suppliers (13).

$$S_{ij} = \sum_{c=1}^{C} W_c \cdot M_{ci} \quad (13)$$

   Where $S_{ij}$ = the score weighted buyer j when selecting potential supplier *i*
   $W_c$=the importance weight of criterion c, $c = \{1, \ldots, C\} = \{$cost, reliability, delivery, distance$\}$
   $M_{ci}$=A normalization value for the measure for supplier *i* under creation *c*
   Based on the scores of $S_{ij}$, each buyer will rank the potential suppliers: $r_1 > r_2 > \ldots > r_S$. Each supplier has its capacity to sell.

2. Each supplier calculates a score for each potential buyer based upon each buyer's annual demand for each commodity. Suppose each supplier has B potential buyers and each buyer (b)'s annual demand is $D_b$. Based on the demand, each supplier will rank the buyers: $r_1 > r_2 > \ldots > r_B$. However, each supplier will set its threshold as a minimum requirement.

3. Buyers and suppliers will be matched iteratively from the market-clearing algorithm for individual commodity. In the algorithm, minimum requirements for buyers and suppliers were specified as a threshold for the decision-making process.

## 3.3 Scoring Parameter Values

Hussain, et al. (2015) used the Hendrikson and Plank Model to construct a behaviorally accurate method for trip depart time using the mixed nominal logit (MNL) depart choice model (Hendrickson and Plank 1984). The actual utility value can be calculated for a particular agent to depart at specific time in an available time window. Suppose that N agents ($a_N$) are in the system and a set of departure times, T ($t_T$) are available. The utility for a particular time $t_j$ of an agent $a_i$ is $V_{a_i t_j}$. The utility function expects negative coefficients for unfavorable factors.

The ABM is also used for investigating the performance of large-scale intermodal facilities (Hoy, Morrow and Shalaby 2016). In addition, the ABM is used for two navigable inland waterway operation procedures under climate changes (Nelson, et al. 2017). Some exemplary values of scoring parameters are listed in Table 3.3.

**Table 3.3** Examples of Values of Scoring Parameters

| | Zhang, et al. (2013) | Rieser, Grether and Nagel (2009) |
|---|---|---|
| Application | Public Transit | Transit |
| $B_{perf}$ | 6 | 6€/h |
| $\beta_{travel}$ | -6 | Car: -6€/h; non-car [-10,-9, …,0, +2] |
| $\beta_{wait}$ | 0 | |
| $B_{late}$ | -18 | -18€/h |
| $t_h$ | 16 hours | |
| $t_w$ | 8 hours | |

## 3.4 Model Validation

Observed traffic counts are used for validation by comparing simulation outputs with actual traffic counts over a period of time (Wang and Mohamed Wahba 2010). Once the simulation determines the agent's best plan, the plan will load routes on a transportation network.

The routes and road segments will be matched to load the traffic volume on a road link. Instead of actual load, a percentage is used for calculating accuracy, called point mean relative error (PMRE) and global relative error (GRE) (14). The GRE can be tested for a sub-region (Zhang, et al. 2013) or for a region (15).

$$PMRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{observed - simulated}{observed}\right)^2} \tag{14}$$

$$GRE = \frac{\sum_{i=1}^{n}|observed - simulated|}{\sum_{i=1}^{n} observed} \tag{15}$$

In addition, the goodness of fit of microdata can apply standardized root-mean-square error (SRMSE) (16), where a lower value indicates better fit (Otani, Sugiki and Miyamoto 2011).

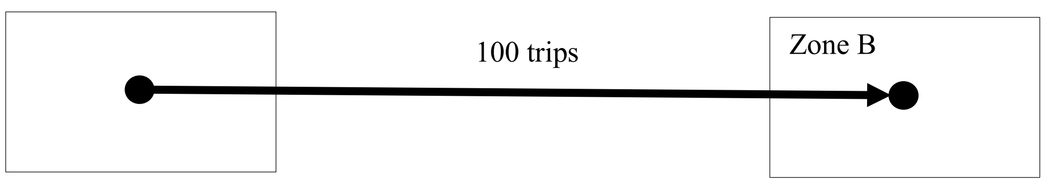
$$SRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(observed - simulated)^2}}{\frac{1}{n}\sum_{i=1}^{n} observed} \tag{16}$$

The simulated traffic will be compared with the counted hourly volumes on road links or with the smaller time windows.

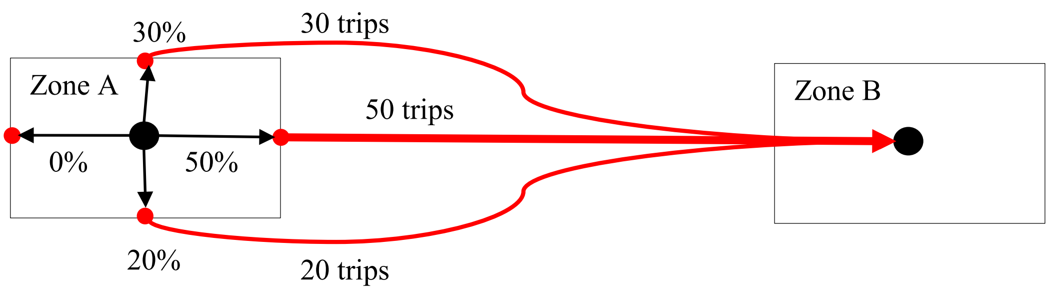
## 3.5 Level of Aggregation

The agent-based modeling does not have to be discrete; however, continuous geographical areas should be discretization.

Assumptions made for this study are as follows: Trips from centroid of an origin zone will travel through several different paths (Figure 3.4). Distance will be used as an impedance of the travel. The trips will be distributed to the closest destination zone. For example, trips from Figure 3.4-B explain that 30% and 20% of the trips originated from the centroid of TAZ are shipped to north and south, respectively.




(a) Trip distribution between zone centroids




(b) Trip distribution between zone centroids using zone cordons of origin zone

**Figure 3.4** Trip distribution from Zone A to Zone B.

Steps:

1. Define traffic analysis zones (TAZ)
2. Calculate distance between origin and destination centroids
3. Sort the pairs in ascending order of distance
4. Find all possible cordons along the TAZ boundary (N number of zones)
5. Calculate distance using shortest paths from all cordons of an origin centroid to all the other centroids of zones (N*K*[N-1] iterations) or using current proportionality of traffic from traffic counters
6. Calculate probability of the trips to distribute (logit using shortest paths)
7. Assign proportionality of the trip from centroid to (N*K*[N-1] iterations)

The number of trips is known, but the traveling ways are randomly known (Figure 3.5). A variety of factors will affect travelers' decision-making processes, and travelers will have different reasons to choose. Thus, the paths between zones A and B are fuzzy. The impedance, such as bridges, congestion, etc., will be critical factors in the fuzzy black box for travelers to determine a path. Trip is a journey from one location to the other location, while path is a specific pathway through road segments. Trips do not consider intermediary roads, while a path should address direction and road links going through.

The impedance can be logical, situational, and physical.

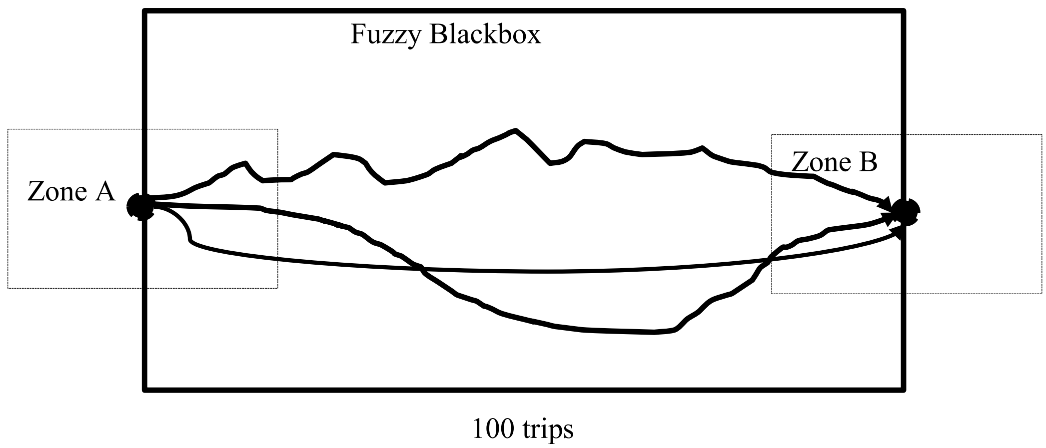



**Figure 3.5** Various impedances and behavioral factors for traveling between two zones.

# 4. A CASE STUDY OF NORTH DAKOTA AGRICULTURAL TRANSPORTATION

Agriculture is one of the key drivers of local economies in the Midwest. Thanks to the region's fertile soil, farmers produce abundant harvests of cereal grains. North Dakota, located in the Midwest, is the largest U.S. producer of many cereal grains. In 2016, North Dakota farmers produced flaxseed (91.2% of U.S. total), canola (86.5%), and durum wheat (56%), to name a few (USDA's National Agricultural Statistics Service & Office [North Dakota Field Office], 2016). Cereal grains ranked as the top two commodities by weight (almost 35 million tons) for all trades (within, inbound, and outbound) according to Freight Analysis Framework (FAF) (Hwang et al., 2016).

Modern supply chains are characterized by rapidly changing market conditions, resulting in varying spatiotemporal patterns. Freight transportation is the most vital element of a supply chain, linking all organizations from supplier to end customer. The North Dakota grain transportation system is an example of large-scale supply chain dynamics, including farmers harvesting and delivering commodities via road networks, a set of elevators and handling facilities for transshipment, and a set of rail networks connecting elevators to either port facilities for further transshipment or final destination. North Dakota is landlocked without direct logistical access to U.S. inland waterways. In 2015, 68% and 32% of total shipments were transported by truck and rail, respectively (Hwang et al., 2016). Given large-scale grain production and being heavily dependent on only two modes of transportation inherently implies the need to develop reliable and flexible analysis tools for studying and forecasting the dynamics of freight movement.

## 4.1 Agent-Based Agricultural Travel Demand Model

Figure 4.1 illustrates the general commodity distribution of the model. The generated commodities are hauled mainly by trucks as there is no rail access from individual farms. The shipment either goes to the elevators or final destinations, such as a processing facility, ethanol facility, or terminal destination. Four main active entities act as agents in commodity distribution: 1) elevators, 2) processing facility, 3) ethanol facility, and 4) destination terminal.

A farm follows the harvesting schedule for specific commodities and stores them in its own silos. Then the stored commodities are hauled mainly by trucks, as there is no rail access from an individual farm. The shipment either goes to the elevators or a final destination, such as a processing facility, ethanol facility, or terminal destination. Decision makers might not be the same across markets since every single commodity has its own market dynamics. Therefore, farms, elevators, and final markets periodically set the selling price, set selling/buying, and set buying price, respectively. An order is an agent type mainly representing the bid price and the amount of a specific commodity a buyer is willing to make in a transaction. The order is sent to either the nearest source or the one with a buying price higher than selling price. The transactions in a freight market assign commodity flow to different carriers who use vehicles/trains to provide the services contracted. The final output is a set of vehicle/train flows. On the other side of the market, a seller, either farm or elevator is set to choose the highest bid from incoming orders. Once the order is accepted by the seller based on a higher bid, it ships the amount of the order onto a truck/train (i.e. an agent), based on the probability calculated by the logit model.

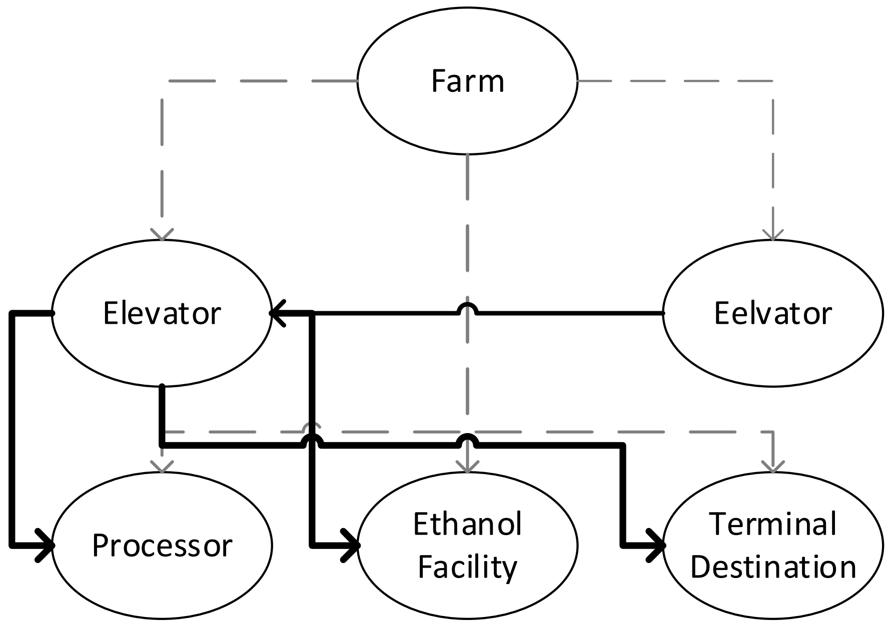



**Figure 4.1** Distribution network

Market price and its underlying factors are not the focus of this study. However, the next study will incorporate the system dynamics of grain pricing into the model. The basic price indication for setting a price bid is based on USDA's Economic Research Service. All price bids follow a uniform distribution with minimum and maximum range average price -/+10%. To make the problem feasible, the farm selling, elevator buying, elevator selling, and processor/terminal buying prices are on average set to $9, $9, $9.50 and $10 per bushel, respectively. A $0.5 increase per bushel is considered as markup for each layer in the grain supply chain.

## 4.2 Data Description

This section gives a detailed description of the data source used for running the simulation. For demonstration, soybeans and Cass County in North Dakota are selected for commodity and farm location, respectively.

The first component of the ABM was to simulate the existing conditions based on given parameters and assumptions. Table 4.1 presents the transportation flow by mode share. As the table shows, rail transportation, as expected, is the dominant mode of transportation for transporting soybeans. However, the model did not generate any shuttle trains. This might be due to several reasons, but the two main underlying factors can be explained as follows:

1) This study does not incorporate any transportation cost. So the difference in transportation rate due to economies of scale is not captured. Since, per definition, unit train and shuttle train both have more than 50 rail cars, the model could not differentiate between these two and picked one with more availability. There are only three elevators with a shuttle train facility in Cass County.
2) The other reason can be explained by randomness in normal distribution.

**Table 4.1** Truck types and size

| Truck Type | Single-axle Truck | Tandem-axle Truck | Tridem-axle Truck | 5-axle Truck | 7-axle Semi | Other | Total |
|---|---|---|---|---|---|---|---|
| Percentage Owned in ND | 18.7% | 22.4% | 10.5% | 40.6% | 3.3% | 4.4% | 99.9% |
| Farm Size (acres) | | | | | | | |
| 300 or Fewer | 7.0% | 5.3% | 0.4% | 8.0% | 0.1% | 0.6% | 21.40% |
| 301 Acres to 705 | 4.8% | 7.1% | 0.7% | 10.1% | 0.1% | 0.4% | 23.20% |
| 751 Acres to 1500 | 3.1% | 6.2% | 1.1% | 15.3% | 0.1% | 0.2% | 26.00% |
| 1501 or More Acres | 1.3% | 3.7% | 0.9% | 22.1% | 0.2% | 0.4% | 28.60% |
| **Total** | 16.20% | 22.30% | 3.10% | 55.50% | 0.50% | 1.60% | 99.2% |

## 4.3 Agents and Their Population and Distribution

### 4.3.1 Agents:

This section describes briefly the number of agents and sub agents built in this model.

- Location-based agents:
  - Farms
  - Elevators: Elevators are the key element of a grain distribution channel, as they act as intermediaries that buy, sell, and store different types of grains. The elevator is mainly used as an intermediate destination in grain movement to take advantage of economies of scale in transportation.
  - Processing Facility
  - Ethanol Facility: Ethanol facilities are the main demand points for corn, so we keep this agent inactive during the simulation.
  - Destination Terminal
- Active agent with people:
  - Truck
  - Train

The truck and train are defined as passive agent types, as there is no decision-making process; rather, they are selected only for transportation based on their capacity. However, such decision making can be done in future studies to model transportation pricing strategy, transportation availability, and other related factors. Trucks belong to different groups that have various parameters, such as destinations, capacity, payload, etc. There are five main types of trucks modeled in this study.

1) Single-axle: capacity 10 metric ton
2) Tandem-axle: 15 metric ton
3) Tridem-axle: 20 metric ton
4) 5-axle: 25 metric ton
5) 7-axle: 35 metric ton
6) Other: 20 metric ton

- Other agents (non-material)
  - Order

The agent ordered is a generic agent, which does not physically exist in the GIS environment of the model. It is generated by a buyer type agent according to a given schedule. An order composed of four variables representing amount (amount to be ordered), bid (price in which buyer is willing to pay for that commodity), destination, and commodity.

In terms of rail car, since there are no accurate data available for hopper rail cars used for grain transportation, the approximate capacity of 90 metric tons—equivalent to 4000 cubic feet of soybeans—is considered (Soy Transportation Coalition, n.d.).

### 4.3.2 Planting and Harvesting Dates

For better real-world simulation, the harvesting period for soybeans in North Dakota is set from September 17 to November 5, according to USDA Field Crops Planting and Harvesting Date. This period is modeled as the time each farm starts harvesting and storing soybeans in the silos (U.S. Department of Agriculture, 2010).

### 4.3.3 Farms Location

Since the exact locations of farms are not available, we can assume the mean centers of the townships where soybeans are planted. The model is capable of mapping the agent based on given longitudes and latitudes. The farms' geographical locations are set to be in Cass County, as it is the nation's number one soybean-growing county. Based on estimates, the geographic mean center of soybean acreage each township was located as production location because the soybeans are fairly distributed across each township. The estimate was based on the assumption that the yield rate over the country is heterogeneous.

### 4.3.4 Farms Yield

The 2016 soybean production in Cass County, measured in bushels, is available from the National Agricultural Statistics Service (NASS) (U.S. Department of Agriculture, 2017). The county level of production was disaggregated into 6-mile by 6-mile townships. The ratio for allocation to each township was based upon the planted area in a 30-m by 30-m spatial resolution (U.S. Department of Agriculture, 2016). The planted acres for each township were divided by the total acres of the county, and then the ratio was multiplied by the production survey of the county to estimate the soybean production for each township (Figure 4.2).

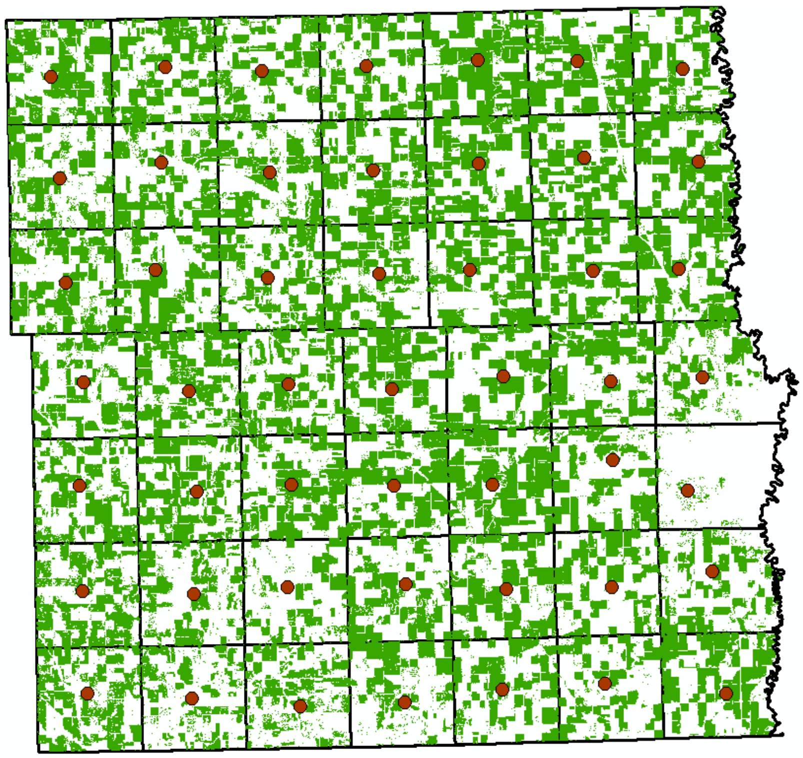


**Figure 4.2** Soybean land planted in 2016 and mean centers of the soybean production for townships in Cass County, ND.

### 4.3.5 Truck Capacity and Size

Table 4.1 describes the truck types owned by farms in North Dakota, according to Northern Plains Grain Farm Truck Fleet & Marketing Patterns (Vachal, 2015). The most commonly owned truck is the 5-axle type. Total percentage is only used to model the probability of truck availability at each farm for grain transportation. Since aggregate yield for each township is used for the simulation, the truck type by farm size is only for the reader's reference.

### 4.3.6 Elevators Location

Elevators as one of the demand points are obtained from two different sources: 1) Dakota Public Service Commission (NDPSC) licensed elevator report (ND Public Service Commission, 2011); 2) BNSF website (BNSF Railway 2018). BNSF is the main rail service provider in Cass County. Throughput information was obtained from the same source comparing against each other, and the highest one was picked for the final database.

### 4.3.7 Demand Points

Besides elevators as intermediate demand points, three different entities are involved in this model: processing facilities, ethanol facilities, and grain terminals. To the best of the authors' knowledge and according to the National Oilseed Processing Plant, North Dakota does not have any soybean processing facilities (National Oilseed Processors Association 2018). Most of the processing facilities are in Minnesota. In the case of soybeans, ethanol facilities are not considered in the simulation. For terminal destinations, there are five major markets considered, according to the Annual North Dakota Elevator

Marketing Report: 1) Duluth-Superior, 2) Minnesota/Wisconsin, 3) Pacific North West, 4) Midland-Southwest, and 5) miscellaneous markets (Vachal and Benson 2017).

Demand points are entities (agents) that place an order of shipment. In other words, a derived demand happens at these locations. Given this explanation, we consider two types of demand points, intermediate and final demand. At intermediate locations, like a grain elevator, the shipment is either transferred to another mode of transportation or consolidated to larger shipments; at final demand points, the shipment is delivered for final processing.

Figure 4.3 illustrates the processing facility that could handle both truck and train shipments. In the case of a truck, once it arrives at the location, it waits in the queue for offloading. The offloading of truck shipment happens in the *agentToFluid* process. All flows of shipments (soybeans) are stored in a silo (tank). In the case of shipments by rail, the train drops off the wagons at the location and leaves the processing facility (agent). The wagons are in the queue to be offloaded like trucks.

The capacity of the queue and tank (silo), as well as waiting time, can be either manually configured or read from the database for different demand points.

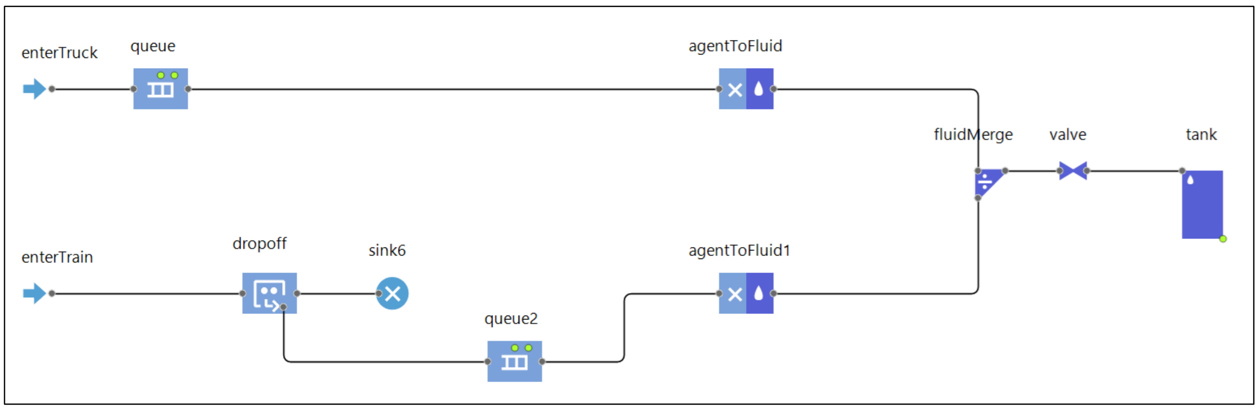



**Figure 4.3** Screenshot of receiving demand at docks

### 4.3.8 Mode Choice

Rail and truck are the two primary modes for transporting grain from North Dakota to different markets. In terms of grain elevator size, the categories shown below can also be used in the model. However, in Cass County, all elevators have access to rail.

1) No Rail
2) Single Car (1 to 24 cars),
3) Multiple Car (25 to 49 cars),
4) Unit Train (50 to 99 cars),
5) Shuttle Train (100 cars or more).

Given these two modes of transportation, truck and train, and available capacity for each mode, there are two decision-making agents – farms and elevators – which will decide on what mode to use for the shipment. For example, a farm agent, depending upon the size of the order, could use either truck or train. In the case of a train, there are multiple choices: single car, multiple car, unit train, and shuttle train.

Based on the Freight Analysis Framework (FAF4), both agents use a binary logit model considering weight and distance to decide on modes of transportation. Figure 4.4 illustrates the overall layout of a farm agent in which the agent decides to move the commodity directly to the final destination by truck or intermediate locations (elevators) by truck, and then consolidates it with a train to a final destination.

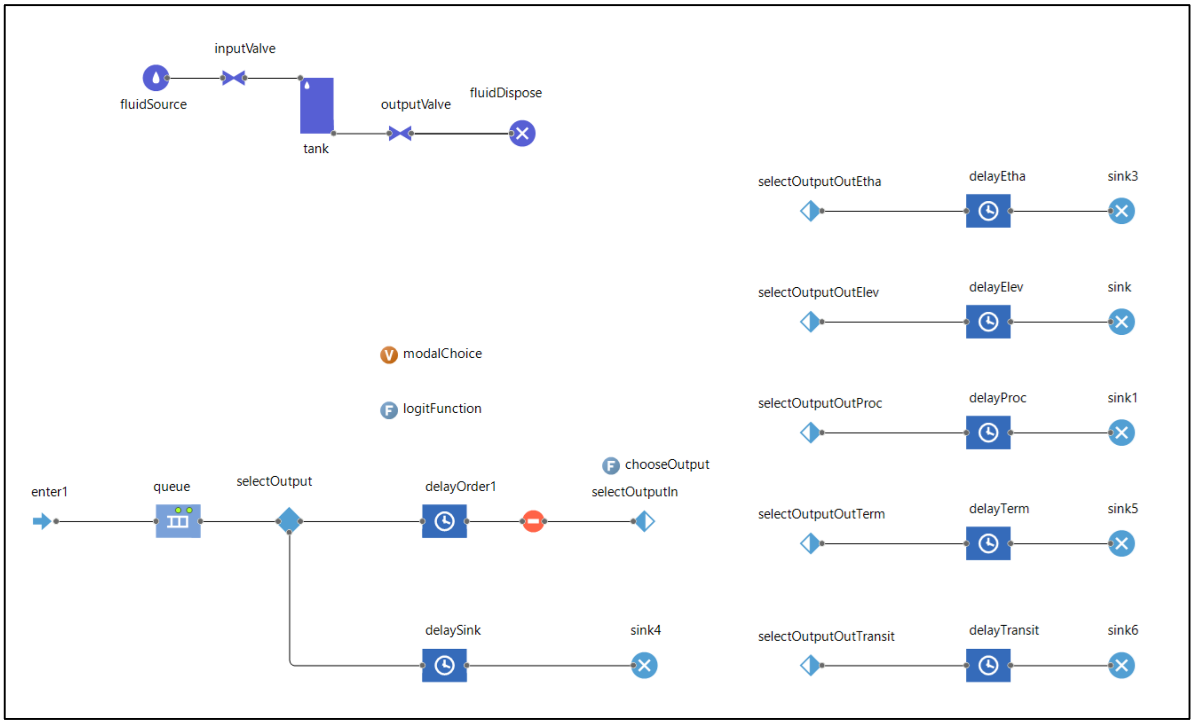



**Figure 4.4** Screenshot of Mode Choice

### 4.3.9 Modal Split

Mode choice is important in shipping commodities efficiently. To study the soybean movements by truck and rail in North Dakota, a binary logit model is developed by using the publicly available FAF4 database. The binary logit model used such variables as commodity weight and distance from North Dakota to other states. Future studies can consider further variables, such as value, network travel time, and fuel cost for the logit model.

The binary logit model is formulated as:

$$P_j = f(U_j) \tag{17}$$
$$U_j = V_j + \epsilon_j \tag{18}$$

where $P_j$ = probability of mode j (j = t or r, truck = t and rail = r); $U_j$ = utility function; $V_j$ = the observable portion of the utility; and $\epsilon_j$ = random portion of the utility. Dropping the random portion in Equation (2), we can write the binary logit model as:

$$P_j = \frac{e^{V_j}}{\sum_{j=\{r,t\}} e^{V_j}} \tag{19}$$

Where

$$\sum_{j=\{r,t\}} P_{ij} = 1 \tag{20}$$

Table 4.2 shows $V_j$ details:

**Table 4.2** Regression results

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 1.3843072805 | 0.2571728763 | 5.38278 | 0.00002 |
| Weight (metric ton) | -0.0000002731 | 0.0000000807 | -3.38252 | 0.00268 |
| Distance (meter) | -0.0000004400 | 0.0000001176 | -3.74242 | 0.00112 |

After 1,200 runs, the critical threshold generating the best classification between rail and truck is 0.7. However, this threshold might vary when other factors, such as transportation rate, disaggregate farm to market data.

Following the mode choice, we use historical data to simulate the share of shipments being shipped under a specific mode. The mode share is defined as the probability of using a specific mode for an order based on historical records. For example, 9% of shipments used to be hauled by a unit train; once the agent decides to use the train, there is a 9% chance to ship that order with a unit train. It is modeled under *chooseOutput* function, as shown in Figure 4.5. However, the model could be extended and incorporate truck and train availability and transportation cost for the study area for better real-world simulation.

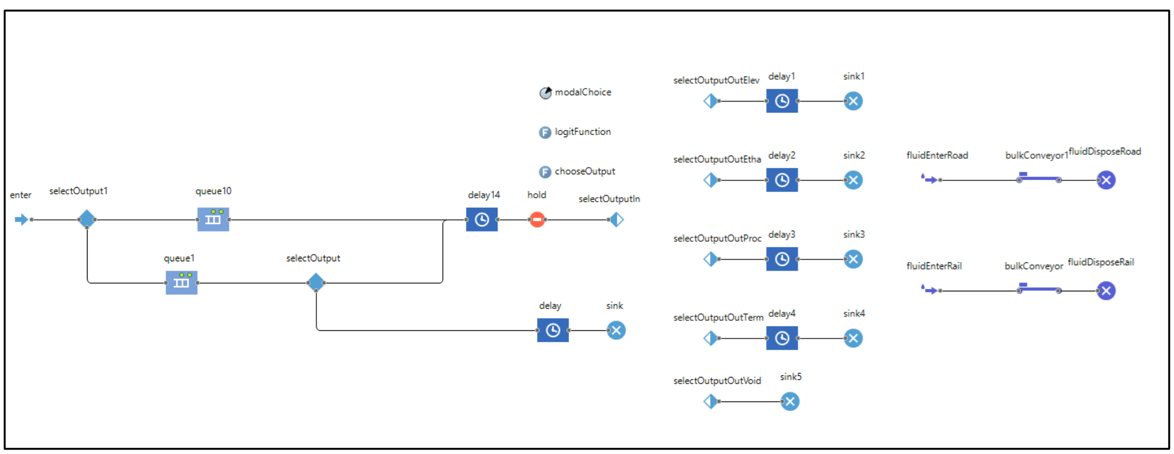



**Figure 4.5** Screenshot of Modal Split

### 4.3.10 Shipment Frequency

Shipment frequency is used to control the number of orders generated by demand points. For the sake of simplicity, it is assumed there is no delay between an order submitted by demand points and shipments generated by elevators or farms. Figure 4.6 illustrates the soybean shipment distribution by month from 2008 to 2016 in North Dakota.

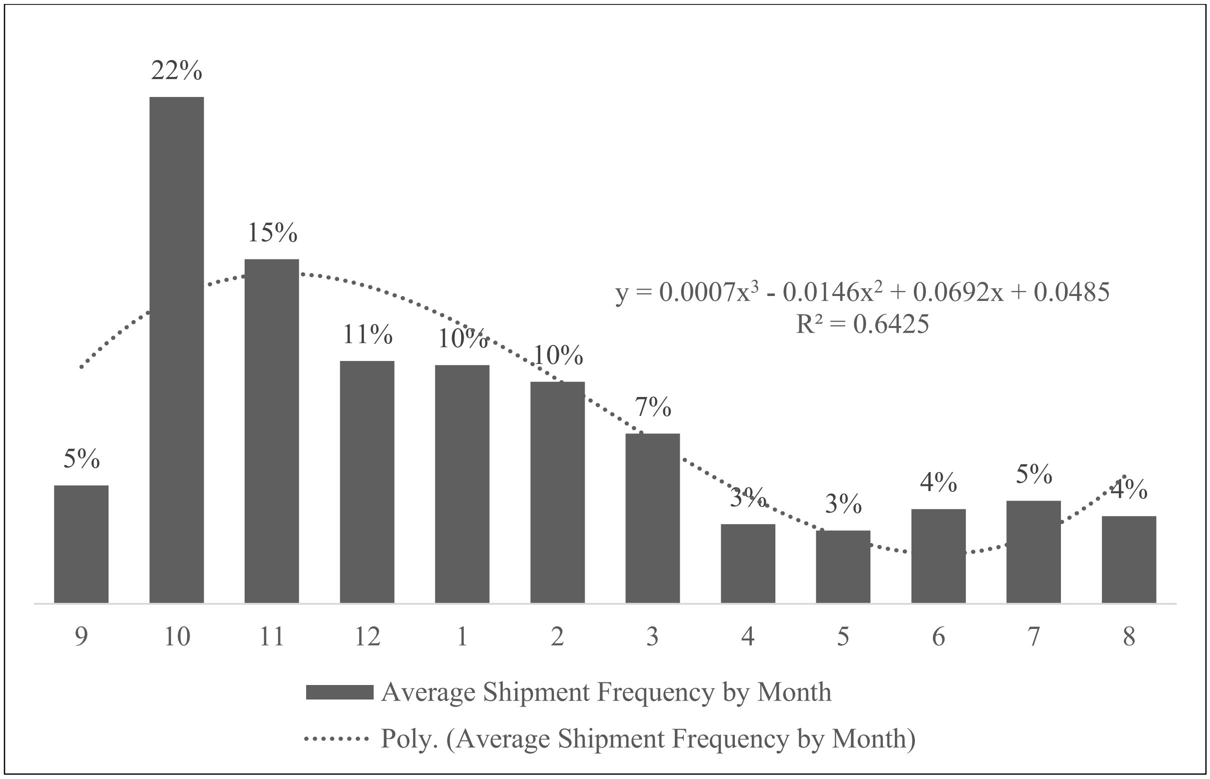



**Figure 4.6** Average shipment frequency by month (2008-2016)

# 5. RESULTS AND DISCUSSION

The first component of an agent-based model was to simulate the existing conditions based on given parameters and assumptions. Table 5.1 presents the transportation flow by mode share. As the table shows, rail transportation, as expected, is the dominant mode of transportation for transporting soybeans. However, the model did not generate any shuttle trains. This might be due to several reasons, but the two main underlying factors can be explained.

This study does not incorporate any transportation cost. So the difference in transportation rate due to economies of scale is not captured. Since, per definition, unit trains and shuttle trains both have more than 50 rail cars, the model could not differentiate between these two, therefore picked one with more availability. There are only three elevators with shuttle trains in Cass County. The other reason can be explained by randomness in normal distribution.

**Table 5.1** Simulation results (Base Case)

| Configuration | Number of Units | Weight (US ton) | Percentage |
|---|---|---|---|
| Sub-Total: Truck | **164,664** | **3,522,967** | **64%** |
| Truck (other) | 18,231 | 401,924 | 7% |
| Single axle | 34,250 | 377,541 | 7% |
| Tandem axle | 43,262 | 715,322 | 13% |
| Semi 5-axle | 57,230 | 1,577,131 | 29% |
| Semi 7-axle | 11,691 | 451,049 | 8% |
| Sub-Total: Railcar | **18,884** | **1,873,444** | **35%** |
| Single Car | 137 | | |
| Unit Train | 105 | | |
| Multiple Car | 66 | | |
| **Total** | **183,548** | **5,396,411** | **99%** |

The second component of the model was to forecast the impact of having a new processing plant in North Dakota. There was a new soybean processing plant being built in Spiritwood at the end of 2017. The plant processes 125,000 bushels per day, which is expected to absorb all soybean shipment flows out of state. Table 5.2 illustrates the results for the second scenario. It generally shows the rail traffic volume with a roughly 30% increase as a result of adding this processing plant.

**Table 5.2** Results of Spiritwood Processing Plant

| | Number of Units | Weight (US ton) | Percentage |
|---|---|---|---|
| Truck (other) | 29,370 | 647,497.66 | 8% |
| Single axle | 35,842 | 395,090.42 | 5% |
| Tandem axle | 55,308 | 914,499.51 | 11% |
| Semi 5 axle | 52,660 | 1,451,192.84 | 17% |
| Semi 7 axle | 7,530 | 290,514.15 | 3% |
| Railcar | 49,344 | 4,895,320.44 | 57% |
| Single Car | 192 | | |
| Unit Train | 202 | | |
| Multiple Car | 40 | | |

# 6. CONCLUSION

This study reviewed agent-based modeling in freight and public transportation planning to fill the gap between traditional modeling efforts and emerging needs of adopting behavioral modeling for an agricultural transportation model. The study then investigated adoption of an agent-based model for a large-scale travel demand model. The objective of the proposed model was to provide a platform to analyze grain transportation movement at the micro-level, since most industry reports lack such micro-level freight analysis while supporting regional and statewide planning. The proposed model is capable of handling sophisticated decision-making processes, such as grain pricing strategies, transportation costs, holding costs, and advanced logistics choice model and the behavioral selection process.

The study should include detailed price, costs, and transportation rate in the future. So, future studies can simulate interactions between agents of farmers and behavior of individual choice of crops, land use, land acquisition, and choice of intermediaries and facilities. Because the tool did not collect traffic information on road links, the validation of traffic volume could not be done. However, the validation process of departing and arriving traffic volumes should be used for validation in a future study.

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