EXPLORING AGENT-BASED MODELLING FOR CAR-BASED VOLUNTEER DRIVER PROGRAM PLANNING

by

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Abstract

Volunteer Driver Programs (VDPs) utilize the service of volunteers to replicate car-based on-demand door-to-door services in rural areas, but little is understood about how external factors (e.g., changes in demand) impact VDP sustainability. Agent-Based Modelling (ABM) simulates operational behaviour of individual agents (e.g., drivers, users) to evaluate their interaction under specified scenarios, and while it has been used in transportation research, has never been applied to VDP analysis. Netlogo was used to develop a simplified VDP ABM, calibrated and validated with one year of program data from the New Brunswick Volunteer Driving Database. Two model scenarios were tested: increased health trip distance and increased service area. Doubling health trip distance resulted in 46% fewer drives, 20% mileage reduction and 30% less driver utilization. Doubling of service area resulted in 47% fewer drives while keeping mileage and driver utilization virtually the same. ABM demonstrated intuitive results and established connection among changing operational scenarios.

Dedication

This thesis is dedicated to the thousands of international students across the world who have been separated from their families and against all odds were able to push through and complete their studies. I also fondly remember my former classmate who lost their life battling Covid-19 but had plans to start their master's journey this year.

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List of Symbols, Nomenclature or Abbreviations

VDP – Volunteer Driver Program

ABM- Agent Based Modelling

NB – New Brunswick

ODD Protocol - Overview, Design and Detail Protocol

1. Introduction

This research explored the use of an Agent-Based Modelling (ABM) technique to quantify and forecast the use of rural car-based Volunteer Driver Programs (VDP) by non-drivers, primarily older adults (aged 65 years and older). ABM is a technique that utilizes software programming to create a simplified purposeful representation of a real-world system. It has previously been used in transportation engineering for modelling pedestrian movements and for freight and logistics operations, but the application to solving rural transportation issues appears unique.

Overarchingly, transportation can be defined as the movement of people and goods from an origin to a destination (Roess et al., 2011), but this can be narrowed by thinking of modern transportation as occurring in two realms, urban transportation and rural transportation. Urban transportation is usually thought of as any movement of people or goods that occur in areas of high population density (e.g., New York, Toronto). Since the 2011 Canadian national census, urban areas have been redefined as population centres: an area with a population of at least 1000 people and a density greater than or equal to 400 persons per km (StatsCan, 2011). Rural areas then were classified as anywhere outside of the urban areas.

The transportation challenges faced by rural communities are a factor of both their location and their demographics. Rural communities are located farther away from essential services and places of commerce and have lower population density than urban areas (ITE, 2011). Census data has shown that the population of rural communities are 'aging' faster than that of their urban counterparts (StatsCan, 2008). Younger persons tend to move away to the city to find better economic opportunity. They leave on average a significantly older population behind (StatsCan, 2008). A 2011 transportation study revealed that a significant proportion of rural older drivers in their sample reported being unable to meet their needs without a car and the involvement of family or friends (Hanson & Hildebrand, 2011). This may be because older persons may be limited in mobility and the current transportation system in rural communities do not allow them to get around comfortably and conveniently (Copp & Hanson, 2019).

Volunteer driver programs (VDP) have emerged as solutions for rural transportation in several New Brunswick communities (Copp & Hanson, 2019). The structure and means of operation have notable similarities. In the New Brunswick examples, vehicles are driven by volunteers who are paid mileage, dispatched centrally, and offer rides to members only. VDP users are not exclusively over the age of 65 years, though tend to make up the majority of users (Goudreau and Hanson, 2019). The availability of a VDP in a community has the potential to provide an older adult an alternative to relying on family and friends, walking long distances, or paying high out of pocket costs for taxis. As the population of Canada ages, it can be expected that more car-dependent older adults living in rural areas will need an alternative to driving. VDPs are showing promise for facilitating that transition to non-driver.

1.1 Problem Statement and Project Significance

The development of volunteer-driver programs in New Brunswick has started to fill some gaps that exist in rural parts of the province (Copp & Hanson, 2019). However, for such programs to be sustainably scaled and implemented it is necessary to know how many users demand the service offered by these programs, the supply of volunteers available to keep it running, what the time commitment of the program needs to be and as programs grow, what the operational limits of their dispatch models will be.

Traditionally, transportation demand is estimated through a four-step planning process of trip generation, trip distribution, modal split and traffic assignment. The traditional four-step process yields a model that responds to changes in demographics, usage of transportation modes and economic conditions. This is then used in the realm of planning for things such as sizing future infrastructure, evaluating the feasibility of a new service, determining the CO_2 emissions footprint generated by travel and more. While it does include a component for estimating trip usage by mode, for a rural area, trips would need to be aggregated over such a large area that all trips may become intrazonal and this would have little utility for planning for a rural transportation system.

Limitations of the four-step planning process occur at every step. Its aggregative nature incorporates large numbers of user population trips between different zones for a limited number of purposes, making it more suited for forecasting urban transportation needs. For smaller locales such as rural New Brunswick, the low density of dwellings would necessitate the aggregation of trips over very large geographical areas. It also does not incorporate any behavioral attributes in the travel process and thus ignores the decision making that goes into trips. Agent-Based Modelling (ABM) might be a good tool to model the system that is a volunteer driver program because it theoretically allows for the behavioural simulation of all transportation users, drivers and the dispatch rules in one model. Research is needed on the use of ABM for addressing this rural transportation planning question as it appears to be a unique application of ABM to a rural operational model (VDP). If successful this will allow a tool that will be useful for rural transportation planning services, specifically future VDPs or similar operations. It will also set a precedent for transportation demand modelling in large, low density areas.

1.2 Research Hypothesis

If an Agent-Based Model can be built to represent the operations of Rural New Brunswick Volunteer Driving Programs, then it may be possible to use it to unearth insights that may be incorporated into the future planning of these services.

1.3 Research Goal and Objectives

The goal of this thesis is to explore the potential of Agent-Based Modelling for Car-Based Volunteer Transportation Program Planning. In order to achieve this goal, the following objectives were completed:

1. Identify suitable behavioural models or data inputs necessary to characterize the interaction of agents (such as drivers, service users and dispatchers) expected from a car-based, centrally dispatched rural volunteer driver program (VDP).

2. Create a rules-based system developed from behavioural models and VDP operational descriptions to describe the use and operation of a VDP in terms of an agent-based model framework.
3. Develop, apply, and validate an agent-based model of a VDP in New Brunswick
4. Apply population growth and dispatch scenarios with the ABM to evaluate the operational limits of the rural VDP model.
5. Assess the potential of the ABM approach for rural transportation planning.

1.4 Scope

This research was carried out using data from the New Brunswick Volunteer Driving Database based on service operation between the period February 1, 2017 to January 31, 2018. Due to the COVID-19 pandemic it was not possible to collect primary data from VDP operators. The ABM was developed within the constraints of the free open-source Netlogo software package and was created based on the operations of combined Small and Medium VDPs. The developed ABM would be done within the context of a non-geographically synchronized environment i.e., no GIS data were used in this implementation. The applications and insights gained from the model were limited to what was observed as a direct outcome of changing model variables. All recommendations for the potential of the ABM approach would be made within the context of what would be possible with the Netlogo environment and would ignore implementations using other software packages.

1.5 Thesis Organization

The remaining thesis has been organized as follows: Chapter 2 gives an introduction to volunteer driving programs. It outlines the challenges with understanding VDPs as a mode of transportation and makes a case for studying rural VDPs in New Brunswick. It then also introduces Agent-Based Modelling and how it is different from the other more well recognized techniques such as the Four-Step Demand Modelling Process. Finally, it concludes by looking at the potential for ABM to investigate demand trends in VDP transportation. Chapter 3 describes the study methodology that would be applied to organize data and develop a model using the Netlogo software platform. It outlines how the model would be validated and the scenarios that would be investigated to gauge usefulness. Chapter 4 goes into detail about the ABM development process in Netlogo. It includes how the ABM was conceptualized, the significance of all the agents and the operational aspects represented in the model. Chapter 5 contains all the results of the study including the calibration run and the various scenarios. It includes limitations of the model and suggestions on how it could be applied further. Chapter 6 summarizes the main conclusions drawn from the study and gives recommendations and next steps for future work.

2. Literature Review

2.1 Introduction

This literature review utilized a systematic approach to obtain sources relevant across all the domains of the thesis topic. This includes pertinent research on the topics of agent-based modelling, volunteer driver programs and rural transportation. The review incorporated a search of eight leading scientific databases (Scopus, Institute of Civil Engineers, Elsevier, TRID, ScienceDirect, American Society of Civil Engineers, ProQuest and Springer) for transportation research and included papers, theses and short articles from all over the world. The following table (Table 1) summarizes the databases utilized in the review, show how topics were searched and quantify the results obtained at the time of searching.

Table 1. Summary of Results from Academic Databases

Search Terms	**No. of Results Found**
Agent-Based Modelling	12,799,622
Agent-Based Modeling	12,799,720
Agent-Based Modeling + Transportation	8473
Agent-Based Modelling + Transportation	8679
Agent-Based Modelling/Modeling + Transportation + Rural	731
Agent-Based Modelling + Transportation + Volunteer Driving	35

The results of Statistics Canada's General Social Survey in 2012, cited by Goudreau (2016), reports that over 1.6 million Canadians in 2011 or nearly 5% of the population received help with transportation to run errands, shop, attend medical appointments or for social events. Even though there have been more recent social surveys performed, this metric has not been updated since and serves as the most recent and accurate dataset to measure a country-wide dependence on transportation assistance. The survey indicated that over 40% of its respondents had no other person available besides a caretaker to provide transportation assistance, but the specific type of assistance and the frequency are unknown.

Volunteer driver programs (VDP) are a formally organized transportation service that utilizes the service of volunteers (and sometimes their vehicles) to provide transportation to others. Users of this service are often members or clients of non-profit or charitable organizations and often the service is used to fill a gap in transit service for locales where a larger more traditional transit system does not exist or is unsuitable (Hanson, 2017). VDPs are used as a means of providing increased mobility by replicating car-based on-demand door-to-door services and have been used to take users directly to their destination and to central transit hubs where longer multi-modal trips are required. Organized VDPs have emerged as solutions to fill the transportation service gap for those unable to meet their personal transportation needs independently with private automobiles and where taxis, transit or active transportation is unrealistic or unavailable (Hanson & Goudreau, 2017). VDPs vary in size, scope of services offered, target population, funding and unique community needs (National Aging and Disability

Transportation Centre, 2019). VDPs are able to serve areas of low population density at a lower overall cost than paratransit by using volunteer labour and vehicles (Hanson, 2017). A key characteristic of VDPs is that they replicate the on-demand travel and social aspects associated with relying on friends and family (Hanson & Goudreau, 2017). Hanson and Hildebrand (2011) showed that from a sample of 60 persons, rural older drivers would seek to make 52% of their trips using assistance from friends and family if they did not have access to a car. In a small study of VDPs across rural New Brunswick, Hanson and Goudreau (2019) found that the most common trip purposes for rural VDP users in New Brunswick, Canada are health, life maintenance, quality of life and work/education.

VDPs have been operating in the United States for well over 60 years with approximately 400 programs listed in existence, the operations are commonly focused on specific demographics such as seniors or rural populations; however, there is no national database for Canada (Hanson, 2013). The National Centre for Mobility Management (NCMM) defaults to a 2018 report by the National Aging and Disability Transportation Centre (NADTC) as a comprehensive resource for the successful operation of a volunteer transportation program. The report describes in detail what VDPs are, how they operate in the US and gives some figures on its adoption by various demographics. According to a 2018 survey done by the NADTC, only 8% of older adults and 27% of persons with disabilities reported using a VDP. Despite the low utilization, the NADTC reports that 43% and 44% of the same demographics would utilize the service if it were available in their communities. Two notable organizations in the US that are impacting volunteer transportation are ITN America and Feonix Mobility Rising (Freund et al., 2019) ITN America is a community-based transportation solution developed to address the challenge of senior mobility. The company's mobility model is centered around the use of a personal transportation account which can be credited in a variety of creative ways such as trading in an unused car, volunteering as a driver, gift certificates, signing up with directly partnered shopping and healthcare businesses and more. The company uses its unique experience to also study mobility and develop models for senior transportation. It also makes its work available to policymakers, students and researchers alike. The company also seeks to influence transportation in the locations where it does not operate by having transportation affiliates. Another important American organization impacting the volunteer space is the consultancy firm, Feonix Mobility Rising. The company seeks to bring improved transportation options to underserved communities and the disadvantaged by partnering with local bodies and developing plans for their mobility challenges. Feonix has created solutions for over 278 communities across 5 states in the United States. They place great emphasis on addressing mobility issues for rural communities, access to healthcare, older adults, persons with a disability, isolated workforces and low-income families and individuals.

Outside of North America, work by Viergutz and Schmidt (2019) elaborates on common issues such as decentralization and low utilization rates experienced by the rural population with conventional public transportation (CPT) in Colditz Germany. Their paper explores the possibility of balancing the shortfalls with a new model of demand responsive transportation.

2.2 Challenges with understanding VDP as a mode of transport

Understanding VDP programs as a mode of transport is inherently difficult because of the way operational metrics from ongoing programs are recorded and how new programs are launched. Often new VDPs use a case-study or best practice approach to develop. That is, they try to duplicate the operational attributes of a successful program without understanding the external factors (if any) that contribute to that success in a particular location. While adopting best-practices is not bad in concept, factors such as demographics, the supply of volunteers, demand for services and potential for success are unique to a location and may be the defining variable between success and failure. Hanson (2018) recommends that further research be done to explore the supply of and demand for VDPs as well as the operation model itself so that it may be better understood where and how new programs may be implemented and allow for existing ones to develop sustainability.

One of the largest user groups of VDPs are seniors 65 years and older (Hanson & Goudreau, 2019). According to the Action for Seniors in Canada report, seniors are a rapidly growing segment of the population and are living longer and healthier lives than the previous generation. The senior population is projected to grow 7.4% by 2030 or by just over 3 million persons across Canada (StatsCan, 2014). However, due to the associated conditions of aging, seniors will inevitably become more reliant on transportation methods that exclude them from personally driving. This is reinforced by Foley et al. (2002), who found that seniors generally decide when to quit driving and it is often due to the onset and progression of medical conditions that affect mental, physical and cognitive abilities, thus by extension their driving. It would be a reasonable assumption if there was a demographic that relies on VDP transportation, a significant increase in that population would result in an increase in demand for VDP transportation. Thus, with an increase in demand, it would be necessary to consider how the operational characteristics of VDPs can be modified to also meet this increase in demand.

From the reviewed literature, the major focus of VDP research has been to isolate methods for consistent data collection and reporting with the aim to do better analysis of the operational metrics. This would allow for an easier and consistent incorporation into formal planning and forecasting. Hanson (2017) profiled existing transport and volunteer data sources in Canada and to a lesser extent the USA and identified challenges with using the sources to understand how older adults use VDPs. Hanson then proposes a framework to focus future VDP research to ensure that it will one day be incorporated into planning. Goudreau's (2019) thesis study collected annual travel data and organizational attributes from eight (8) VDPs operating in NB. It looked at the operational metrics such as trip purpose, distances travelled and number of drivers and made strong correlations between the number of riders and the program budget. Hanson & Goudreau (2019) later aggregated the results of seven (7) car-based VDPs in New Brunswick and sought to identify common trends amongst the operational metrics in hopes to create a foundation on which programs could be planned and contribute to wider forecasting for future VDPs. The aim of the study was to provide a basis for VDP operators to better manage the service and allow for planners to assess VDP implementation as a tool for meeting rural transportation needs. Earlier work on VDPs saw a small study done by Hanson (2013) which analyzed stated preference surveys distributed to potential users and volunteer drivers by a non-profit group looking to organize a service. The surveys involved anticipated factors critical to the success of rural VDPs that focused on medical appointments. It suggested further research to predict ridership, volunteer supply, trip preferences and policy development. Copp and Hanson (2017) later looked at what drivers do to support VDP clients (beyond the driving task) in NB in order to gain insights into considerations for transportation planning for autonomous vehicles. They found that clients depended on additional driver tasks for the majority of the stops. The study then suggested that work be done on needs of VDP users by age group. Hanson and Caissie (2016) assessed VDP operators of seven (7) organizations in NB and recorded operational metrics in order to identify opportunities for consistent reporting to enhance daily operations and contribute to long-term planning. This study revealed stark differences in operational management and even how basic metrics such as 'trips' are defined. Hanson (2017) sees an in-depth review of five (5) VDPs in NB and provides a preliminary estimate of usage as well as results of an exercise to develop a common reporting tool among VDP programs in NB. The paper concluded that participating VDPs made positive strides towards developing a common data collection standard and while findings have hinted at the importance of service in NB better data is needed to refine the estimates. Hanson further emphasizes that there is a need to better understand the travel behaviour of program users in terms of their choice to use this program when compared to other options so that better planning can be made for ridership. A unique find, Gibbs (2019) examines the motivations of VDP drivers for a senior ride program in Tennessee. The study involved the use of an online survey that assessed demographics and a volunteer function index (VFI). The study then did statistical analysis on the aggregated results to determine factors that would motivate persons to volunteer. The results were used to identify suggestions for recruitment and retention of volunteers.

Lastly, Tuokko and Gruppuso (2015) profiled Volunteer Driving in the Greater Victoria Area in British Columbia. Their study was done in partnership with three community organizations, The James Bay Community Project, Capital City Volunteers and the Saanich Volunteer Services Society. The purpose of the study was to investigate how programs can maintain a satisfied and productive team of drivers by investigating the characteristics and qualities of the drivers, and the facilitators and challenges to driving. The study then summarizes all the findings and looks at how the service can be improved from both a driver and organizational perspective.

2.3 A case for studying rural VDPs in New Brunswick

Volunteer Driver Programs serve a variety of needs in rural New Brunswick. According to Hanson & Goudreau (2019), growth of the programs seemed to gain prominence with the establishment of an anti-poverty entity in New Brunswick in 2009. The entity's role was to help replicate the on-demand, car-based, membership-supported VDP programs. At the time only one other such organization existed, the Charlotte-Dial-A-Ride. The Charlotte-Dial-A-Ride was seen as a model for rural transportation and helping non-driving older adults. According to Hanson & Goudreau (2019) several similar programs have emerged serving primarily rural areas. These programs often represent the only formalized and organized alternatives available to driving in respective communities. What remains as an uncertainty, however, is whether or not these programs can be sustained with the volunteer approach in the event of growing demand. The study of these programs, particularly in NB, one of the most rapidly aging provinces (StatsCan, 2014) will continue to lead to insight into the applications for non-driving adults and give lessons for other jurisdiction with similar challenges. Studying the programs may also be useful for two other reasons. Firstly, because of the operational insights to be gained for new services and secondly, because metrics demonstrate the value that these programs have in meeting local transportation needs.

VDPs in rural NB typically work with a central dispatcher who allocates available volunteer drivers from a pre-existing pool, who then is assigned to a particular member who books a ride or requests service. This service may consist of a drive with multiple trips (or stops) for a variety of purposes such as health, shopping, groceries or even social events. Oftentimes riders will even be assisted by volunteer drivers (in the event that they require it) to do tasks such as shopping or opening doors, and this is typically seen with the senior demographic. Different metrics are logged from each trip such as the distance, driver name, time taken, stops made and more. However, while the VDPs in rural NB operate similarly in concept there have been instances where their management and metrics are not synchronized enough in order to aggregate data and make inferences about the wider user base. Until enough can be learned about the wider user base in order to provide a forecasting component it will be difficult to incorporate VDPs into the formal planning process.

2.4 Activity-Based Modelling and the Four-Step Demand Modelling Process

Prior to the 1950's transportation planning was done by relying on uniform growth factors and extrapolating their trends for future use (Weiner, 1987). In North America there was a requirement for a more formalized process of transportation planning and so accurate forecasting became a need. In the early years of demand modelling however, forecasting was used to ensure sufficient highway capacity was available to meet the growing demand for automobile trips. Little effort though was devoted to predicting the demand for other modes of transport such as cycling, walking or transit. Much of the work and analytical techniques developed between 1950 and 1960 became the foundation of the four-step demand modelling process (ITE, 2016).

The four-step demand modelling process (4SDMP) consists of the four sequential steps of trip generation, trip distribution, mode choice and trip assignment. Though the steps have remained the backbone of major modelling since their development in the 1950's, methods utilized to perform each step have changed over the years (ITE, 2016). Trip Generation, or the first step of the process, determines the productions and attractions of trips in different geographical zones based on specific trip purposes. This is then recorded as a function of factors such as land use, demographics and vehicle ownership. Trip distribution, secondly, assigns the productions and attractions into origins and destinations with corresponding barriers to travel or friction factors, which are things such as travel time and cost which can negatively impact one's desire to travel. The next step in the 4SDMP, is mode choice which seeks to predict the number of trips that will use each of the available modes of transportation. These predictions depend on demand on a mode's utility of attractiveness to a user for a particular trip. The attractiveness could be affected by distance, travel cost, wait time or other factors such as avoidance of particular routes. Finally, once the first three steps have been followed, the trip assignment step sees trips allocated to different links in the network between origin and destination with the intention of having the shortest travel time or lowest cost.

While the steps have been around long enough to breed familiarity among transport planners worldwide, a 2014 paper by Mladenoviç & Trifunoviç highlights detailed shortcomings of each step in the 4SDMP and gives several recommendations for improvement. The authors highlight that a general shortcoming of the 4SDMP is that it not highly accurate for travel demand forecasting due to the nature of behavioural consideration in the decision-making process. This means travel patterns and traffic, often predicted through this method, may have a lower degree of certainty. They then point towards activity-based models as a solution.

An early alternative to the 4SDMP has been the use of activity-based models. In use since the 1970s, activity-based models predict activities and travel decisions across time and space. The activity-based models are developed on the premise of using an individual's behavioural properties by computing relative utility of completing a trip for individual travelers and are better for modelling biases, maximizing statistical efficiency and model transferability (Mladenoviç & Trifunoviç, 2014). According to Miller (2017), Agent-based micro-simulations may be a viable route if an agent's history, learning, and adaptation to a changing environment is to be modeled. This modeling may require the use of dynamic time-series data to incorporate such features. Miller, however, is of the opinion that ABMs represent a first generation of operational models and while there is significant opportunity in the realm of ABMs, they will require new behavioral foundations on which to be laid.

Not to be confused with activity-based models, Agent-Based Modeling (though similarly abbreviated) is a distinct departure from the concepts of activity-based models. ABMs model individual travelers or drivers (agents), their attributes and their end goal within their environment. The interactions of the modeled agents are governed by rules that the developer sets and the outcome is the result of all the interacting properties and the trends that emerge as a result. The next segment will go more in-depth on Agent-Based Models and its potential for investigating demand trends for VDP.

2.5 Agent-Based Modelling and its potential for estimating VDP demand.

Agent-Based Models (ABMs) are models where agents are described as unique and autonomous entities that usually interact with each other and their environment locally. Agents may be organisms, persons, businesses, institutions or any other entity that pursues a certain goal (Railsback & Grimm, 2019). The uniqueness of agents speak to their differing size, location and resources and their autonomous nature means they work to achieve their own personal goals or objectives. This occurs in a geographically framed space or network, with the presence of other agents or neighbours. Agents in a model adapt their behavior to current states of being, other agents and the environment. Techniques such as ABM deal with a very important characteristic of system dynamics, emergence. Emergence essentially concerns the behaviours that arise as system components or agents interact. Thus, better studies can be made on how the individual members of a system who interact may affect a common goal of a group or organization (Railsback & Grimm, 2019).

ABMs are still relatively novel and have not garnered widespread adoption compared to traditional demand estimation techniques due to their complex intricate programming needs. However, a few researchers have utilized it to study transportation problems in the realms of cycling, pedestrian movement, freight and even urban demand models. Miller (2017) states that the advent of new technology has really opened up the gates for the collection of better data for transport planning, new services (ride-share), better information systems (ITS, ATIS) and more. Miller (2017) also states the need for the development of "significantly more powerful agent-based micro-simulation models" with the hopes that they will allow for new behavioural representations and easier-to use, more flexible representations of a variety of mode and travel behaviours.

2.5.1 How have ABMs been used in solving Transportation Problems

ABMs have been used to solve problems of mobility, marketing, traffic and transport simulation, behavioural analysis, car-sharing and more. In its infancy many early studies only sought to catalogue the existing research and thought on agent-technology. A few authors managed to conclude that agent technology has the potential to improve the performance of traffic and transportation systems (Bo & Cheng, 2010). In Bo and Cheng's 2010 paper they did a review on this specifically looking at roadway transportation, air traffic control and management and railway transportation.

The work of Chiu & Arian (2017) used social science theory along with ABM in Python to develop a model to represent the adoption of new mobility options among a user base. The model simulated the reaction of commuters and travelers to the introduction of an innovative mobility option and business model. The study used a synthetic social network and proved the concept that new ideas and how they spread can be represented in an agent-based model. While the study yielded a favourable outcome, the authors looked at the possibility of embedding cultural and demographic variables in the model to improve accuracy. In a similar fashion ABM has been applied to decision-support tools for demand-based transportation. The outcomes of behavioural applications seem to be much sought after as they are thought to provide more accurate results for modelling. Dia (2002) investigated driver-route choice behaviour with the use of ABM. Her study suggested using ABM to assess the impact of an advanced vehicle traveller information system (ATIS) while modelling driver behaviour for a corridor in Brisbane, Australia. The research combined ABM using data from behavioural surveys and discrete-choice models to represent how drivers chose their routes within a dynamic environment.

The City of Zurich in Switzerland seems to lead the frequency of case-studies that exist on the implementation of ABM in solving transportation problems. Researchers from the city have thus far focused on ABMs with free-floating car-sharing and urban transport demand models. Balac et al. (2014) studied how ABM could be used to improve the service levels of free-floating car-sharing in the city. The ABM use came as an alternative to mathematical optimization techniques and sought to more accurately represent the complexities of daily change in supply and demand with several multi-day models. The study used synthetic data based on the Swiss transportation environment, but it was still unclear how a car-sharing business' usage patterns were affected by competition. The study concluded it provided guidance to carsharing operators with respect to pricing operational attributes. Erath et al. (2012) looked at a large-scale transport demand model for the city nation of Singapore as a collaboration of the Future Cities Laboratory, the Swiss Federal Institute of Zurich and the Institute for Transport Planning and Systems. The working paper explores the use of open-source multi-agent based travel demand simulation (MATSim) to simulate integrated traffic flows for both private and public transportation methods while including realistic elements such as dynamic pricing. The system can incorporate up to 7.5 million agents, over 1 million links and 1 million destinations.

While ABM may be applied to solve transportation problems and systems at a larger scale it can also be useful in improving many of the fundamental principles of modelling. Borysov et al. (2019) presented a new approach to generating synthetic populations that are more statistically significant than existing methods. Their work utilized deep generative modelling by way of a “variational autoencoder network” (VAE). This VAE network outperforms Bayesian networks and Gibbs’s sampling methods for large scale modelling. While there is more work to be done on the simulation approaches for different pools of micro-agents, the VAE framework was proven to effective and more accurate at population synthesis.

2.5.2 How can ABMs be applied to solve the problem of demand for VDPs in rural areas?

In figuring out how ABMs can be used to solve the problem of demand for VDPs it is important to look at how VDPs typically operate in rural areas as well as some of their existing transportation issues. Rural transportation has been frequently regarded as a critical infrastructure for economic development (Gerpe and Markopoulos, 2020). Gerpe and Markopoulous’ (2020) work explored the use of ABM technology with software engineering techniques such as multi-criteria decision making (MCDM) to investigate how rural merchants select delivery options based on price, delivery time and their trust of the driver. Their work proved the hypothesized concept and concluded that agent-oriented programming can be used with MCDM systems to create interface between human users and intelligent agents. Looking at the issue of public transit in rural areas, Viergutz and Schmidt (2019), sought to investigate the operative parallels between demand-responsive transportation (DRT) and conventional public transit (CPT) in the rural town of Colditz, Germany. The study used a synthetic population formed from local travel data. The paper sheds light on how problems of efficiency and low density can be solved by using a demand-responsive system. It also further revealed the positive environmental and societal impacts that such a non-traditional solution may. While DRT is not a silver bullet for rural scenarios, they can form the base of studies to better solve rural transportation problems (Viergutz and Schmidt, 2019).

2.5.3 Summary

This literature review examined the gaps in formal transportation that resulted in the development of VDP across North America. A few of the challenges that prevent VDPs from being understood as a conventional mode of transport were also reviewed and a case for studying rural VDPs in New Brunswick was made. The traditional four step demand modelling process was then compared to activity-based models. Agent-based Modelling was then introduced and its potential for estimated VDP demand was discussed.

Rural transportation services need to address mobility issues associated with a decentralized population and a general lack of regular high quality mode choices. VDPs are being used in New Brunswick as a means of offering higher quality, reliable transportation options to the rural population, but lack a means to use their data to assist in future planning. This prevents programs from being able to accurately predict operational metrics in a new service area or maximize their effectiveness in their current area. ABM has the potential to be utilized to investigate the fundamental operations of these programs, isolate useful metrics and identify hidden relationships. Then it may be possible to improve both the quality of the rural transportation options as well as set a precedent for the improvement of VDPs.

3. Study Methodology

This section outlines the methodology used to develop an ABM for VDP planning.

3.1 New Brunswick Volunteer Driving Database

The primary dataset that is used in this study represents a one-year aggregation of the operations of seven (7) car-based VDPs and was taken from the NB Volunteer Driving Database maintained at UNB by Dr. Trevor Hanson, with metrics profiled in Hanson and Goudreau (2019).. Below is a summary of the recorded metrics that will be used to inform the ABM and the assumptions made while doing analysis.

In previous work by Hanson and Goudreau, VDPs were classified as small, medium and large based on the number of registered riders. Small organizations had fewer than 50 riders, medium had between 51 and 100 riders and large had between 100 and 300 registered riders. In order for the group anonymity to be retained during the research process, attributes were combined for the Small and Medium VDPs and the comparison between them and larger programs were made. Small and Medium programs serve an average geographical area of 900 sq.km. Large VDPs operate within an average service area of 3014 sq.km. The combined averaged attributes for all classifications are also seen in Table 2 below. The attributes outlined for the VDPs were utilized as a primary dataset to inform the rules of the upcoming Overview, Design and Detail (ODD) protocol and thus the ABM. However, certain operational metrics were isolated solely from the four programs in the Small and Medium category.

Table 2. Summary of VDP Group Attributes and Service Area (Goudreau, 2019)

	VDP Maturity Classification		
Metrics	**Small and Medium**	**Large**	**Combined**
Number of Programs	4	3	7
Average Service Area	897 sq.km	3,014 sq.km	1,805 sq.km
Service Area Pop.	11,459	38,594	23,088
No. of Drives	533	5,236	5,769
Annual drives per group	133	1745	824
Drives per 1000 population	29.7	55.4	40.7
No. of stops	1,255	7,773	9,028
Stops per drive	2.4	1.5	2
Km driven	39,165	314,338	353,305
Km per drive	73.5	60	61.3
Km per stop	31.2	40.4	39.2
Total riders	659	7,850	8,367
Riders per drive	1.2	1.5	1.5
Passenger-km	48,423	471,267	512,698
Passenger-km-per organization	12,105	157,089	73,243

In addition to these group attributes, other operational metrics were used including: the number of unique drivers for each VDP classification; the trip purpose; average distance per driver for each trip purpose; average hours per drive by purpose; total annual volunteer hours driven; and the sum of volunteered time.

It is to be noted that this research and ABM development primarily focused on the parameters from the combined Small and Medium category which was taken from the primary dataset.

3.2 The Modelling Cycle for ABMs

When creating an ABM or model in general there are some important steps to follow to ensure that final products yield quantitative outputs that are useful for analysis. Railsback and Grimm (2019) outlines a particular cycle in the development of models that was followed in this research process and it can be seen in Figure 1 below. This cycle consists of six steps which are considered iterative and will more often see a developer going back and forth in small loops. The steps are listed as follows:

1. Formulating the question
2. Assembling hypotheses for essential processes and structures
3. Choosing scales, entities, state variables, processes and parameters
4. Implementing the model
5. Analyze, Test and Revise the Model
6. Communicate the Model

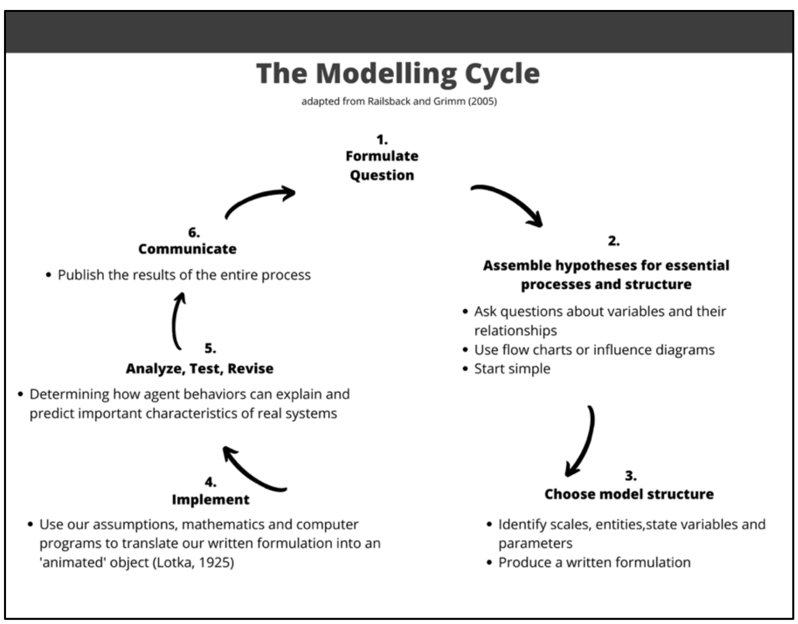


Figure 1. The Modelling Cycle (Railsback & Grimm, 2005)

Question formulation (Step 1) begins with a clear research question which acts as a guide and filter for designing a model. The question formulated for this study was "Can ABM be used as a tool to represent a Rural NB VDP and unearth useful metrics for transportation planning?" After formulating the question, the hypotheses are assembled for essential processes and structures (Step 2). This step is challenging early on as it can be difficult to determine what processes are essential prior to developing a model and seeing the outcome of it. However, the most important processes that were to be considered were thought out and are described in detail in the next segment as well as the model development chapter. Step 3 can be thought of as the detail step as it incorporated thinking about the number of agents in the model, how they move about and how their distance and time were represented. Implementing the model (Step 4) is using the written assumptions and goals to write software syntax that will develop a simulation or 'animated object'. Lotka (1925) describes model implementations as animated because they are driven by the internal logic of our written code. Despite whether the accuracy or assumptions are true, the model will run in the way it is written. After implementing a model, the tricky part comes with ensuring its accuracy by analyzing the results (Step 5). This was to be done with comparison to the developed datasets taken from the NB Rural VDP Database. While analyzing, it was necessary to make tweaks and refine the model. Lastly after the model was analyzed and tested, it was necessary to communicate its findings (Step 6) so as to inform stakeholders of its usefulness in achieving the outcome that was sought.

While the cycle described above is a general start for any model-based solutions, ABMs have their own recommended protocol for development. This protocol helps to describe their operation and helps a developer to formulate the intricacies needed to achieve their goal. While a few steps are common to both the modelling cycle and the later elaborated ODD protocol, they essentially will achieve the same goal.

3.3 ABM using Netlogo and the ODD Protocol

Netlogo is an open-source Integrated Development Environment (IDE) that can be used to simulate real scenarios using a graphical interface. It specializes specifically in allowing a user to develop agent-based models. The program typically sees four types of agents: Mobile agents, Patches, Links and the Observer. Mobile agents, arbitrarily called Turtles are the agents that move around in the world and their image or shape is customizable. Patches represent the two-dimensional square space within which the Turtles move. Links connect two Turtles and provide a way to represent relationships among them such as through a network. The Observer represents the overall controller of the model with all the displays and toggles and is often thought of as the person operating and initializing the model. Netlogo has built in its own programming language and set of commands known as “primitives” which must be learned and adhered to in order to successfully design intended models.

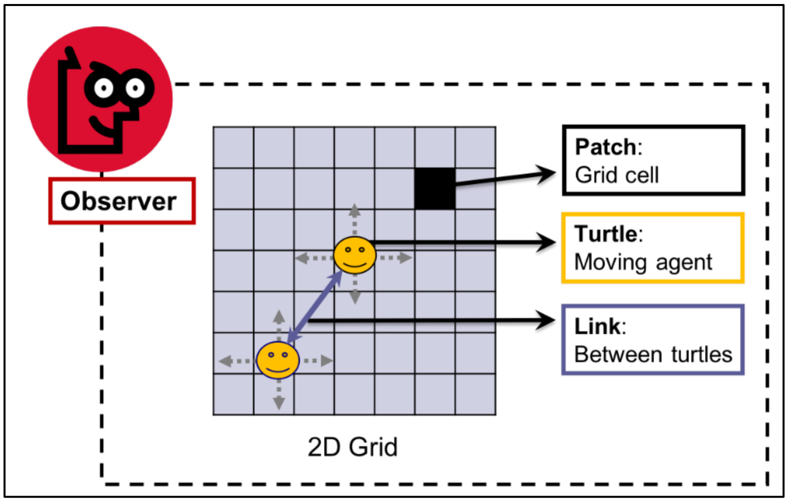


Figure 2. Netlogo Agents, Agent based Evolutionary Game Dynamics, (Izquierdo et al. 2019)

The ODD or Overview, Design and Detail protocol was used to develop an ABM for exploring rural VDP demand. This procedure standardizes the ABM process and allows for the creation of factual model descriptions that are complete, quick and easy to grasp. This protocol has been used in over 1500 published model descriptions (Railsback & Grimm, 2019).

The ODD Protocol (Railsback & Grimm, 2005) has seven (7) steps:

1. Purpose and Patterns
2. Entities, State Variables and Scales
3. Process Overview and Scheduling
4. Design Concepts
5. Initialization
6. Input Data
7. Sub-models

3.3.1 Protocol: Purpose and Patterns

Purpose and Patterns require a clear and concise statement of the question or problem to be addressed by the model. This can be determined by asking, “What system am I trying to model?” and “What am I trying to learn about the system?”. Secondly, this section should include a statement of the patterns used to determine how useful the model is for its purpose. This requires a review of what patterns exist in VDP data that would permit the replication of the actual system in a model. This could be a number of parameters such as the distribution of trip purposes, the number of drives made per purpose and number of vehicle-km driven per trip.

The purpose of the model is to simulate the systematic operation of a rural volunteer driver program in New Brunswick. The usefulness of the model is gauged by its ability to replicate the patterns of the operator, driver and rider/client and how they interact as one system. The model seeks to use operational attributes of the VDP such as the number of unique drivers, average trip distance and average trip time as dependent variables to determine what can be learned about the demand and supply interactions of rural VDPs.

3.3.2 Protocol: Entities, State Variables and Scales

Entities is a collective term given to the elements that are represented in the model and the variables and attributes that are used to describe them. An entity can be a turtle, patch or just the global environment. These entities are then characterized by assigned state variables which can dictate properties such as their shape, color or behavioral attributes such as their searching behavior. State variables can either remain constant throughout a simulation or can be changed by a process and updated. Lastly a model's temporal and spatial scales refer to how time and geographic space is represented. Temporal scales relate to how long a simulation runs and the time steps within which it advances. A model could illustrate a month of driving activity and advance in time steps of one hour, one day or one week if need be. However, it is not limited to this and can represent virtually any timeframe for which it is programmed. Spatially the extent of a model refers to the geographic size that is being described. This is represented by the grid cells or patches in the Netlogo IDE. The spatial resolution or the size that each grid cell represents can be set at the beginning of a model when the space to be represented is determined.

The agents to be represented in the model are the turtles which represent volunteer drivers and the patches which simulate the service area of the VDP. Drivers are defined by state variables such as their driving status, trip purpose, total distance covered and the average distance and time for the trip they have been assigned. The driver starts at an arbitrary location and move for the duration of the assigned trip distance. The Dispatcher/Operator, while not observable as a physical entity in the model, is a sub model that governs how trips are assigned to the drivers. Driver demographics are not considered relevant for this exercise.

The model is built around a simple spatial representation of the geographical area served by a Small and Medium VDP. It has tiles that characterize roads, land and homes. The distinction is made using attributes such as tile color and spatial coordinates. The spatial extents of the model are governed by the geographical limits of the VDP. This incorporates both the maximum trip distance served as well as the fixed operational limits of the VDP. The temporal extents of the model are one year of VDP rides. The total annual operational hours of the VDP are used to determine the total time extents of the model and day-to-day scheduling patterns are ignored.

3.3.3 Protocol: Process Overview and Scheduling

Process Overview and Scheduling deals with the dynamics or the processes that change state variables. This requires understanding and detailing what the entities are doing and what behaviors the agents display as the time steps progress. Simple processes tend to be fully described but the more complex ones are made into sub-models and given a name. The schedule or sequence of actions represents the order in which the processes are executed by the computer and can provide a concise, complete outline of the whole model.

The process breakdown of a small rural VDP begins with the transportation demand or need of an individual (considered a client or rider in this system) to fulfill a trip purpose (health, life maintenance, education, quality of life). This need is then met by a VDP who responds to the demand by the client by providing them with a driver at the specific time frame requested. Driver picks up rider, takes them to their destination/s (characterized by trip purpose) and will return them home at the fulfillment of their trip. Some trips have more than one stop.

However, it was determined while working on the prototype in Netlogo and discovering the complexity of the software implementation, that to keep the scope of the research manageable within the given timeframe, the operations would be modelled from a driver perspective and will involve the trip assignment, trip completion and reassignment of drivers for single purpose trips only. This allowed for functional elements of a VDP operation to be modelled and validated while allowing for further scaling up in later research.

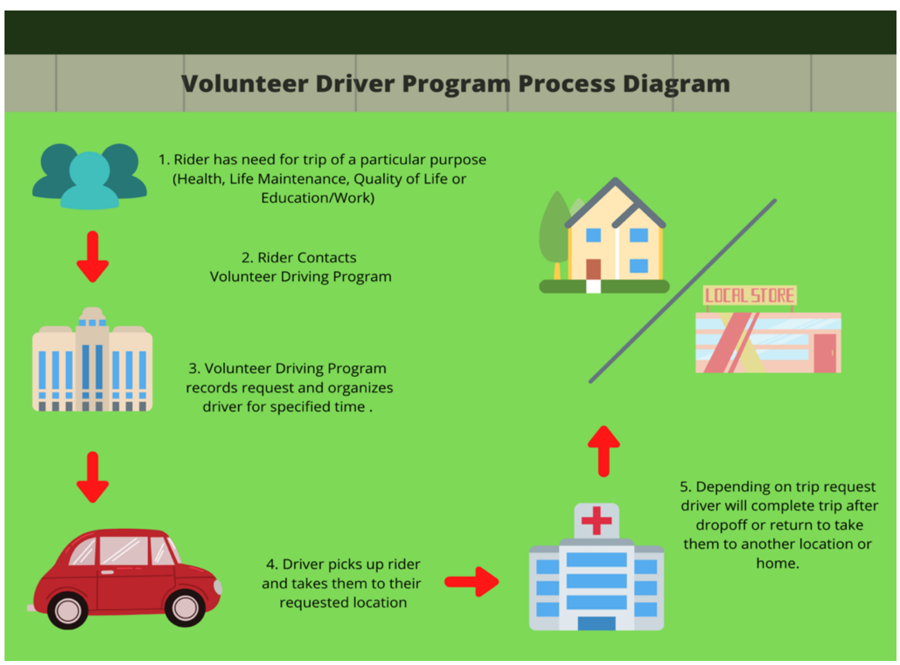


Figure 3. Volunteer Driver Program Process Diagram

The process therefore outlines a pseudocode for the following elements, preceded by a general initialization step:

1. Environment Setup
2. Driver Setup
3. Trip-Assignment
4. Run Volunteer Driver Program
5. Trip Re-Assignment

General Initialization

The model initialization sets up the virtual environment, drivers and their state variables i.e. The model generates a conceptual layout to represent the driving environment, VDP drivers and sets their initial variables.

Trip Assignment

The trip assignment portion of the schedule sees each driver being assigned a trip from one of the four purposes (health, life maintenance, quality of life and education/work). This is assigned randomly but according to the probability of the number of trips of each purpose type in the database. The trip purposes each contain their own variables such as their average distance (which is assigned to the driver with a normal distribution) and average trip time in hours. The driver agents in the model also change color to reflect each trip purpose.

<u>Run Volunteer Driver Program</u>

The VDP operations begin with each driver moving around in a systematic pattern but arbitrary motion. Each motion records their distance covered and adds to an individual and collective total for drive distance. A trip is then logged as completed once the driver reaches the assigned distance for each. Drivers are then reassigned more trips until the model time elapses. Other metrics such as the number of drives and the number of volunteer hours also get recorded. A drive is complete when each driver has reached their distance target signifying the completion of their trip. The volunteer hours are counted by subtracting the average trip time assigned for each trip from the initial annual volunteer hours as each trip is completed.

3.3.4 Design Concepts

While design concepts are not necessary to describe an ABM model, they may help both users and the scientific community to understand what is being done fundamentally and gain greater context of outputs. The following design concepts have been identified as useful to the creation of this Rural VDP ABM:

Collectives – These represent multiples of the different kinds of agents who have the same goal. That is, several different types of turtles can be created and classified based on their goal. VDP Drivers will be represented as a collective and are setup at the start of the model. Drivers have the same goal of moving around and completing their assigned trips.

Observation – The outputs for the ABM partly correspond to volunteer metrics that are already known and are a means to validate the model. A combination of monitors has been used to display things such as number of stops, total number of km driven and more.

Sensing – Agents use environmental variables such as grid location, grid-color, time and then specific variables such as volunteer hours, trip purpose and distance. While some variables are taken from the makeup of the Netlogo environment others are initialized based on the code and probabilistic distributions.

Adaptive Behavior – Agent adaptive behavior and decision-making fall to only the turtle-based entities. For drivers they actually move around the different elements of the road network and communities for a certain distance or time dictated by their average allocated trip distance and volunteer hours.

Interaction – Agents interact in the world in many different ways. Patches represent the size of the geographical background or community within which VDPs operate. Turtle agents (Drivers) interact according to the procedural necessities and variables. For example, as a driver moves over a patch, it increases its drive distance variable by 1. This variable updates the total drive distance counter.

Scheduling – Time is represented in time-steps of one hour up to a maximum of 12 months of VDP data. The 'go' procedure' which is equivalent to the play button on a video, begins the entire process of a rider booking a trip and everything plays out afterwards.

Stochasticity – Elements of randomness are introduced in the trip-assignment portion of the model. Each trip is assigned to a driver randomly according to a probability or frequency of that purpose. The average driver distance for each purpose is then assigned according to a normal distribution with a corresponding standard deviation.

Emergence – Model emergence is what behaviors or results emerge from the complex interactions that are unpredictable. Model emergence can be anticipated but not predicted.

3.3.5 Initialization

The initialization of the model world is concerned with the state at which variables are in at time = 0. Initialization values depends on whether a model's results are to depend on initial values or to be independent. The initial state of all the state variables of entities must be specified in order to make a model and its results reproducible. Our model uses pre-coded initialization values.

Variables specified at initialization are: the geographic or environmental variables (patches); the mobile agents (volunteer drivers,); and the timer. The following are the variables to be associated with each entity:

1. Environmental Patches: Color, Location, Label

2. Timer: Start at t = 0

3. Volunteer Drivers: Number of Drivers, Shape, Color, Trip Purpose, Driver location, Number of Available Volunteer Hours per Year, Number of Drives, Total Distance Driven, Driving Status.

3.3.6 Input Data

Input Data are data files that get read into the model from a source external to Netlogo. This often is the case when large datasets are utilized for variables. This research did not require feeding input data into the model.

3.3.7 Submodels

Submodels are all the major processes in the ABM which contribute individually in a modular way and make up the entire program. The Submodels are independent of each other and usually are designed and 'tested' as separate programs from a computer science perspective. That is, scientifically reproducible ABMs require an outline of all the equations, logical rules and algorithms that make up each sub-model.

1. Model Environment Setup – Segment of code responsible for setting up the model environment within which the important VDP operation processes occur.
2. VDP Operator Driver Assignment – Process of an operator assigning trip to an available volunteer driver.

3. Movement of VDP Drivers – Will Incorporate movement within a predetermined area at a specified rate and manner.
4. Volunteer Driver Trip Termination – Process by which driver ends their trip and after logging duration and km of trip.

The analysis of the submodels can be seen in Appendix 2 under "Submodel Testing and Analysis" and describes the software code that achieves the purpose of each Submodel.

3.4 Analysis and Validation

After the model was developed its validity was determined by its ability to reproduce key operational metrics as compared to the existing NB Rural VDP data, specifically at its ability to return the total distance or driver kilometres, the number of drives and the number of annual volunteer hours.

3.5 Model Scenarios

Following a successful validation, the usefulness of the model for formal planning was assessed further by observing the outputs of the model under the following scenarios:

1. Doubling the average healthcare trip purpose distance.
2. Significant service area growth.

For both scenarios a sensitivity analysis was also done to better reveal any relationships between the changing variables.

3.6 Limitations

The ABM here was limited by the degree of complexity that is chosen to simulate. Certain elements of a VDP may not be necessary to model in order to achieve usable results to inform operation. This may include certain demographic information about riders and volunteers, such as their age, gender, occupation and more. This information can be included in more advanced versions of the model as more is understood about how well-suited ABM is for representing VDP operations. Given the complexity associated with ABM development, the scope of the thesis was adjusted to focus on understanding the impacts of user demand on organizational metrics with drivers as the agents, rather than a user-based agent approach. The ABM did not utilize or model rider metrics, multi-purpose trips or stops. The calculated metrics highlighted by Hanson & Goudreau (2019) were then be filtered to isolate aggregate metrics associated with single-purpose trips (stops) and simplified to the assumption that each trip has only one rider to one driver. This allows for the VDP operations to be viewed from the realm of supply of drivers to meet specified user demand. This component is not necessary to test the concept of ABM for the VDP operations.

4. Model Development

This chapter details the process by which the Rural Volunteer Driver ABM was developed in Netlogo. It provides the reasoning behind all the assumptions that were made to create the rules by which the model abides, and it illustrates the step-by-step modelling cycle approach (The Modelling Cycle, Railsback & Grimm, Figure 4) which in many different forms is the nature of many software-based solutions.

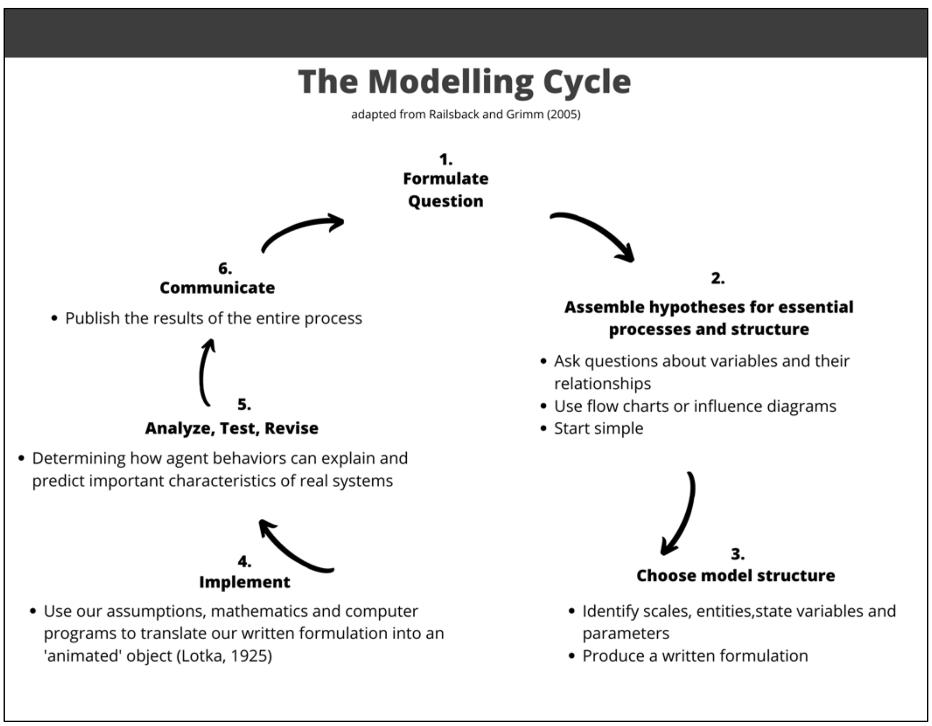


Figure 4. The Modelling Cycle (Railsback & Grimm, 2005)

1. **Formulate Question**: The question that was formulated prior to determining how the ABM would be developed was “How does a volunteer driver program operate?” VDPs are distinct in that they are operationally different from demand-responsive transit, dial-a-ride and flexible transportation services. Transparently outlining the processes by which one is able to book a trip, get picked up and be transported to a destination through a VDP answered the question that was formulated.

2. **Assemble Hypotheses** - After listing out the processes involved in VDP operations, the important variables and their relationships were identified. The number of drivers, their volunteer hours, their size of the communities served, and more were all noted and initially thought essential for developing the structure and processes that would achieve a VDP model.

3. **Choose Model Structure** - The model structure was identified by considering the geographical size of the communities served by the programs and the timeframe within which corresponding operations data were available. The geographical area modeled was 900 sq.km and the timeframe of trip data utilized was 12 months or 2610 hrs of operation. The entities modeled in this version of the program were primarily the volunteer driver but through the lens of an operator who would be managing the trips.

4. **Implement** - After several rounds of trial and error an animated 'object' or simulation was produced in Netlogo based on which drivers would simulate the trip assignment and driving of single purpose trips within the VDP database.

5. **Analyze, Test, Revise** - The model was then analyzed , tested and revised over a period of time to debug parts of the code, to expand on results observed and to allow for its application to serve a wider variety of inputs.

6. **Communicate** - All the results through the model runs were collected through the Netlogo BehaviorSpace module, which allows for running and exporting model results to spreadsheets. The data were organized and the findings communicated.

4.1 Volunteer Driver Program Process Flow

In order to replicate the operations of a volunteer driver program the process flow must first be explicitly identified. This enables a look at all the procedures that are to be featured in the model. The following is the process flow for a typical volunteer driver program:

1. Service User (Rider) phones Dispatch to book a ride (2 days in advance)
2. Dispatch books Volunteer Driver.
   a. (Dispatch may assign an additional Rider to the Driver if times and locations align
3. Volunteer Driver accepts the Drive and is no longer free to accept other Riders

4. Volunteer Driver travels to pick up the Rider(s) within the Geographic Area
5. Volunteer Driver transports the Rider(s) to their destination(s)
    a. Rider(s) may demand several "stops" to fulfill their travel needs
6. Volunteer Driver is free to pick up other Riders once commitment to current Rider(s) end
    a. Commitment end by returning the Rider(s) home or by taking them to a destination where the Rider(s) has secured transportation to complete the rest of their journey.
7. Volunteer Driver is no longer free to be booked once its supply of "Hours" is exceeded.

4.2 Source data

The data used in the model was taken from the New Brunswick Volunteer Driving Database which is maintained by Dr. Trevor Hanson. The model specifically uses the VDP data from the driving year February 2017 to January 2018. In that year Hanson and Goudreau classified three different divisions of programs, based on the number of registered riders. Small programs had less than 50 registered riders, medium programs had 51 – 100 riders and large , 100 – 301 riders (Hanson & Goudreau, 2019). While all three classes of programs followed the same processes above, the input parameters they provide for the model are a little different. In order to keep the integrity of the data for the VDP groups the Small and Medium categories had their metrics combined. For the purpose of this thesis, data from the Small and Medium category was used for the ABM proof of concept as the smaller figures would allow for less complexity in the development process. However, the comparative table below indicates that large VDPs account for most of the drives, km driven, riders and total number of stops in the database. Thus, upon completing a proof of concept with the ABM from this study it is recommended that the methods be also applied to large VDPs so that the insights gained may be applied right across the board.

Table 3. Comparison of Trip Metrics for Different Sized VDPs

Comparison	**Small & Medium**	**Large**
	% in VDP database	
Number of Drives	9.2	90.7
Number of Km driven	11.1	88.9
Total Riders	7.8	92.2
Trip Scenarios		
Driver transports only one passenger to one destination of the four main trip purpose destinations and does not return them home (one-way).	• 57.8% of total stops. • 55.3% of total km. • 55% of total drives.	
Driver makes one stop per drive	35% of all overall stops	

After the database was sorted for Small and Medium Volunteer Programs a few new insights were made. Of the 533 trips in the database for Small and Medium programs, 403 were single purpose trips (75.6%). Of those single purpose trips, they had slightly different average attributes than the overarching Small and Medium Program attributes found in Table 1 from Hanson and Goudreau, 2019. The following tables show the total volunteer hours, average volunteer hours, the hours per drive, drives per volunteer, total distance and the average km covered per trip purpose for single purpose trips. It is also noteworthy that trips with single occupants or just one rider account for 84.6% of the single purpose drives.

Table 4. VDP Metrics for Annual Single Purpose Trips for Small and Medium Programs

Trip Purpose	No. of Trips	Percentage
Health	179	44%
Life Maintenance	114	28%
Quality of Life	87	22%
Education/Work	23	6%
Total	403	100%

Volunteer Average Km per Drive (SM Single Purpose)	
Overall	70.36
Health	96.81
Life Maintenance	47.11
Quality of Life	63.54
Edu/Work	11.57

Volunteer Average Hours per Drive (SM Single Purpose)	
Overall	2.80
Health	3.14
Life Maintenance	2.99
Quality of Life	2.45
Edu/Work	0.83

Annual Hours per Driver
26

Total Annual V. Driver Hours
1144

Drives per volunteer
9.16

No. of Trips
403

4.3 Identifying the Agents in the model

The agents in the ABM represent the volunteer driver and the community environment within which drives occur. The dispatcher was not included as an agent as their role of booking trips could be represented in a simpler manner. It is assumed for each driver there is one rider and so the user population and mapping multiple riders to vehicles was not included in the current version of this research.

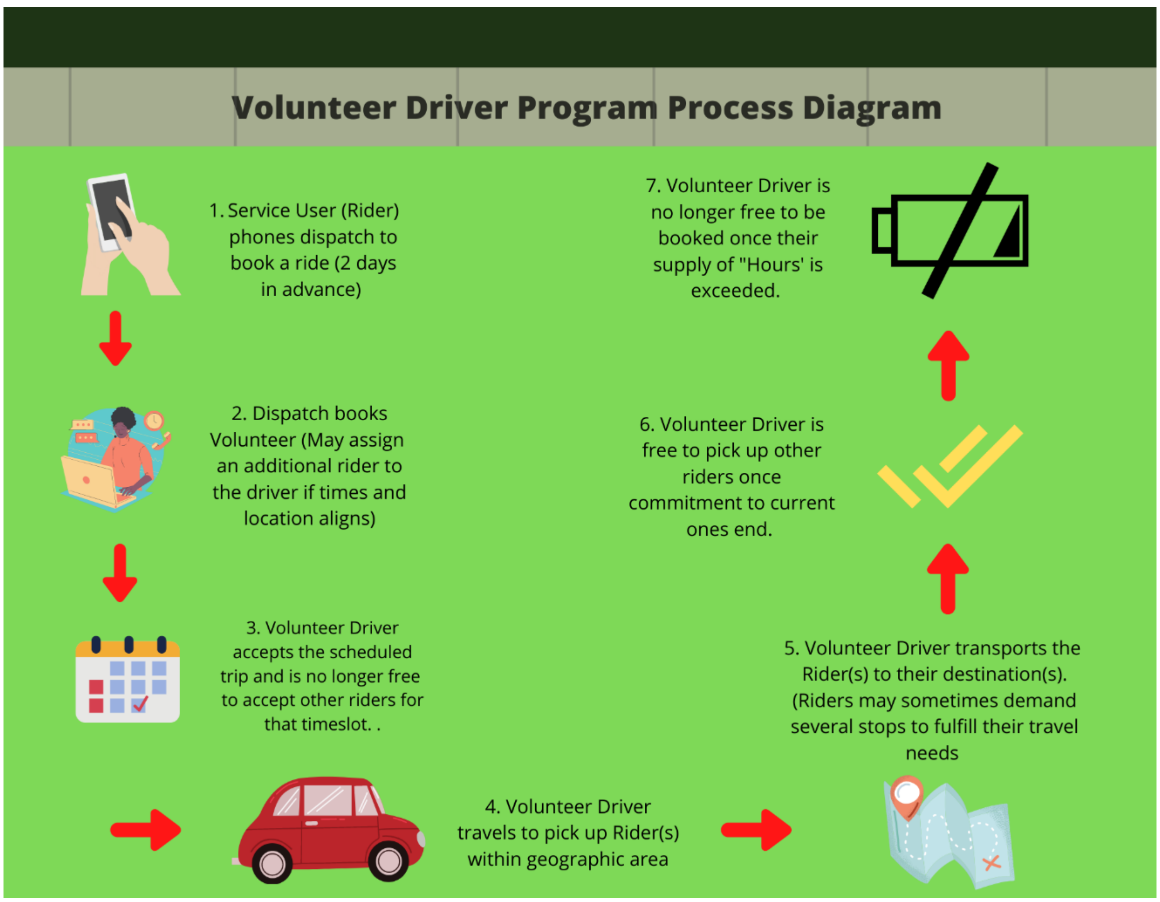


Figure 5. Volunteer Driver Process Flow

Volunteer Drivers (Turtles): In Netlogo the agents that can move around are called turtles. Turtles are represented by a default shape that resembles an arrow-head but this shape can be changed to a wide variety of others more specific to your model such as a car, person, tree or even a custom icon design. Volunteer Driver agents in the VDP ABM are represented by turtle agents in the shape of a car. There are also four distinct turtle "nodes" that stay hidden in the four corners of the black landscape. While these do not move, they are necessary to enable relative motion between those points and the drivers. Turtles have default variables such as their location in the environment, color, size, shape, turtle number and more. These variables can be increased to facilitate the necessary functions of a program.

Patches: As described earlier in the methodology, a patch is the two-dimensional ground environment on which everything occurs. It is essentially a functional background. Patches by default have variables of location, colour and size. Additional properties can then be assigned by declaring specific variables to them. The model shows an environment with a majority of patches being of the colour green, black or grey. The scale and size of the patches are consistent to the average service area of the Small and Medium VDPs. However, the arrangement of these patches merely contributes to an abstract representation of the VDP environment. The four striped squares in the corners of the model are also patches and represent the various trip purposes modeled in the ABM: health, quality of life, life maintenance and work/education.

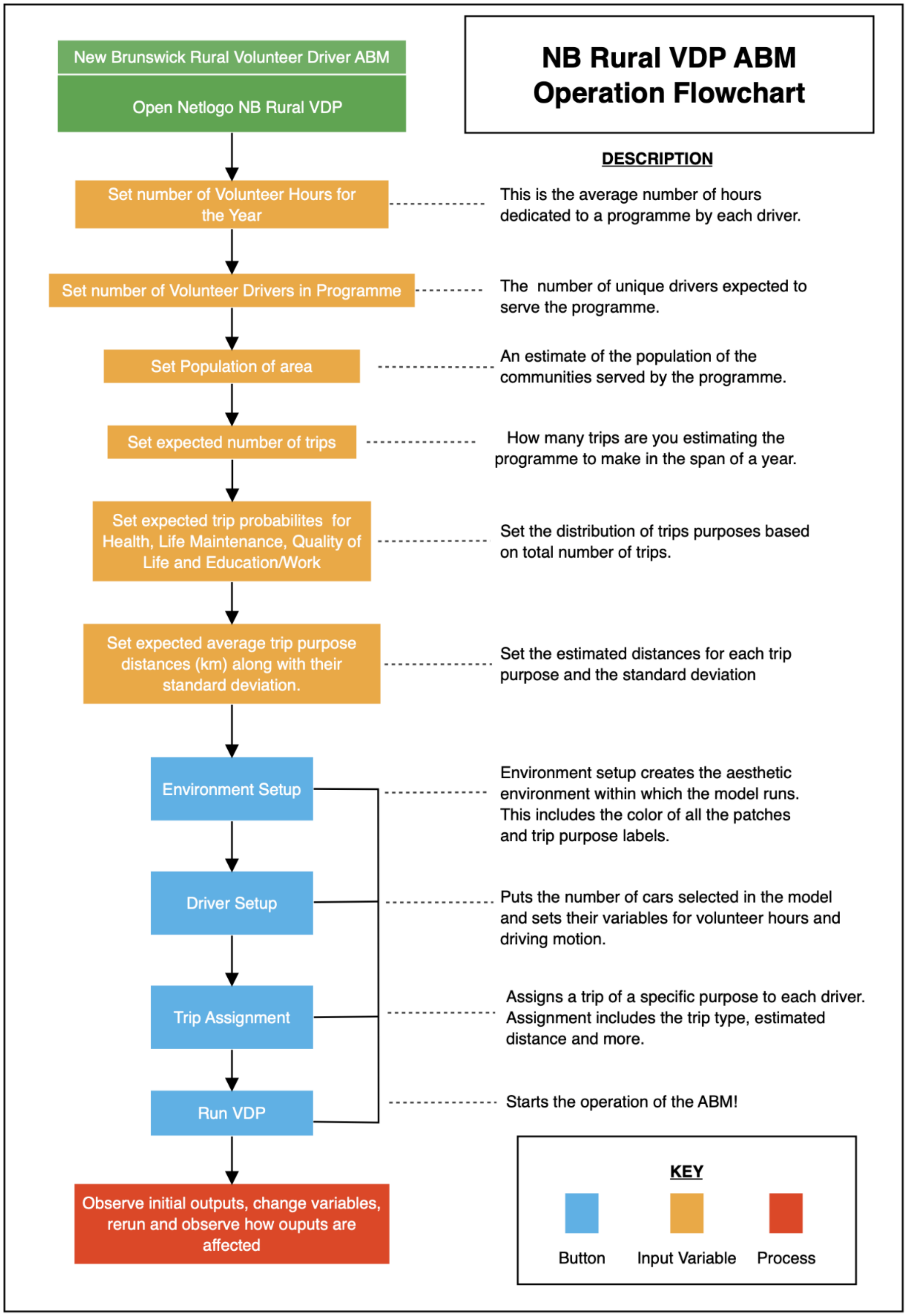
Links: Links are agents that connect two turtles. They can be directed or undirected. Links were not utilized in this ABM.

Observer: The observer is thought of as the overall controller or facilitator of the model and its display. Often times the developer is considered as the observer.

4.4 Establishing the model parameters.

The most important components of the ABM are data, how it gets manipulated in the processes and the assumptions that are made to guide the writing of the code. Previously described in the study methodology chapter, ABM rules are developed by first following an established protocol such as the ODD protocol and then infusing it with data and information suited to the purpose of the model. The following parameter is information that is required to inform the model development, with aggregate values drawn from Hanson and Goudreau's study of 1 year of VDP data in Rural New Brunswick.

Table 5. NB Rural VDP ABM Process Flowchart



Initial model parameters:

1. Size of the ABM universe – This is essentially the average geographical area served by the VDP. For the purposes of this study the ABM utilized the area served by combined Small and Medium VDP operators which is approximately 897 sq.km. This was rounded to 900 sq.km. This is an important input because it sets the limits of where the agents can operate and allows for the creation of a more realistic simulation. Using the values for Small and Medium operators allowed for a simpler initial model to be made to test the viability of the method.

2. Population of community served by VDP – The average population of the service area was also consistent with the combined values for Small and Medium VDPs and is 11,459 or 11,460 individuals. Population is an important metric because of how it may influence or correlate with the demand for VDP services. As a population increases there may be more persons who demand service from a VDP.

3. VDP Driver Population – This is the total number of unique drivers or persons who have signed up to volunteer their driving for the program. Across the combined Small and Medium VDPs, the number of unique drivers is 44 (NB Volunteer Driving Database). It is important to distinguish the total number of unique drivers in a service as on any given day or any given month the same persons will not be operating as there may not be a set schedule. The entire operation of the VDP is subject to the availability and goodwill of each driver.

Though this parameter was put in as a variable with the option to increase or decrease the number of drivers, it acts as a fixed parameter in the initial simpler versions of the model.

Model Variables:

1. Number of volunteer hours – The volunteer hours in the model are expressed as the total number of volunteer hours for the year, the average annual number of hours volunteered per driver and the average number of hours that a particular trip purpose takes. The total number of volunteer hours in the model can be found by calculating the sum of all the volunteer time for each trip in the database or by multiplying the average annual volunteered driving time per driver (26 hrs) and the number of unique drivers (44 initially). The number of volunteer hours is important because it dictates how many drivers are available to carry out the operations of the VDP at any given time.

2. The total number of drives – This metric is a record of the number of drives recorded by the VDPs in the one-year period. The initial version of the model simulated a single purpose drive.

3. The trip purpose – One of the most important metrics is the purpose of each drive. A trip may have different purposes for each stop and so the most common configurations have been recorded for the VDP metrics. The initial version of the

ABM only used data for the four main trip purposes of health, quality of life, education and life maintenance.

4. The distances covered per drive – This is a function of the total distance and the total number of drives.

The metrics listed above were used to both inform the model as well as test for validation.

4.5 The Operational Aspects of the Model: Trip Assignment and Vehicle Behaviour

The intention of this ABM is to, in the simplest way possible, replicate the functional aspects of a rural New Brunswick VDP. To achieve this the main operational aspects were taken out and scaled down. In this model the agents represented by car icons were moved around a road network or area after being assigned a trip of respective purpose. The trip purpose was be represented by the colour of the car's icon. The car continued to move around in a systematic manner until either the trip duration (time) was complete or the distance for the trip was achieved. The colour of the cars icon will return to its default state, meaning it is unbooked. This remaining number of hours were then subtracted from the time each driver has (3 hrs) and successive trips calculated from that remaining total. When a driver had no more hours left the car disappeared. This is a simplistic version of the true picture of the VDPs which sometimes have multiple stops per trip and multiple passengers. However, the early versions of this program did not include those functional aspects. As the operations are carried out, the metrics were viewed with a series of monitors and graphs that were used to evaluate consistency with the known VDP data.

4.6 Developing the Prototype

The ABM development began with developing a prototype model aimed at representing the environment of the VDP as best as possible and then encoding the vehicular and operational behavior of the agents. This section details how the environment and the operational behaviour of the VDP were developed by taking a look at the Netlogo software application settings and the creation of a pseudocode algorithm to guide the programming.

4.6.1 The Model Environment

The model environment reflects a simple aesthetic representation of a rural community served by a volunteer driver program. The look of Netlogo's environment is controlled by the use of "patches". Patches are a square geometrical unit, distributed in a grid-like manner and have a size and location attached to them. They can be thought of as being similar to pixels in an image. By manipulating the patch size and the number of patches in the model it was possible to create an environment with the same area or square footage of a small-medium sized VDP (900 sq.km or 30 km by 30 km). *(All figures based on earlier research on VDPs done by Hanson and Goudreau, 2019)*

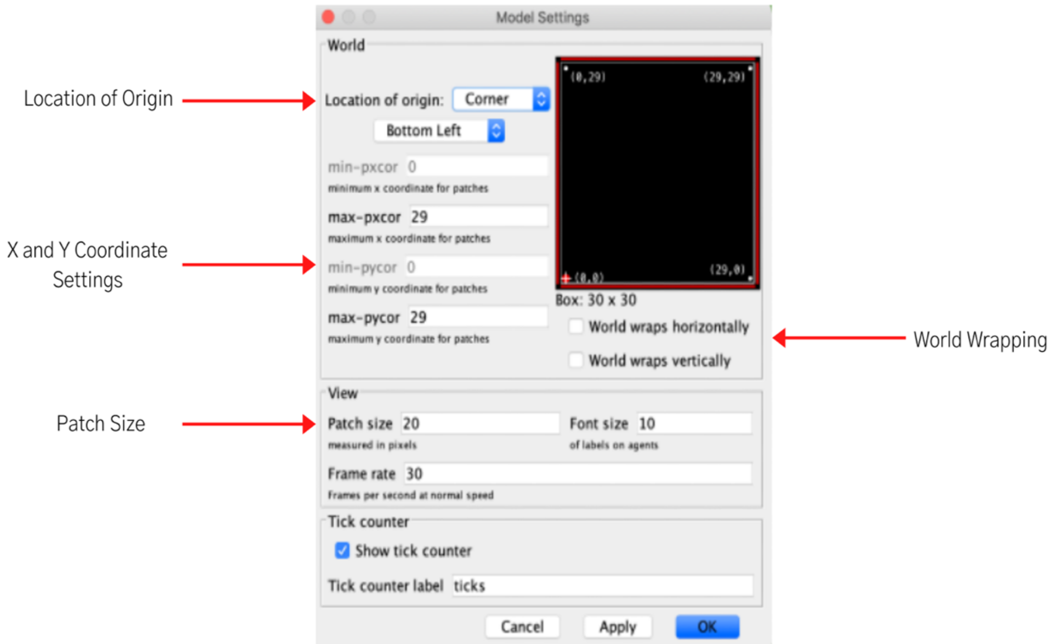


Figure 6. Model Environment Settings

Figure 6 above shows the model settings interface manipulated to achieve the required settings. The max pxcor and max-pycor is Netlogo jargon for the size of the extent of the grid in the x and the y direction, or how far the model window will stretch. The inputted values of 29 x and y coordinate units are used to represent 1 sq.km each. A few other settings relevant are the location of the origin, the patch size, tick counter and world wraps. The location of the origin is important because the patch coordinates are all set relative to this. In this model the origin is set in the bottom left corner and thus all coordinates are positive and change by going upwards and to the right. The patch size which can be thought of as similar to pixels can directly control the size of the model window by increasing the size of the patches. For this model patch size was set to 20 as it gave a large enough window to view all the activities occurring without scrolling in either direction. The tick counter is an informal time that monitors the runs in the model. One tick essentially is one iteration through all the commands in the model. This is not necessarily attached to a formal temporal constraint. The tick counter being visible is useful as it is a means to gauge how many runs the model has made and is even more significant when you want to vary the speed at which the model makes its runs. Lastly is the world wraps option. World wraps are possible in both a vertical and horizontal direction. While not necessary for the model to run, world wraps essentially control if movement to the furthest part of the horizontal and vertical edges of the model will result in an agent appearing on the other side (similar to Pac-man). This feature was not deemed necessary and thus deactivated.

After modifying the model interface settings to create a scale of similarity that is consistent with the operational area of Small and Medium VDPs the next thing to do was to ensure that it aesthetically represented the concept of a transportation related ABM. A conceptual sketch was developed, and the model environment was coded to best represent the conceptualization.

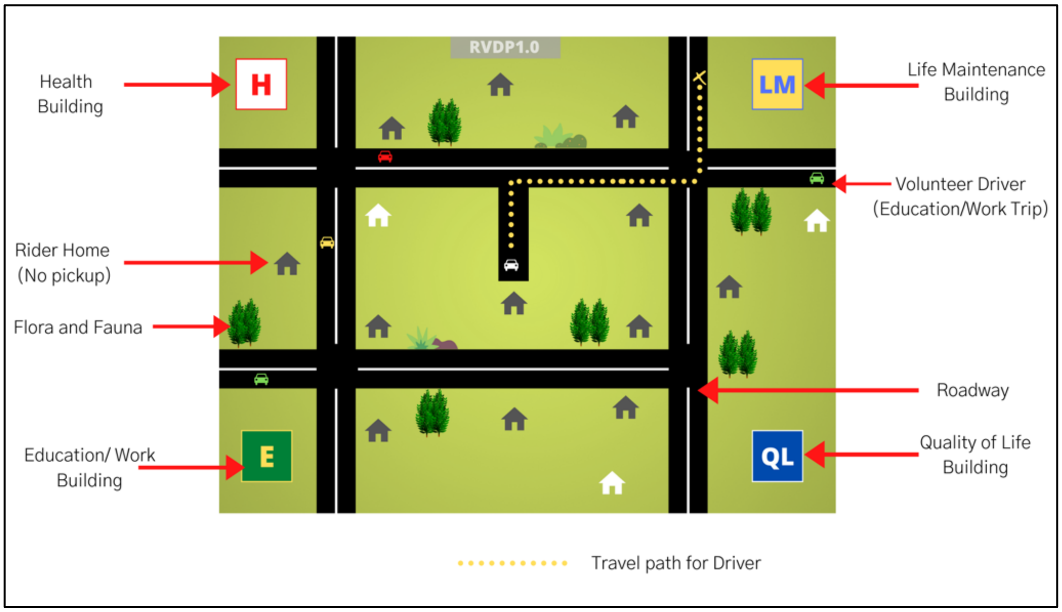


Figure 7. Conceptual Sketch of Rural VDP ABM.

The conceptual sketch in Figure 7 above is meant to represent a community in which a VDP would operate. It includes a small road network, houses that are arbitrarily distributed with a very light density and four main blocks or buildings that are to represent the trip purposes for which drives are being made. The workings of the model are further described in sections 4.6.5 to 4.6.8, with an overview of the final version in section 4.7. Having an idea of what you want your model to look like in Netlogo is critical as it would be almost impossible to develop features and processes in an abstract background.

In order to achieve the conceptual representation above the patches had to be coded specifically for different colours. Further manipulation can attach other variables to patches such as elevation, roughness or anything else deemed suitable.

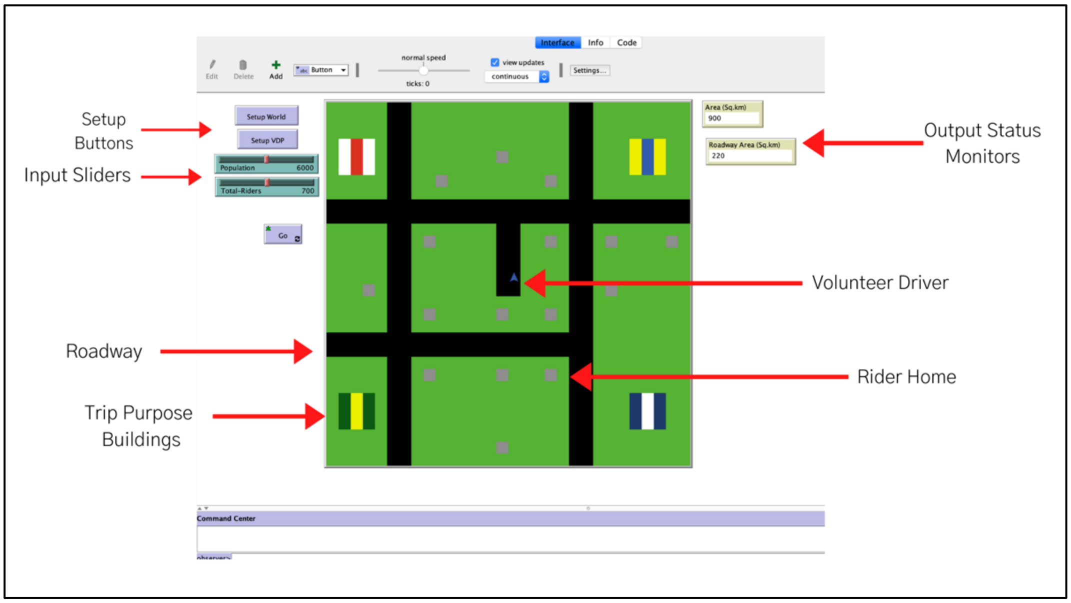


Figure 8. Rural VDP ABM version 1 within Netlogo

Figure 8 depicts the result of the coding process in Netlogo to achieve aesthetic similarity with the conceptual sketch. While it was not possible to exactly replicate the concept, the functional elements were kept, and the aesthetic components left to be refined afterward. This environmental representation formed the background for which the first prototype of the model was constructed.

4.6.2 Pseudocode

Prior to using the coding tab, the required operational behavior needed was written in a simple pseudocode format in order to guide the development process and act as a simple first principle when deciding on the correct language syntax for Netlogo. The pseudocode can be seen below:

Pseudocode

Declaration of variables

Vhours – Volunteer Hours, represents the average number of volunteer hours for each driver.
CVhours – Current volunteer hours. Running log of total hours all drivers have left.
TripPurpose – This is the purpose of the trip for each driver (Health, Education etc.)
TripDistance – This is the distance covered on a trip
Numofriders – The number of persons who occupy a vehicle

Setup

i. Clear screen
ii. Setup-patches
iii. Setup-drivers
iv. Reset-ticks
v. End

Setup Patches

i. Set color green for outer perimeter patches on map
ii. Set color black for inner area patches on map
iii. Create 4 trip purpose patches in the corners of map

Setup Cars

i. Create number of cars proportional to the number of VDP drivers.
ii. Place the cars within the represented driving area
iii. Set the color of the cars akin to their status

Run-VDP (Go procedure)

i. Assign Trip Purpose
ii. Move Drivers
iii. Check distance
iv. Check Volunteer Hours
v. Advance Clock/Ticks

End

Figure 9. Pseudocode for ABM

The pseudocode reveals three main components of the program: the variable declaration, the setup procedure and the go procedure. The variable declaration is the programmer listing the names of all the variables to be utilized within the software sequence. Without doing this a program would not be effective as it would have to rely on built-in variables which typically would limit functionality, the creative process and thus the applications of the program. The setup procedure initializes the state of all the conditions at the beginning of the program run. The setup procedure was used to develop the aesthetic software environment within which the program runs. This includes the color of the patches, the number of driver agents, timer and where and when the cars move. Lastly, the go procedure runs the processes that define the operation of the ABM. This includes the movement of the turtle agents or cars, the timer conditions within which the model runs and the recording of variables that will be needed for data analysis afterward.

4.6.3 Prototypes

Prototype 1: Defined Roadways, Visual Community-scape, Users at Predetermined Locations

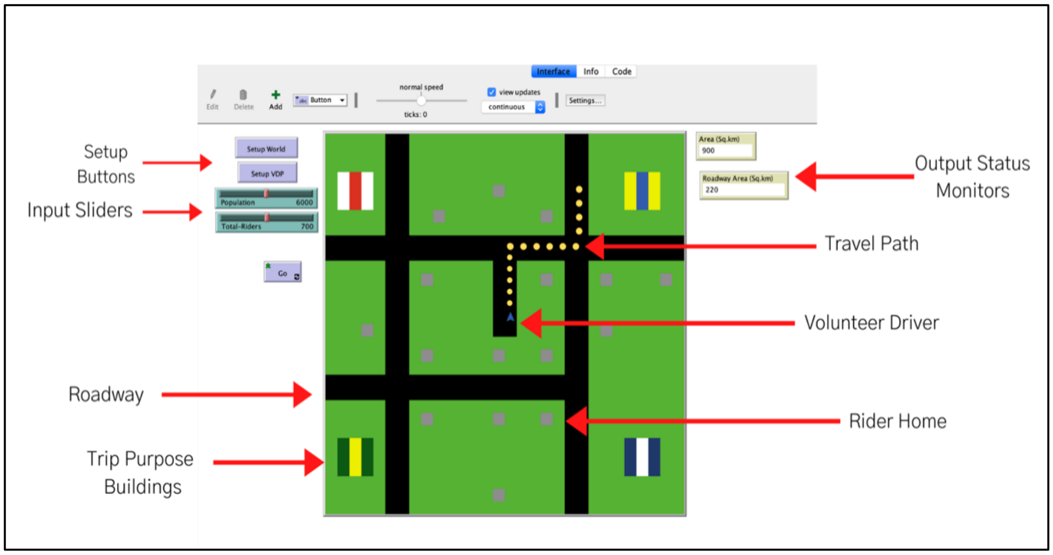


Figure 10. NB Rural VDP ABM Prototype 1 Version 1

Prototype 1 shows a defined community-scape with preset squares representing homes and large striped blocks which each stands in place of a trip purpose. The visual also shows a defined roadway network along which agents or cars may travel along to carry out the VDP pickup and drop off operations. This version, while still retaining the foundational principles behind the development of this ABM, required complex movement and searching algorithms to allow the cars to navigate along the preset roadway, stopping and starting according to the operational requirements in the code. This version sees 3 buttons, 2 sliders and 2 monitors. The three buttons “Setup World”, “Setup VDP” and “Go”. The two sliders to control the population and total number of driver agents in the model and the two monitors display the total area of the model in sq.km and the total roadway area. The pros of this approach would be a more visually accurate representation of a transportation system. However, the cons, would be the complex motion algorithms required to allow for driver pickup and drop off. Also, the modelled roadway area would get too congested and not allow for proper observations of the processes. It was determined that the environment could be more simplistically represented while achieving the same functional outcomes.

Prototype 2: Simplified Movement Area, Symbolic Community-scape, Randomized Motion

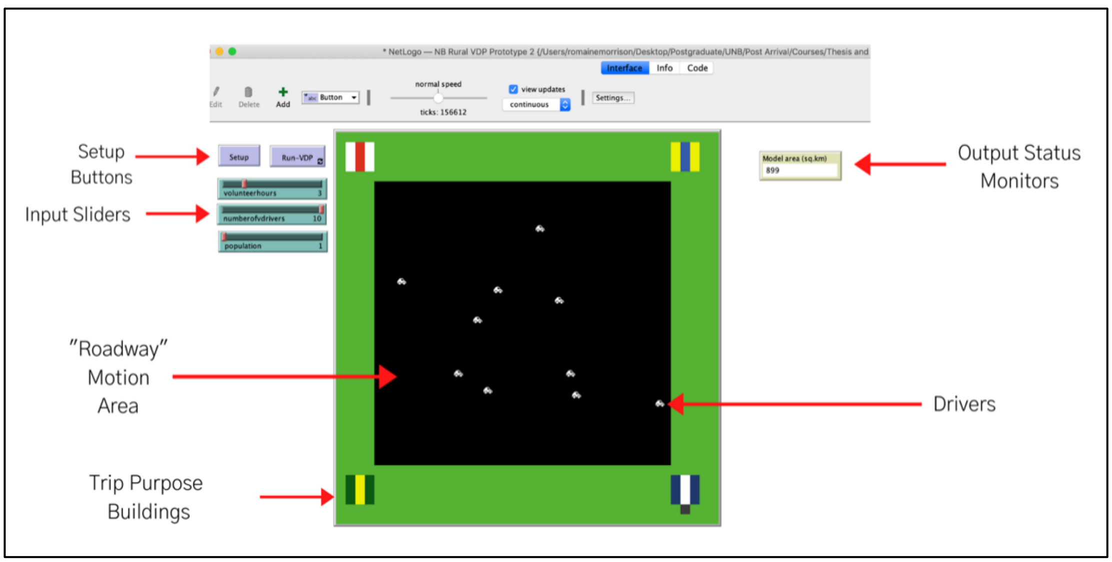


Figure 11. NB Rural VDP ABM Prototype 2

Version 2 of the Rural VDP ABM simplified the movement area of the driver agents by taking away a defined road network layout and replacing it with a large open obstacle-free square area. The drivers move around in this area with the same operational characteristics as before, but their movement behavior does not include the seeking or searching for particular spots. The functionality will be the same as cars indicate trip purpose by changing color. The movement that was coded in this version was random and confined to the limits of the black area which was to scale at ~900 sq.km. This version also introduced a working slider functionality for the population and number of driver variables, meaning that as the number is changed on the slide, the model will put that same number of "houses" or "cars" within the environment. In the example above it can be seen that there is one house (represented by the gray patch in the southeast corner) and 10 drivers. The pros of this approach allowed for the concentration on the model functionality and a simpler easier to program set of operations. The cons are that the motion becomes more conceptual and abstract and reliant on an explanation of the operations.

Final Version: Simplified Movement Area, Symbolic Community-scape, Systematic Motion

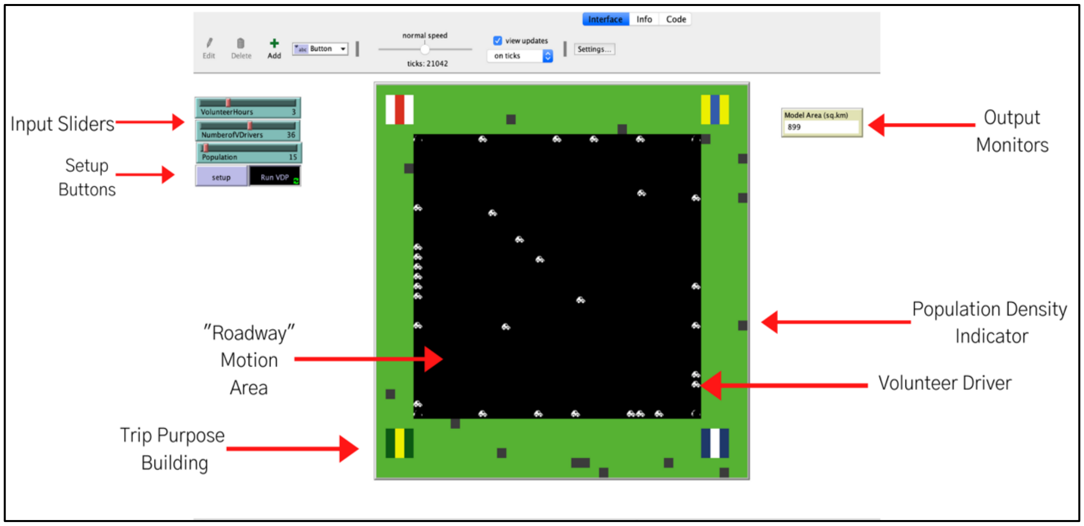


Figure 12. Final Version of NB Rural VDP ABM

This version while aesthetically similar to version 2 incorporates new motion commands into the model. The driver agents which have the shape of white cars now move around the model in a manner more realistically similar to traffic. They go between four nodes or established waypoints in the extents of the black roadway area. As in the previous version the number of drivers and the population can be increased with the sliders. This motion was adapted from a built-in Netlogo code created by Uri Wilensky entitled "Move to Target". All copyrights to which have been waived by the author. The pros of this model are that the conceptual motion now is more systematic and can be easily understood from observation. The wide moving area also allows for a higher cluster threshold or more driver agents to be put in, while maintaining the functionality and comprehension of the model processes. The cons of this are the same as for the previously explained model version in that the defined roadway removal would lose a bit of the realistic replication aspect of the transportation mode. A breakdown of the versions of the prototype done in the model development process can be seen in Table 6 below. The table highlights the benefits and limitations of each version as well as the features included and excluded.

Table 6. Summary of Model Prototype Versions

	Model Features				
Model Version	**Defined Roadways**	**Driver Agents w/ searching behaviour**	**Predetermined stop points**	**Benefits**	**Limitations**
Prototype 1	Yes	Yes	Yes	Ideal implementation. Point to point pickup and dropoff representation.	Requires larger more complex environment that would likely take a long time to develop. The visual depiction of required number of drivers would congest road network.
Prototype 2	No	Searching motion replaced with a systematic traffic network motion	No	Simplified motion allowed. Better visual depiction of the moving drivers.	With the removal point to point pickup and dropoff will have to rely on aggregated metrics such as distance and time travelled.
Prototype 3 (Final Version)	No	Systematic traffic network motion	No but drivers move node to node along defined paths.	Functional aspects kept without complexities of keeping to specific road area and going to a particular location for pickup dropoff.	Implementation hinges on the alignment of the aggregated agents to the figures in the VDP for drives,

It must be noted that with departing from a defined road network that no mapping or GIS implementations were done with the final version. Distance was perceived and recorded with the movement and motion of the driver agents across patches. This was limited by the average trip purpose distance for each assigned trip and route considerations factored by utilizing the trip purpose time. This is intended to keep the functionality of having a geographical network without the complexity of building one.

4.6.4 Model Timing and Ticks

The timing in a model is controlled by two discrete systems. The realistic or actual time that elapses in seconds, minutes and hours as well as the number of runs that occur between as the model iterates. As the model completes an iteration it keeps count by recording a “tick”. These ticks are then shown on a counter and the rate at which they occur or the rate at which iterations happen can be viewed and controlled by the tick counter and speed bar. To view a model that may have processed occurring faster than can be humanly observed, the number of ticks per second can be slowed or the speed bar moved to the extreme left. Conversely to speed up, the bar can be moved to the extreme right. When models run at their fastest the results they obtain seem to come almost instantly as the processes often occur faster than the human eye can perceive.

In setting the timing of the model it is important the rate at which the ticks occur and the duration of the processes and the results to be obtained align or are set to a scale. In determining the scale which would be developed for this ABM, it was important to look at the timespan within which the data were collected.

The available VDP spans the period February 2017 – January 2018 or 12 months. This 1 year or 365 days of travel data was further broken down to include the days in which the Small and Medium VDPs operated (Monday – Friday). This reduced the count to 261 days. The 261 days were then reduced to their operational hours (The VDPs operate approximately 10hrs a day or 7am – 5pm). Note fluctuations in demand during a day will be left out of this version of the model. The 261 days of operating for 10hrs yield a total of 2610 operational hours. Over the course of these 2610 operational hours, 1582 driver-hours were recorded in the database.

The 2610 hrs were then converted to seconds or 9,396,000 seconds. Since the model requires that the drivers move across patches that represent 1 sq.km km each, the time taken to cover each patch at an average speed of 60km per hour was approximately 60 seconds. Thus, each tick was made to represent 60 seconds of operation and the model temporal extent capped at 156,600 ticks.

4.6.5 Trip Assignment

This component of the model sought to simulate the process by which a VDP is booked by a rider for a trip. These trip destinations have been classified by their purpose in four main categories. These categories are Health, Education, Life Maintenance and Quality of Life. Previous research by Hanson and Goudreau isolated data on the trip purposes of riders for Small and Medium VDPs over a one-year period. From the total number of trips, the proportion that was dedicated to each trip type was recorded. These figures were then used in the model to probabilistically inform the code that was written to assign trips to the different driver agents.

As the model assigns a trip purpose to each driver or car agent, they change color to indicate which trip purpose they have been assigned. Health trips are Red, Life

Maintenance trips are Yellow, Quality of Life trips are Green and Education trips are Blue. When a driver agent has an unassigned trip purpose, they will have the color white.

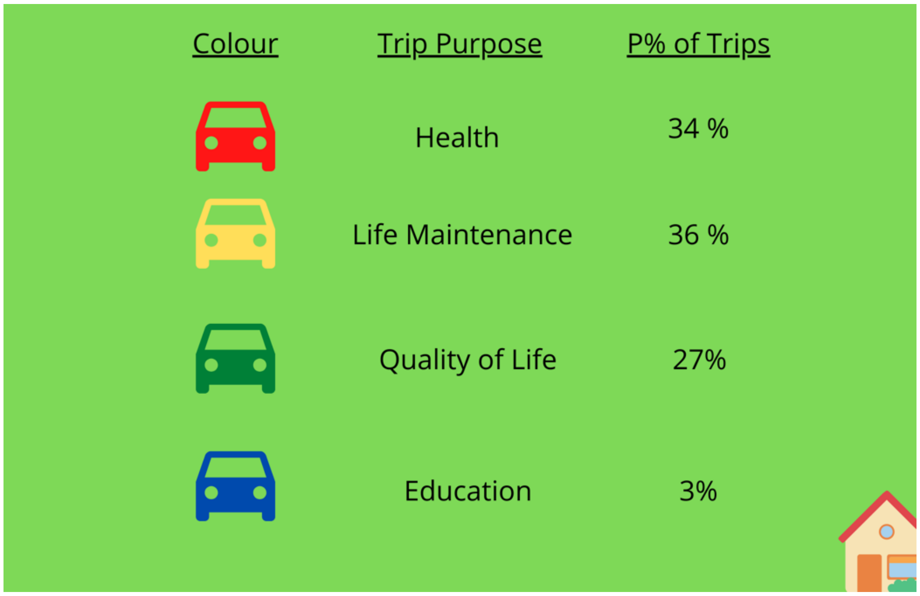


Figure 13. Trip Purpose Colour Assignment and Probability

A few monitors have also been created to keep track of the number of drivers for each trip purpose to ensure that the distribution is always intact. These monitors seen on the right side of the model environment on page 66, counts the number of drivers of each color as well as keeps a record of the total number of drivers.

4.6.6 Logging kilometres – The Distance Counter

An important element of the ABM is the recording of the distance covered by each driver in km. The environment was scaled to allow for a simple easy way to track this. Each patch represents a square km. As a driver agent moves in whichever direction, their distance counter, named “drivedist” increases by the corresponding number of patches that they cover. This is an important metric to note as there are many significant attributes that can be extrapolated and manipulated based on the distance covered by drivers.

4.6.7 Drive Counter

VDPs employ terminology to describe the operational metrics in terms of Drives and Stops, which are analogous to transportation planning terms of trip chains and trips. A drive is a trip chain or all the one-way stops (trips) to a destination and it ends when the obligation to the client does (Hanson & Goudreau, 2019). Drives do not have to end when a client returns home, just when they do not need service anymore. The drive counter in the ABM was built on this definition. Its implementation was simplified in the model since the trips on which the model was built were all single purpose trips with one stop only.

The drive counter increments when the distance of the trip they are on reaches the limit of a trip it has picked from the source data i.e., DriveCount : DriveCount + 1 when DriveDistance > DriveLimit.

4.6.8 Towards Calibration

Calibration of the ABM constitutes the model achieving the same output figures based on the inputs used from the data source, the New Brunswick Volunteer Driving Database. The specific metric that was gauged was the total distance or driven km based on the number of trips per driver. In attempting to calibrate the model there were a number of approaches that were taken to assign the trip drive distance and volunteer hours variables to the respective drivers.

Initially the average value of the drive distance and the trip time for each trip purpose was selected and assigned to the drivers. This however, ignored the true picture of the program which has a wide spread of trip distances for each purpose. The volunteer hours however were a better suited choice for that as within each trip purpose there was high similarity between trip times and the larger deviations from average more uncommon.

In an attempt to remedy that situation and develop a model closer to reality, the database approach was then tried. This involved creating a database or list of all the trip distances throughout the data period, putting it into the model sorted by trip purpose and allowing each driver on trip assignment to be randomly assigned a distance that corresponds with each purpose. This approach also distorts the reality of the operation as it allows for trip purpose distances to be paired with volunteer hour times that do not correspond logically to their distances. It also removes the element of randomness that would arise when using the model for predictive purposes when other variables are put in and thus reduces its usefulness or scalability.

The solution to these issues of maintaining randomness and scalability was then to allow the user to set a mean for the trip distances for each purpose and then a standard deviation for it. These values would then be randomly normally distributed for each trip assignment. This approach simulates the reality of the VDP operation and allows for scalability as any values can be put in and their effect on the larger system observed.

There are a few elements of the model and the volunteer driver operation that may be outside the realm of calibration. One such element is the interaction of distance and time in a manner that accurately represents reality. Agent-based modelling typically allows for aggregated values to inform system variables and then observe their effect on outputs as they change. This aggregation extends to the timesteps within which activity in the model occurs. The model utilizes the timeframe of 1 year of VDP data. This was converted into days, hours and minutes. The limit for the model was set as 156,600 minutes or the number of minutes for which the VDP is operational for, each tick then advances the model counter by 60 mins or an hour. While the model timeframe advances on an hour-by-hour basis, the volunteer drivers move forward by 1 km for every timestep. This keeps the important aspect of the ABM process, visualization at a level where actions and movements are discernable by anyone using the model. If the model were to be slowed down, then the actions would not occur at a rate that seems to bear much significance and the modelling process would approach more microsimulation than ABM. Another element that cannot be specified is which driver does what. In reality there may be patterns that emerge based on actions carried out by specific drivers. This cannot be replicated in the model due to data being unavailable that identifies each unique driver. Additionally, a lot of the metrics available do not explicitly represent single purpose trips. It is also difficult to say what the overall impact is on a specific trip purpose without isolating them prior. Finally, it difficult to account time in a VDP operation that is spent outside of picking up and dropping off riders. These additional times may impact the overall operation but are not quantified. This could include travel time to and from pickup or drop-off locations, wait times for riders and stop times while travelling.

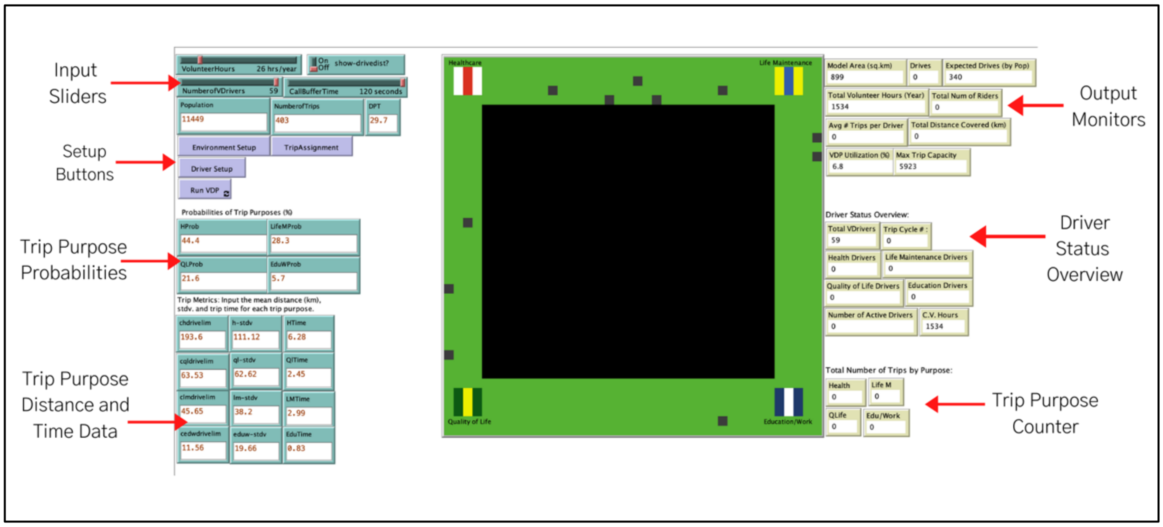


Figure 14. Fully Operational Model Version - New Brunswick Rural VDP ABM

4.7 Final version – The New Brunswick Rural VDP ABM

After going through the model environment development in the prototypes, deciding on model timing, implementing trip assignment, distance and drive counters, the final fully operational version of the ABM can be seen in Figure 14 above. This version sees the complete array of input sliders utilized for assigning variable values, such as the number of volunteer hours per year, the number of volunteer drivers, the number of expected trips per year and the population. It also displays the trip purpose input boxes for probabilities and the average distance and time for each. On the right side of the ABM, there are a series of output monitors that are used to keep track of the variables that are changing due to the model processes. It includes a monitor for total volunteer hours, average number of trips per driver, expected drives, total distance covered and more. Below those monitors are the driver status overview monitors. Those include the total number of volunteer drivers, the total number of active drivers, the number of drivers for each trip purpose and the current number of available volunteer hours. Lastly there is a set of cumulative counters for each trip by purpose at the bottom.

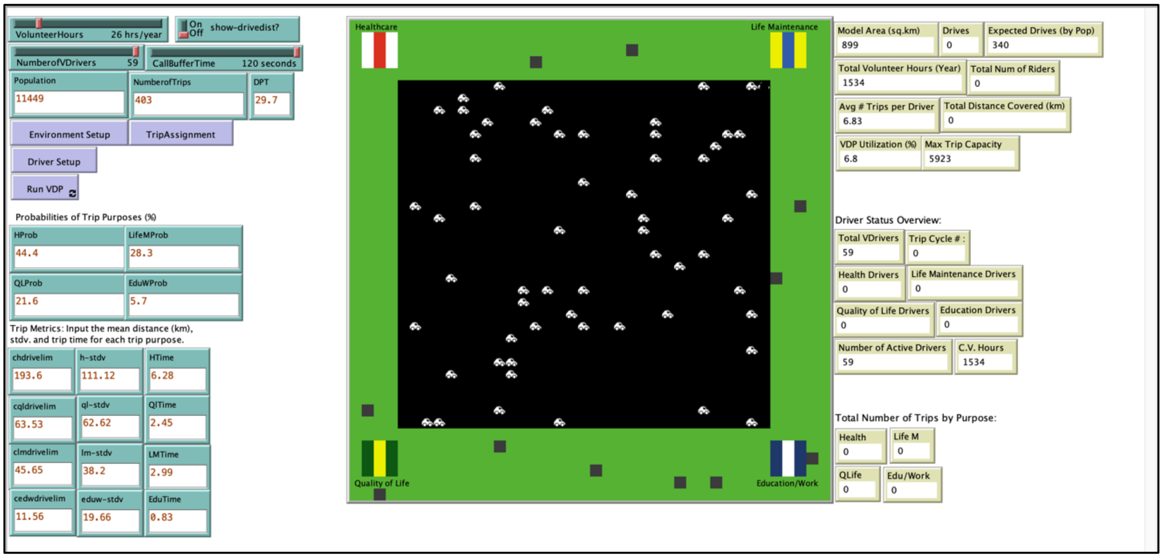


Figure 15. NB Rural VDP ABM after "Setup-Drivers"

The model works by first inputting the number of volunteer drivers and their average annual volunteer hours using the sliders. After doing so, you set the frequency of trips for each of the four purposes (health, life maintenance, quality of life and education/work) as a number out of a hundred. Then the trip-distance and time inputs are populated with the average travel distance and volunteer hours utilized for each trip purpose. After putting in all those inputs, the model setup is started by first pressing the "setup-environment" button. This will allow all the patches to be turned on and the right colors and shapes visualized to host the model. Then the "setup-drivers" button follows directly after (Figure 15). This initializes the VDP driver agents, which will now show up as white cars in the black “roadway” movement area seen in the VDP. After this the “trip-assign” button is pressed (Figure 16). The trip assign button distributes trip purposes to each of the number of drivers input according to the probabilities in the input variables. Their color changes according to each purpose. Their average trip distance and volunteer time are then assigned using a random normal distribution. After the trip assign button is pressed, the VDP starts by hitting “Run VDP”. This begins the operations, and the drivers or cars begin to move in a systematic manner from waypoint to waypoint and logging their distance as they do. As the drivers reach their trip distance limits (average trip distance assigned), they stop operating and disappear from the movement area; however, their metrics are kept in a cumulative counter and stored for analysis later. As long as there is more time in the model, the driver operations loop and the drivers are setup and more trips assigned again. This continues until the model reaches its pre-programmed temporal extents or is stopped by the user. Model information and outputs can then be analyzed by exporting data using built-in Netlogo experiment tool, BehaviorSpace.

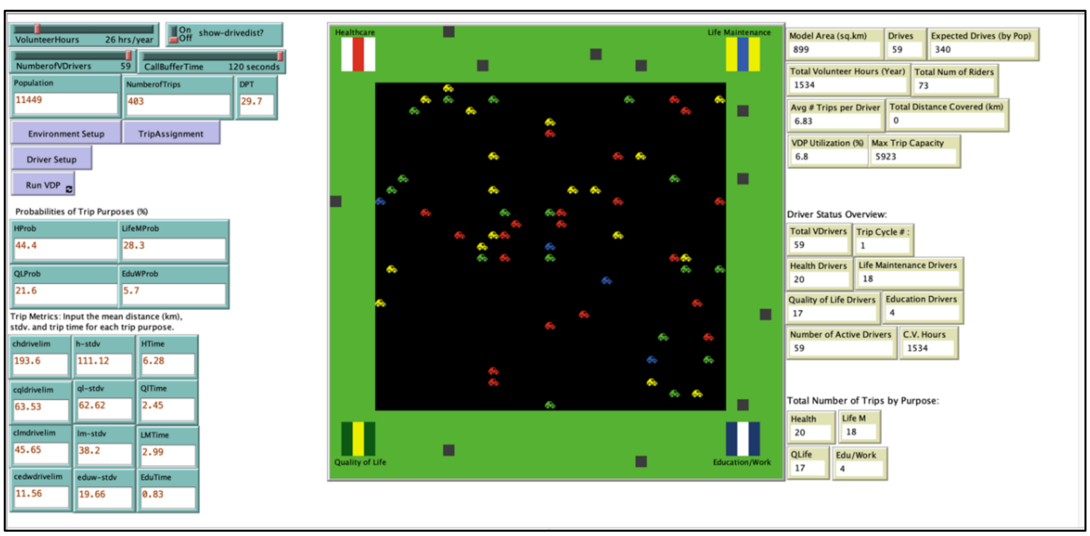


Figure 16. NB Rural VDP ABM, after "Trip-Assign"

4.8 System Architecture Diagram

The finalized system architecture of the VDP ABM is displayed below. Figures 17 and 18 show a system overview and a detailed Submodel breakdown respectively. The complete VDP ABM shows that the VDP model as a whole is made up of four constituent Submodels: setup-environment, setup-drivers, trip-assign and move-drivers.

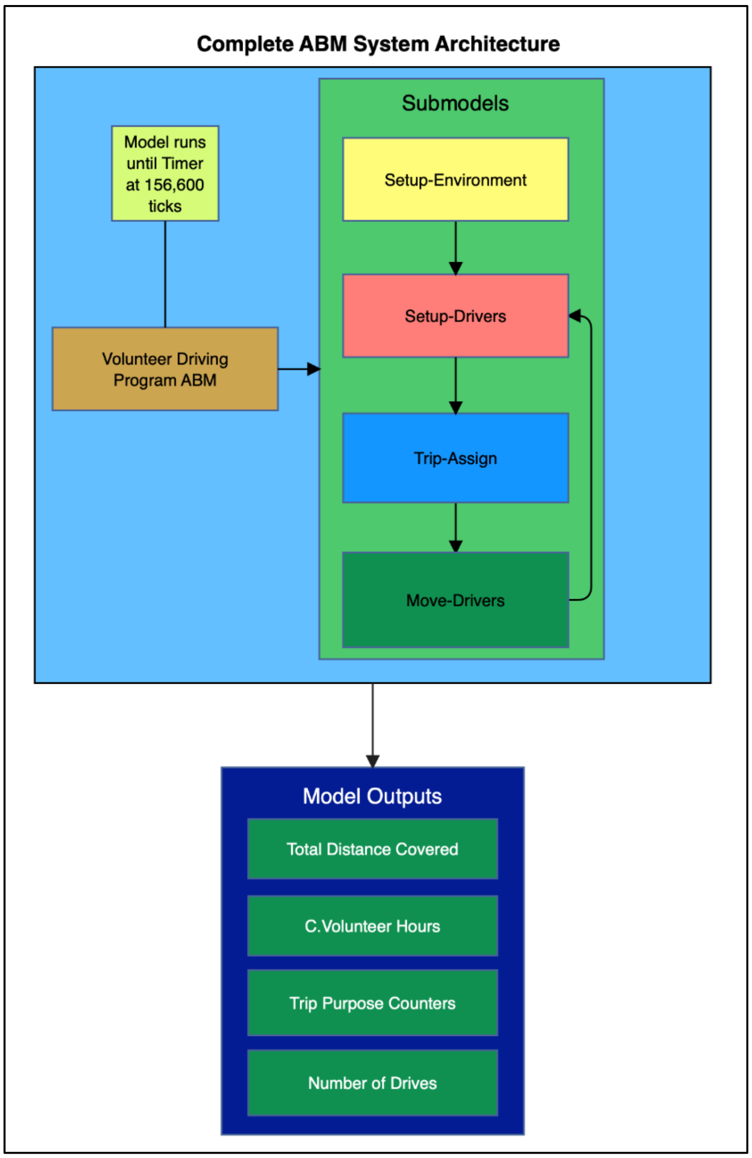


Figure 17. VDP ABM System Architecture Overview

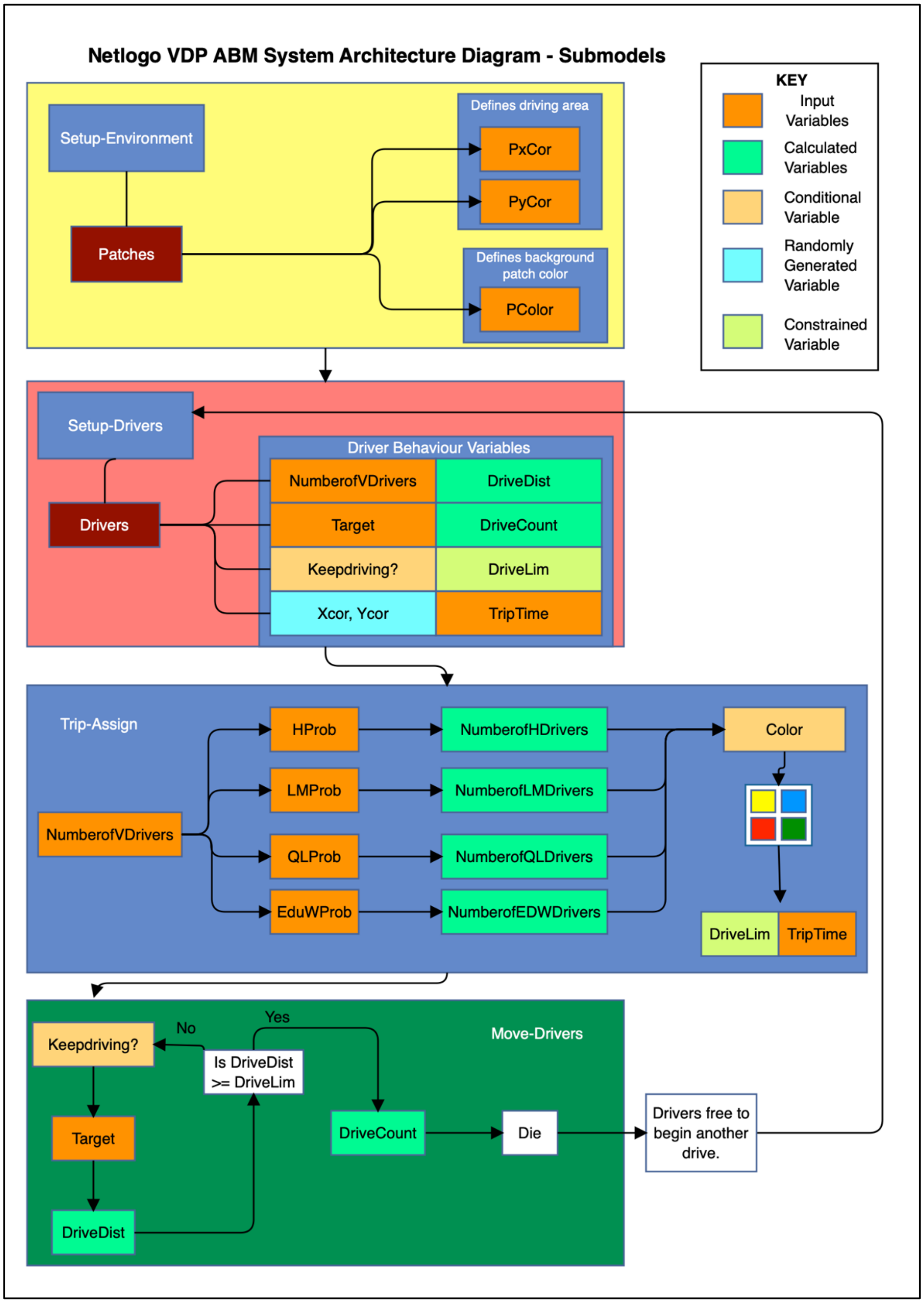


Figure 18. VDP ABM System Architecture - Submodels

These four sub-models, each responsible for different aspects of the greater system, have unique variables and processes. There are five different types of variables within the system. Input variables, which are set before the model runs. Calculated variables, which are determined from input variables and mathematical processes while the model runs. Conditional variables, which are a Boolean, can be true/false based on a condition and their value in relation to that condition. Randomly generated values are created once the model starts and vary on different runs. Finally constrained variables are randomly generated but distributed within a predetermined range. The following describes the Submodel, their variables and how they all interact to create one system.

Setup-Environment, the first Submodel is linked to the patch agents in the model which each have input variables “Pxcor”, “Pycor” and “Pcolor” which correspond to their location and color. Those control the visual background within which the other processes operate.

Setup-Drivers is the initialization step for the VDP driver agents. This is connected to variables that characterize the VDP driver agents such as the number of volunteer drivers (and thus agents) in the model, target, “Keepdriving?”, “Xcor” and “Ycor”, “Drivedist”, drivecount, “DriveLim” and “TripTime”. The number of volunteer agents in the model can be set by an input slider within the Netlogo interface. “Target” controls the direction of motion of the drivers. “Keepdriving?” is a conditional variable that assesses the ability of the driver agent to continue with their movement. Like patches, Turtle or Driver agents also have location coordinates; however, the driver agents are specified by variable names “Xcor” and “Ycor”. The “DriveDistance” and “DriveCount” are calculated variables that are updated based on the motion activity of the driver agent. “Drivelim” is a constrained variable that is assigned based on a normal random distribution with an input standard deviation. Finally trip time is an input variable.

After the environment and drivers are setup, trip-assign contains the procedure that allows the tracking of different trip purposes as the drivers move about. This starts off as being connected to input variable “NumberofVDrivers” and connects to input variables “HProb”, “LMProb”, “QLProb” and “EduWProb”. Those variables each correspond to one of the four trip purposes and are responsible for the probability of the trips assigned for each purpose. These then feed into the number of drivers for each purpose and their color variable is changed to represent that and a drive limit and trip time variable within the range for each purpose is assigned to the drivers.

Finally, the Move-Drivers Submodel sees a conditional assessment of each driver agent as they go about. These drivers head towards their input target location and log their drive distance while doing so. If their “DriveDist” variable is equal to their “DriveLim” then they log their trip as a drive, the “DriveCount” variable is increased and then they disappear from the environment and are later reassigned; that is the Submodel loops back to Setup-Drivers, Trip-Assign and Move-Drivers. When all the operations have been completed within the time confines of the ABM, then you can view or export four significant metrics like the Total Distance Covered, Current Volunteer Hours Utilized, The Number of Drives and the Trip Purpose Counters which are stored in a spreadsheet.

5. Results and Observations

This chapter contains the results obtained from running a variety of scenarios with the completed version of the Rural VDP ABM. The results were obtained through Netlogo's integrated experiment tool BehaviorSpace. BehaviorSpace allows for the setting of initial model variables and how they vary across different runs. As the model is run all the outputs are recorded and everything exported into a spreadsheet for analysis. To assess the potential of the ABM approach for rural transportation planning the model was assessed in three unique scenarios: base or initial conditions, healthcare and a service area scenario. The base or initial conditions represent the VDP as was in the primary dataset. The healthcare scenario seeks to investigate the VDP response to a 100% increase in the average trip distance for health purpose trips. The service area scenario looks at how a VDP may respond to an increase in the service area size by 100%. These scenarios each had specific variables that reflect a change in the operational environment of the VDP. Each scenario was run 25 times and the results for each output variable averaged. The model's results from each were then used to assess how the program is affected by the change and ascertain possible solutions for any deficits that may arise.

5.1 Model initial conditions

The initial model conditions were set based on the values and variables for single-purpose trips from the New Brunswick Volunteer Driving Database. The data were specifically used from the Small and Medium VDPs. Below is a summary of the initial conditions and variables set. This scenario is done to establish validity of the model results and form the basis of comparison for the other two scenarios. It represents the VDP as it is currently or without any changes to attributes of the system.

Table 7. Variables for Initial Model Runs

General	
Population	11449
Number of Volunteer Drivers	44
Number of Trips (Expected)	403
Avg. Volunteer Hours per Year per Driver	26
Total Volunteer Hours (Annual)*	1144
Probabilities of Trip Purposes (%)	
Health	44.4
Life Maintenance	28.3
Quality of Life	21.6
Education/Work	5.7
Average Trip Distance by Purpose (km)	
Health	96.8
Life Maintenance	63.5
Quality of Life	45.6
Education/Work	11.6
Average Volunteer Hours per Drive by Purpose (hrs)	
Health	3.14
Life Maintenance	2.45
Quality of Life	2.99
Education/Work	0.83
**Note, while the average total volunteer hours was 1582, only single purpose trips were used in the model for simplicity (total of 1144 hours)*	

The items in the table above are important variables for each model run. The general values are specific to the particular VDP being represented and includes the population of the service area, the number of volunteer drivers in the program, the average number of hours per year they commit to the program and the number of trips actually completed from data records. The trip purpose probabilities represent the frequency with which a volunteer driver is assigned to carry out a single purpose return trip within each of the four categories. The average trip distance by purpose then addends the probability by including the average distance for each trip category and lastly the average volunteer hours is the average quantity of time spent on a trip for each purpose.

5.2 Validating model output

Using the above variables, the ABM was run 25 times and a summary of the results obtained in terms of the total distance, total drives and the volunteer hours per run. The validation procedure was done by comparing the output metrics to input metrics at a time step in the model where total km driven in the model was equivalent to the average annual km driven per group. These results can be seen in the tables below.

Table 8. Total Distance in km (Validation) for 25 runs

Total S/M VDP Distance (km)	28423
Mean Total Distance Modelled (km)	27576
Standard Deviation (km)	888.70
Difference (Actual and Modelled) (%)	2.98%
Elapsed time in the model to reach 1 year of data	107,940 ticks

In this case, the model reaches the average yearly metrics for the Small and Medium VDP by an average of 107,940 ticks, or 8 months into the yearlong ABM. The calibration process involved letting the Netlogo model run to its full extent (156,600 ticks), then applying a ratio of ticks for a year's worth of VDP data to the ticks for the full extent. The ratio applied or 0.689 corresponded with the percentage of time in which the model reaches the average yearly ticks. This approach is better because it allows for users to keep both perspectives of the model in terms of its original theoretical outputs as well as the calibrated relatable operational VDP data.

The Total Small and Medium VDP Distance represents the average of all the single purpose trips for the Small and Medium VDPs taken from the NB Rural VDP Database. This value was used to test for calibration of the model by comparing the model results with this hard figure. At the same number of drives run in the model, the mean total distance achieved was 29,399 km or within 3.3% of the actual figure. This value was consistently achieved prior to the completion of the model time and thus it became relevant to examine where the total distance and drives would terminate at the end of the model time.

Table 9. Summary of VDP Metrics from 25 Model Runs

	Model extent (156,600 ticks)	Calibrated to 1 year Data extent (1 year)	Average values from source data	% difference (calibrated and source)
Mean Distance	40,333	27,576	28,423	2.98
Standard Dev.	1691.56	n/a	n/a	n/a
Mean No. of Drives	591.36	403	403	n/a
Standard Dev.	28.63	n/a	n/a	n/a
Mean Annual Volunteer Hours	1503.58	1035.96	1144	4.9
Standard Dev.	79.75	n/a	n/a	n/a
Elapsed time in the model	156,600	107,940	n/a	n/a

The results obtained from this initial run indicates a mean total trip distance of 40,333 kilometres over 25 iterations in the total model time extent, which was calibrated to 27,576 km to represent annual VDP data. This is an aggregation of the sum of the individual trip distances for all 44 VDP drivers in the model. Similarly, a total of approximately 591 drives on average were completed, calibrated to 403. Finally, the volunteer hours at the run's end were also tabulated. Across the 25 iterations, the ABM recorded an average total of 1503 driver hours, calibrated to 1035 driver hours in one year. This represents the total of the average individual trip purpose times. In addition to three categories of results mentioned, the change in trips by purpose can also be observed in addition to their probability. The recorded results for number of trips by purpose can be seen in Table 10 below and their probabilities can be found in Appendix A1.

Table 10. Summary of Trips by Purpose (Initial Conditions - Calibrated)

Runs	Health	Life Maintenance	Quality of Life	Education/Work
1	157	128	127	28
2	156	135	119	30
3	141	146	123	30
4	156	140	117	27
5	152	134	118	36
6	157	122	129	32
7	147	134	128	31
8	155	137	118	30
9	159	133	116	32
10	158	129	120	33
11	148	128	137	27
12	152	129	131	28
13	153	140	117	30
14	157	138	123	22
15	157	131	122	30
16	160	132	120	28
17	146	136	125	33
18	158	138	114	30
19	149	137	122	32
20	158	133	120	29
21	160	125	126	29
22	150	138	127	25
23	147	145	120	28
24	152	137	124	27
25	157	128	127	28

Average	153	135	123	29
Standard D	5.31	6.00	5.28	2.86
% Total	34.8%	30.6%	27.9%	6.7%

5.3 Scenario 1 – Health Trips

In order to gauge the usefulness of the model for planning, a few scenarios that simulate real-life situations were assessed. Scenario 1 explored the change in the model's outputs for total trip distance, number of drives and volunteer hours to a 100% increase in the average trip distance for the health purpose. This is intended to simulate what would occur if in reality a hospital or major medical center were to be relocated resulting in an increase in user travel distance. Below is a table of the new variables to run this scenario:

Table 11. Variables for Health Scenario

General	
Population	11449
Number of Volunteer Drivers	44
Number of Trips (Expected)	403
Avg. Volunteer Hours per Year per	26
Total Volunteer Hours (Annual)	1144
Probabilities of Trip Purposes (%)	
Health	44.4
Life Maintenance	28.3
Quality of Life	21.6
Education/Work	5.7
Average Trip Distance by Purpose (km)	
Health	193.6 *(from 96.8)*
Life Maintenance	63.53
Quality of Life	45.65
Education/Work	11.56
Average Volunteer Hour per Drive by Purpose	
Health	6.28 *(from 3.14)*
Life Maintenance	2.45
Quality of Life	2.99
Education/Work	0.83

The changes made from the initial model conditions were: adjusting the average trip distance from 96.8 km to 193.6 km and the average time for the trip from 3.14 hours to 6.28 hours. The results in the model to this change can be observed in the table below.

Table 12. Summary of Results from Health Scenario

Variable	Initial Conditions (Calibrated)	Scenario 1	Difference	% Change
Total Distance (km)	27,576	22,354	-5435	-19.5%
Drives per Run	403	219	-188	-46.2%
Volunteer Hours	1035.57	729.65	-305.92	-29.5%

The above table summarizes the results obtained from 25 iterations of the model with new variables to reflect a 100% increase in the average healthcare trip distance. This saw a corresponding effect of the total distance at the end of model extents falling by 19.5%, the total drives for the run falling by 46% and the total volunteer hours used falling by 29%. This reduction across all three metrics can be attributed to the fact that trips were twice as long and so there were fewer total drives. The increased length for one trip to end caused the driver to take longer on to their next trip. This propagated and saw a net decrease in the number of drives completed by each driver. The healthcare purpose being also the most frequently requested, means there were more drivers assigned to it than any other. If the distance of the trips were twice as long there would be more drivers who are preoccupied and unable to do new trips. Further investigation into the number of trips and the trip purposes reveal exactly that the trips across each purpose is significantly reduced which is what contributes to the greater significant decline. The trip purpose decrease hits the health drives hardest with them seeing on average 64 fewer drives, 60 less for life maintenance, 53 less for quality of life and 13 less for education-work trips. The table showing this can be viewed below.

Table 13. Table Showing Effect on Trips by Purpose for Health Scenario

Summary of Comparison Between Initial Conditions and Health Scenario				
Trip Purpose	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
Average Number of Trips	-64	-60	-53	-13

5.4 Sensitivity Analysis – Health

A sensitivity analysis was conducted to establish a relationship between the total distance, number of drivers and total volunteer hours in response to a change in the average trip purpose distance for health. This was done by increasing the average trip purpose distance for health by 10%, 25%, 50% and 100%. The results were then aggregated and analyzed for any trends or relationships and can be seen in the table below.

Table 14. Sensitivity Analysis for impacts of increasing average health trip distance

Average Metrics	**Initial**	**Increase in average health trip distance**			
		10%	**25%**	**50%**	**100%**
Total Distance (km)	27789	27258	25036	24001	22354
Total Drives per Run	407	381	341	287	219
Volunteer Hours	1035.57	1003.23	939.47	813.56	729.86

Table 14 shows the results from the sensitivity analysis done for the health care trips. All three observed metrics seem to show a consistent linear-like trend of decrease as the average trip distance for health is increased, an example of which can be seen in Figure 19 below. Larger more expansive data tables and graphs can be seen in support of the observed trends in Appendix 1.

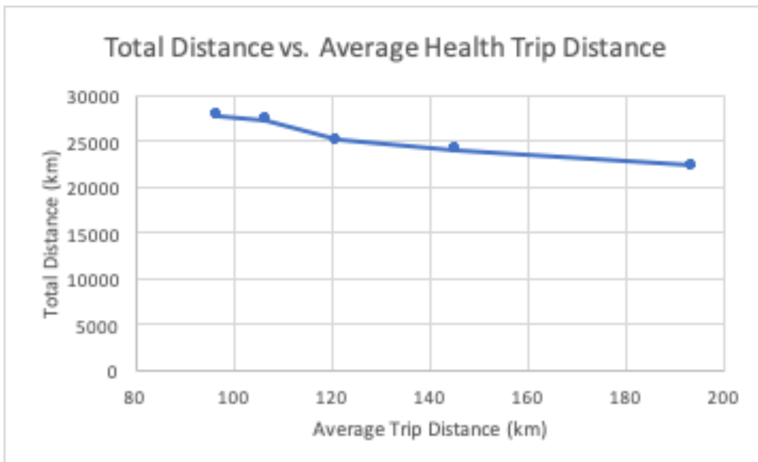


Figure 19. How Average Health Trip Distance Impacts Total Average Distance

5.5 Scenario 2 - Environment or Service Area Change

This scenario seeks to simulate the reality of a service provider expanding their offering into larger territories. It simulates a 10%, 25%, 50% and 100% increase in the service area of a VDP and looks at the impact on the total distance driven, total number of drives and the total volunteer hours.

Table 15. Environmental Scenario Results Summary

Average Metrics	Initial	10%	25%	50%	100%
Total Distance (km)	27576	28443	27710	27704	28203
Total Drives per Run	403	374	328	275	213
Volunteer Hours	1035.97	1040.69	1024.31	1007.14	998.15

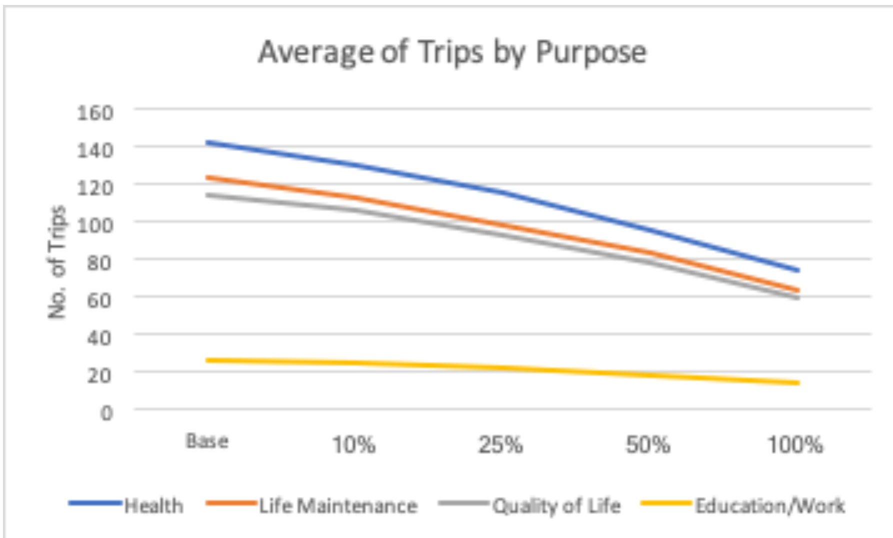


Figure 20. Number of Trips vs. Service Area Increase

Assessment of the "Environmental/Service Area" size change was done by modelling how a change in size of an area should theoretically affect the variables for average distance and average trip purpose time. The variables were increased by the corresponding 10, 25, 50 and 100 percent. The results show that the total distance observed for the model run was virtually unaffected and no predictive relationship could be determined from the results. The total drives per run, however, steadily decreased with an increase in the service area. At 100% increase the total drives decreased by 47.5%.

The total volunteer hours utilised in the model runs however, did not have as significant a change as the drives. The trend however, seemed to be downward as the 100% change saw a decrease of 3.65% in the total volunteer hours. Further inspection of the trip types showed that each type correspondingly decreased as the distance and time required for each was increased for each incremental scenario.

This indicates that perhaps while the total distance travelled by the 44 volunteer drivers is roughly the same in larger areas, the number of trips or drives will decrease; fewer drives are producing the same distance. A natural correlation and consequence of the drives being longer in both average distance and volunteer hours utilized.

5.6 Using the model to determine how to solve the shortfalls of scenarios.

An advantage of ABM is the ability to see how the impact of variable changes can affect the aggregated whole of the output metrics. In the two scenarios run, changing the average healthcare trip distance and the size of the service area has significant effects on metrics such as average total distance, total number of drives and total volunteer hours. The model can then be used to investigate how to solve or make up for the change in the output variables by changing another. In this case, it can be investigated how many additional volunteer drivers it would take in order to make up for the decrease in all three metrics. This was the final scenario and would hint at the possibility of the model being used in a predictive sense.

Table 16. How Increasing Volunteer Drivers Can Mitigate Drive Reduction in Health Distance Doubling Scenario

Number of Volunteer Drivers	Target Values	44 (base value)	57	58	59
Total Annual Distance (km)	27789	22354	27137	27691	28450
Total Drives per Model Run	407	219	273	278	287
Volunteer Hours	1035.6	729.7	889.2	904.6	947.3

Table 16 above illustrates how an increase in the number of volunteer drivers can impact the overall model. The impact of the health trip purpose distance increase by 100% on the total distance covered can be mitigated by increasing the volunteer drivers by 13-14 drivers. It can get the total distance driven by the drivers back to the initial base figures observed. While the total number of drives is slower to recover, they still experience a gradual increase, indicating that there is a higher trip turnover rate. The total volunteer hours also steadily trend upwards with the addition of each driver and returns to within 91% of the target values with the addition of 15 drivers.

5.7 Further Work

5.7.1 Additional Scenarios

The three scenarios worked out here do not display the full extent of the model's usefulness in investigating the potential of an ABM for rural transportation planning. While the scenarios examined the impact of varying trip distances and average trip purpose time; the trip purpose frequency, number of drivers and the number of volunteer hours each driver can commit are also good variables to investigate from a driver perspective.

Examining the trip purpose frequency would allow us to see how VDPs would respond to having a different probability distribution for each trip purpose. Each purpose then with its own unique average distance and average volunteer time would impact the output of the number of trips, total distance covered and the average volunteer time. The number of drivers in VDP will affect the total number of trips that are done and thus the net overall distance and the volunteer hours. The ABM can allow a VDP to investigate how hiring an additional 5 drivers with their current metrics can possibly improve the number of trips they are able to complete and see the impact on drive distance and total volunteer hours. The number of hours committed to a VDP each year by drivers will directly affect the ability of the program to meet the needs of a community. If there is a need for a particular number of trips that will take a predetermined time but there is not enough driving time availability, then the VDP will be unable to meet its service base and they will suffer.

To also investigate the model's fit for more complex scenarios, the ABM was reconfigured with the variables and properties of the large VDP in New Brunswick. Compared to the Small and Medium VDP, the large programs represent a 300% increase in service area, a nearly 1000% increase in drives, 800% increase in driven km, 165% more drivers and a 900% increase in volunteer hours. While the model operational structure was kept the same the new configuration saw the addition of an extra trip purpose for "Home-Based" Trips along with their corresponding average trip distance, trip probability and trip time. The immediate observations of the model to test for its calibration with the larger VDP revealed that the model mechanics held steady for this implementation; however, the model time extents were only achieving at most 25% of the driven km expected. This disconnect is attributed to the large disparity in model variables between the Small and Medium and Large programs and alludes to a sort of emergent time dependence. Models with this many agents may require a much more efficient motion and timing mechanism that allow for a truer result. This particular implementation may greatly benefit from Netlogo's Time Extension which brings date/time utilities and discrete event scheduling into the models.

5.7.2 Understanding impacts on the dispatcher

A significant component of VDP operations is the dispatcher. The dispatcher controls the trip booking process and assigns and maintains the schedule. While the model developed does not include any metrics that specifically measure impact on a dispatcher such as a call time or trip assignment time it can allow VDP operators to make clear assumptions and conclusions about the number of trips per year and the driver availability. If there are more trips being booked, then depending on the configuration of their booking system, a VDP may need to increase their capacity to do so.

5.8 Limitations

The development of this ABM does have limitations. Noting these limitations will provide the basis for improving on the efficiency and accuracy of the techniques used in the study.

1. The aggregate nature of ABM removes specific details and thus the results are not expected to be predictable and readily reproducible. Instead, values are within a certain range and their validity is assessed based on an average over many runs. This is observed with the total distance, the total number of drives and the total average volunteer hours across the 25 runs.

2. The model was developed based on single purpose trips within this data period for Small and Medium VDPs. Trips were either of the category: Health, Life Maintenance, Quality of Life or Education/Work. While these trip types are significant, VDP complexity goes beyond this to include stops or multi-purpose trips.

3. The ABM results represented the events of a Small and Medium VDP versus that of the Larger. While the Large VDPs make up the majority of drives and thus total km driven, the operations of the combined Small and Medium VDP were simpler to start out the study and scale in Netlogo to test a proof of concept.

4. When observing the model's outputs and allowing it to run it is important to note that calibration is not achieved by getting the expected metrics in the timeframe of the model but getting the at the point in which they should correspond with each other. Model time may not account for wait time, traffic stops or any other unquantifiable temporal events.

5. While observing the scenario of increasing service area it is noteworthy that an area twice as big does not necessarily mean that the average distance to trip purposes will increase. A larger service area could mean that there are many more options for health centres, grocery stores, schools and places of employment even in a rural landscape. More options or a higher destination density could potentially mean that drivers may have similar, smaller or the same average trip distance as a smaller service area with fewer trip destinations. It is important to verify in a service area increase how the average trip purpose distance will be affected.

6. Conclusions and Recommendations

This research aimed to explore the potential of Agent-Based Modelling for use in Car-Based Volunteer Transportation Program Planning through five major objectives. Firstly, it set out to identify whether any suitable behavioral models or databases were available that could characterize the interaction of agents expected from a car-based centrally dispatched VDP. Then after to undertake the creation of a rules-based system developed from the findings of those models or data inputs that could be used to describe the operation of the VDP. From the rules-based system, an ABM would be developed, applied and validated. The model would then be tested with a few scenarios which would enable the investigation into an evaluation of operational effectiveness. Finally, the potential for ABM use for rural transportation planning would be considered. The following sections will outline the major conclusions drawn from the study and give recommendations for future work.

6.1 Conclusions

No suitable behavioral models were identified that represent the operation structure and processes of a car-based VDP; however, useful data inputs were gathered from the New Brunswick Volunteer Driving Database. These inputs were used to characterize the interaction of the drivers and service users expected from a New Brunswick car-based centrally dispatched rural VDP. A rules-based system was then developed utilizing the data inputs and operational process descriptions of the VDPs that would allow for their translation into the ABM platform Netlogo. This along with the Modelling Process and

ODD protocol was used to develop an ABM, which was later validated and calibrated. The ABM after those processes were applied to two scenarios, a service area increase and trip purpose location modification. The potential of the ABM was then assessed for usefulness in rural transportation planning.

The initial run or base conditions of the model produced results that were consistent with the actual operation of the VDP. The model's calibration was assessed and verified when outputs for total distance, number of drives and total volunteer hours utilized corresponded in the same timestep. As described in section 5.1 and 5.2, this timestep was not at the end of the model and occurred at 107,940 ticks or timestep 1800/2610 which represents 68.9% of the model extents. This does not represent a mismatch or an error in the model but instead is representative of the difference in efficiency with the model executes and could be due to circumstances like unaccounted for wait times, pauses or gaps in service in the VDP. Because the model runs continuously, these gaps are minimized, and the timing is more efficient than normal.

Under initial conditions the model saw an average total distance of 27,576 km over 25 runs. This was only 2.98% lower than the database value for the total distance of the Small and Medium VDPs for single purpose trips. This figure corresponds with the total number of drives of 403 as in the VDP database and approximately 1036 utilized volunteer hours versus 1144.

The model's initial conditions and insights provided the backdrop against which potential scenarios could be examined. The health scenario investigated the event of a hospital or major healthcare provider moving away to twice their original distance. The results from that concluded that longer more frequent trips would take away from the total number of drives of the overall system as theoretically drivers would be occupied for longer and thus turnover less frequently. This is a consistent and logical occurrence and saw a 19.5% reduction in total kilometers, 46% fewer drives and 29.5% less utilized volunteer hours.

A sensitivity analysis was then done to identify any relationships between the increase in average healthcare trip distance, total drives and volunteer hours utilized. Four different simulations of 25 runs each were done for corresponding increases of 10%, 25%, 50% and 100% in average healthcare trip distance. All three observed metrics seemed to follow a negative linear-like trend as the average trip distance for healthcare increases.

Similarly, the effect of service area increase was also modelled at the same intervals as healthcare. The total distance remained fairly consistent, seeing at most a 3.1% increase. The same held true for the number of volunteer hours which saw at highest a 3.6% decrease. Both of these metrics though virtually consistent, oscillated and did not trend in a particular direction and so no strong correlations could be inferred. However, the total drives per run experienced a steady decrease as the service area was simulated to increase by 10%-100%. At 100% increase, the drives decreased by 47.5%. The conclusions that could be drawn from this is that a larger service area will not necessarily see a huge increase in volunteer hour usage and total distance. And it may be insufficient to make such an assumption. But it will allow for less trips to be made on the basis of trip duration being longer (Both in distance to and from a destination). To remedy this, it would be necessary for more volunteer hours to be available for drivers or to have more drivers to meet the need.

Overall, the model has good usefulness for observing the impact on Small and Medium VDP operations. It particularly is relevant in assessing how trip distances, trip purpose probabilities and average trip time can affect a VDP system. Its outputted metrics can be used to optimize VDP operations in terms of number of drivers and volunteer hours , which can then be used to help VDP businesses determine if they are able to meet the operational demand. The model also proved useful in being able to explore how changing VDP characteristics such as the number of drivers could remedy a problem such as the health scenario and get back to their original level of service.

The techniques utilized and the model developed can be applied to larger VDP with a few tweaks and used to gain insights in the same way. The model, however, does not necessarily predict rider demand in its current state and can be further expanded with more research into informing what requirements are necessary to meet users need for the service.

6.2 Recommendations and Next Steps

To get a more inclusive picture of NB Rural VDPs would require increasing ABM complexity by incorporating multi-purpose trips. Multipurpose trips are a significant portion of the total number of trips by VDPs. Since it has been noted that ABMs can be used to model VDP operation for single purpose trips the research can be taken a step further to incorporate trips for multiple purposes by including stops as a feature of the ABM. This would require changes to the motion algorithm of the Netlogo code to allow for a portion of the drivers, to simulate trips with more than one stop. After incorporating stops, multi-rider trips can be explored by modifying the trip assignment component of the Netlogo code. While this study assumed each driver had only one passenger, VDP trips are not always limited in this manner. More than one rider will sometimes go to the same destination, or they will be along a similar route with a different destination. As these features are added a fuller complete picture of VDP operations can be explored. If both those implementations can be successfully done, then it would be good to upgrade the model by utilizing a built in GIS toolkit for Netlogo that can combine models with scaled geographical areas and allow for more accurate location implementations.

Finally, it is recommended that this study be taken further by incorporating both planning metrics and operational business insights such as investigating the effect that trip purpose scenarios, trip frequency and the addition of drivers and volunteer hours have on the service utilization. VDPs are businesses that operate in the realm of supply and demand and a way to investigate the potential for the demand is to investigate how different metrics are affected by the current supply.

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Appendix A1: Netlogo Model Results

1. Netlogo Model Results (Base Conditions)

Total Distance in km for Model Runs to Run Extents vs. Calibrated (Initial Conditions)

Runs	Uncalibrated Distance	Calibrated
1	40239.00	27724.67
2	42271.00	29124.71
3	41439.00	28551.47
4	40668.00	28020.25
5	37874.00	26095.18
6	39457.00	27185.87
7	37624.00	25922.93
8	40252.00	27733.62
9	43696.00	30106.54
10	42664.00	29395.49
11	41694.00	28727.16
12	41196.00	28384.04
13	39629.00	27304.38
14	38157.00	26290.17
15	41578.00	28647.24
16	39388.00	27138.33
17	39982.00	27547.59
18	42067.00	28984.16
19	39072.00	26920.60
20	40955.00	28217.99
21	38844.00	26763.51
22	40368.00	27813.55
23	38490.00	26519.61
24	37668.00	25953.25
25	43060.00	29668.34

Table 17. Total Number of Volunteer Hours Utilized per Run (Base Conditions) Cumulative Volunteer Hour Total vs. Adjusted Total

Volunteer Hours at Run End			
Runs	**Volunteer Hours Utilized in Model Run**	**Total Hours**	**Calibrated**
1	-307.31	1451.31	1000.0
2	-430.26	1574.26	1084.7
3	-430.92	1574.92	1085.1
4	-434.22	1578.22	1087.4
5	-171.46	1315.46	906.4
6	-294.92	1438.92	991.4
7	-308.9	1452.9	1001.0
8	-304.91	1448.91	998.3
9	-418.71	1562.71	1076.7
10	-423.21	1567.21	1079.8
11	-422.28	1566.28	1079.2
12	-427.29	1571.29	1082.6
13	-302.96	1446.96	997.0
14	-305.18	1449.18	998.5
15	-436.83	1580.83	1089.2
16	-301.94	1445.94	996.3
17	-319.19	1463.19	1008.1
18	-416.25	1560.25	1075.0
19	-312.11	1456.11	1003.3
20	-418.95	1562.95	1076.9
21	-308.57	1452.57	1000.8
22	-308.93	1452.93	1001.1
23	-317.99	1461.99	1007.3
24	-312.2	1456.2	1003.3
25	-554.14	1698.14	1170.0

Average	-359.5852	1503.58	1035.97
Standard D	79.75183201	79.75	54.94

Table 18. Total Number of Trips for Each Purpose Per Run(Base Conditions – Calibrated)

Runs	Health	Life Maintenance	Quality of Life	Education/Work
1	157	128	127	28
2	156	135	119	30
3	141	146	123	30
4	156	140	117	27
5	152	134	118	36
6	157	122	129	32
7	147	134	128	31
8	155	137	118	30
9	159	133	116	32
10	158	129	120	33
11	148	128	137	27
12	152	129	131	28
13	153	140	117	30
14	157	138	123	22
15	157	131	122	30
16	160	132	120	28
17	146	136	125	33
18	158	138	114	30
19	149	137	122	32
20	158	133	120	29
21	160	125	126	29
22	150	138	127	25
23	147	145	120	28
24	152	137	124	27
25	157	128	127	28

Average	153	135	123	29
Standard D	5.31	6.00	5.28	2.86
% Total	34.8%	30.6%	27.9%	6.7%

Table 19. Trip Purpose Distribution Percentages per Run (Base Conditions)

	Trip Probability			
Runs	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
1	35.68%	29.09%	28.86%	6.36%
2	35.45%	30.68%	27.05%	6.82%
3	32.05%	33.18%	27.95%	6.82%
4	35.45%	31.82%	26.59%	6.14%
5	34.55%	30.45%	26.82%	8.18%
6	35.68%	27.73%	29.32%	7.27%
7	33.41%	30.45%	29.09%	7.05%
8	32.95%	32.73%	27.95%	6.36%
9	35.23%	31.14%	26.82%	6.82%
10	36.14%	30.23%	26.36%	7.27%
11	35.91%	29.32%	27.27%	7.50%
12	33.64%	29.09%	31.14%	6.14%
13	34.55%	29.32%	29.77%	6.36%
14	34.77%	31.82%	26.59%	6.82%
15	35.68%	31.36%	27.95%	5.00%
16	35.68%	29.77%	27.73%	6.82%
17	36.36%	30.00%	27.27%	6.36%
18	33.18%	30.91%	28.41%	7.50%
19	35.91%	31.36%	25.91%	6.82%
20	33.86%	31.14%	27.73%	7.27%
21	35.91%	30.23%	27.27%	6.59%
22	36.36%	28.41%	28.64%	6.59%
23	34.09%	31.36%	28.86%	5.68%
24	33.41%	32.95%	27.27%	6.36%
25	34.55%	31.14%	28.18%	6.14%

2. Netlogo Model Results (Health Scenario)

Table 20. Total Distance in Km (Health Scenario)

Runs	Max Distance (km)	Max Distance Calibrated (km)
1	28419	19581
2	33791	23282
3	37260	25672
4	31100	21428
5	30448	20979
6	31550	21738
7	32687	22521
8	33511	23089
9	32139	22144
10	28750	19809
11	31946	22011
12	33954	23394
13	31555	21741
14	34806	23981
15	31324	21582
16	31242	21526
17	33987	23417
18	32075	22100
19	33225	22892
20	31121	21442
21	33141	22834
22	32077	22101
23	34515	23781
24	33082	22793
25	33398	23011

Mean Distance	32444.12	22353.98
Standard Deviation	1886.74	1299.96

Table 21. Total Drives per Run (Health Scenario)

Drives per Run		
Runs	**Drives**	**Drives (Calibrated)**
1	264	182
2	308	212
3	352	243
4	308	212
5	308	212
6	352	243
7	308	212
8	308	212
9	308	212
10	264	182
11	308	212
12	352	243
13	308	212
14	352	243
15	308	212
16	308	212
17	352	243
18	308	212
19	352	243
20	308	212
21	308	212
22	308	212
23	308	212
24	352	243
25	352	243

Average Drives	318.56	217
Standard Dev	26.28	17.47

Table 22. Total Number of Volunteer Hours Utilized per Run (Health Scenario)

Volunteer Hours at Run End			
Runs	**Current Volunteer Hours**	**Total Hours**	**Total Hours (Calibrated)**
1	322.37	821.63	566.10
2	109.49	1034.51	712.78
3	-50.75	1194.75	823.18
4	129.18	1014.82	699.21
5	127.46	1016.54	700.40
6	-48.64	1192.64	821.73
7	118.28	1025.72	706.72
8	104.58	1039.42	716.16
9	121.57	1022.43	704.45
10	318.44	825.56	568.81
11	107.33	1036.67	714.27
12	-26.3	1170.3	806.34
13	124.76	1019.24	702.26
14	-78.1	1222.1	842.03
15	144.01	999.99	688.99
16	135.71	1008.29	694.71
17	-44.32	1188.32	818.75
18	113.81	1030.19	709.80
19	-50.75	1194.75	823.18
20	101.83	1042.17	718.06
21	106.2	1037.8	715.04
22	135.17	1008.83	695.08
23	128.1	1015.9	699.96
24	8.76	1135.24	782.18
25	-40.98	1184.98	816.45

Average	84.69	1059.31	729.87
Standard Deviation	104.92	104.92	72.29

Table 23. Total Number of Trips by Purpose (Health Scenario)

No. of Trips By Purpose (Calibrated)				
Runs	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
1	56	60	55	10
2	78	62	59	13
3	88	75	65	14
4	73	64	62	13
5	75	57	68	12
6	87	73	66	17
7	78	65	56	14
8	77	65	56	13
9	74	70	54	14
10	62	54	52	14
11	79	61	60	12
12	81	70	72	19
13	75	62	61	14
14	90	76	63	14
15	70	69	60	14
16	74	65	59	14
17	86	72	68	17
18	77	61	59	15
19	85	72	70	14
20	79	60	61	13
21	79	63	58	13
22	73	63	62	14
23	76	63	61	12
24	76	74	75	18
25	81	74	71	16
Average	77	66	62	14
Standard Dev.	7.51	6.08	6.01	1.86

Table 24. Trip Purpose Percentages per Run (Health Scenario)

	Trip Purpose Percentages			
Runs	Health	Life Maintenance	Quality of Life	Education/Work
1	31.1%	33.0%	30.3%	5.7%
2	36.7%	29.2%	27.9%	6.2%
3	36.4%	31.0%	27.0%	5.7%
4	34.4%	30.2%	29.2%	6.2%
5	35.4%	26.9%	31.8%	5.8%
6	35.8%	30.1%	27.3%	6.8%
7	36.7%	30.5%	26.3%	6.5%
8	36.4%	30.8%	26.6%	6.2%
9	35.1%	32.8%	25.3%	6.8%
10	34.1%	29.9%	28.4%	7.6%
11	37.3%	28.9%	28.2%	5.5%
12	33.5%	29.0%	29.8%	7.7%
13	35.4%	29.2%	28.6%	6.8%
14	37.2%	31.3%	25.9%	5.7%
15	32.8%	32.5%	28.2%	6.5%
16	35.1%	30.5%	27.6%	6.8%
17	35.5%	29.8%	27.8%	6.8%
18	36.4%	28.6%	27.9%	7.1%
19	35.2%	29.8%	29.0%	6.0%
20	37.0%	28.2%	28.6%	6.2%
21	37.0%	29.5%	27.3%	6.2%
22	34.4%	29.5%	29.2%	6.8%
23	36.0%	29.5%	28.6%	5.8%
24	31.3%	30.4%	31.0%	7.4%
25	33.5%	30.7%	29.3%	6.5%

3. Netlogo Model Results (Service Area Scenario)

Table 25. Total Distance in Km per Run (Service Area Scenario)

Total Distance in km (Max)		
Runs	**Total Distance**	**Total Distance (Calibrated)**
1	36345	25042
2	42732	29442
3	42714	29430
4	38756	26703
5	39630	27305
6	42552	29318
7	37563	25881
8	40099	27628
9	40903	28182
10	40065	27605
11	44388	30583
12	40500	27905
13	44150	30419
14	39767	27399
15	40747	28075
16	42302	29146
17	41245	28418
18	39481	27202
19	42241	29104
20	41697	28729
21	42391	29207
22	40806	28115
23	41432	28547
24	38499	26526
25	42320	29158
Mean Dist	40933	28203
Standard Dev	1895.30	1332.79

Table 26. Total Number of Drives per Run (Service Area Scenario)

Drives per Run		
Runs	**Drives**	**Drives (Calibrated)**
1	264	182
2	308	212
3	308	212
4	308	212
5	308	212
6	352	243
7	308	212
8	308	212
9	352	243
10	308	212
11	308	212
12	308	212
13	308	212
14	308	212
15	308	212
16	308	212
17	308	212
18	308	212
19	308	212
20	308	212
21	308	212
22	308	212
23	366	252
24	264	182
25	308	212
Average	310.32	214
Standard Dev	21.38	14.73

Table 27. Total Number of Volunteer Hours Utilized per Run (Service Area Scenario)

Volunteer Hours at Run End			
Runs	**Current Volunteer Hours**	**Total Hours**	**Total Hours (Calibrated)**
1	-63.47	1207.47	832
2	-296.67	1440.67	993
3	-304.24	1448.24	998
4	-321.84	1465.84	1010
5	-305.22	1449.22	999
6	-547.31	1691.31	1165
7	-292.64	1436.64	990
8	-315.83	1459.83	1006
9	-545.2	1689.2	1164
10	-326.69	1470.69	1013
11	-284.38	1428.38	984
12	-289.68	1433.68	988
13	-314.45	1458.45	1005
14	-309.89	1453.89	1002
15	-311.16	1455.16	1003
16	-298.98	1442.98	994
17	-315.03	1459.03	1005
18	-299.18	1443.18	994
19	-293.69	1437.69	991
20	-304.75	1448.75	998
21	-310.91	1454.91	1002
22	-287.61	1431.61	986
23	-327.92	1471.92	1014
24	-51.01	1195.01	823
25	-299.79	1443.79	995

Average	-304.70	1448.70	998
Standard D	100.49	100.49	69.24

Table 28. Total Number of Trips by Purpose per Run (Service Area)

No. of Trips By Purpose (Calibrated)				
Runs	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
1	64	54	51	13
2	79	60	57	17
3	76	60	62	14
4	75	67	59	12
5	74	61	65	13
6	82	79	64	17
7	69	63	63	17
8	76	66	57	13
9	84	73	68	18
10	74	69	57	12
11	73	66	54	19
12	69	65	63	16
13	72	69	59	12
14	73	66	59	14
15	74	62	63	12
16	74	65	58	15
17	74	66	59	14
18	68	68	61	14
19	76	61	59	17
20	78	59	61	15
21	72	68	58	14
22	73	63	59	17
23	79	64	57	12
24	66	51	50	14
25	79	55	65	13
Average	74	64	60	15
Standard D	4.68	6.02	4.11	2.04

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Table 29. Trip Purpose Probabilities per Run (Service Area Scenario)

	Trip Probability			
Runs	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
1	35.2%	29.5%	28.0%	7.2%
2	37.0%	28.2%	26.9%	7.8%
3	36.0%	28.2%	29.2%	6.5%
4	35.4%	31.5%	27.6%	5.5%
5	34.7%	28.6%	30.5%	6.2%
6	33.8%	32.7%	26.4%	7.1%
7	32.5%	29.9%	29.9%	7.8%
8	35.7%	31.2%	26.9%	6.2%
9	34.7%	30.1%	27.8%	7.4%
10	35.1%	32.5%	26.9%	5.5%
11	34.4%	31.2%	25.6%	8.8%
12	32.5%	30.5%	29.5%	7.5%
13	33.8%	32.5%	27.9%	5.8%
14	34.4%	31.2%	27.6%	6.8%
15	35.1%	29.2%	29.9%	5.8%
16	34.7%	30.8%	27.3%	7.1%
17	34.7%	31.2%	27.6%	6.5%
18	32.1%	32.1%	28.9%	6.8%
19	35.7%	28.6%	27.9%	7.8%
20	36.7%	27.6%	28.6%	7.1%
21	34.1%	32.1%	27.3%	6.5%
22	34.4%	29.9%	27.6%	8.1%
23	31.4%	25.4%	22.7%	4.6%
24	36.4%	28.0%	27.7%	8.0%
25	37.3%	26.0%	30.5%	6.2%

4. Sensitivity Analyses

Table 30. Total Distance in Km (Health Sensitivity Analysis)

Total Distance in Km (Calibrated)					
Runs	**Base**	**+10%**	**+25%**	**+50%**	**+100%**
1	27725	25960	26619	24814	19581
2	29125	26284	27161	19971	23282
3	28551	28564	26083	24475	25672
4	28020	25765	24509	24927	21428
5	26095	26753	26023	24658	20979
6	27186	28253	26232	23443	21738
7	25923	26796	26323	22988	22521
8	27734	27850	26433	23518	23089
9	30107	28673	24796	25775	22144
10	29395	28456	28480	22875	19809
11	28727	27986	23505	23132	22011
12	28384	28993	27590	26327	23394
13	27304	29287	23325	22814	21741
14	26290	26704	25968	24503	23981
15	28647	26933	25391	25143	21582
16	27138	27848	25684	22461	21526
17	27548	26741	28086	24068	23417
18	28984	26008	25483	23108	22100
19	26921	26173	25926	23429	22892
20	28218	27022	28788	25567	21442
21	26764	28260	25437	25222	22834
22	27814	26532	24359	25889	22101
23	26520	27847	27126	22448	23781
24	25953	27378	25458	22335	22793
25	29668	24391	26162	26139	23011

	Base	+10%	+25%	+50%	+100%
Mean Dist	27789.6	27258.3	25036.4	24001.2	22354.0
Standard Dev	1189.52	1677.83	1373.06	1504.15	1299.97
Difference	n/a	-531.30	-2753.22	-3788.43	-5435.63
% Difference	n/a	-1.9%	-9.9%	-13.6%	-19.6%

Table 31. Total Drives per Run (Health Sensitivity Analysis)

Total Drives per Run					
Runs	**Base**	**10%**	**25%**	**50%**	**100%**
1	394	394	364	303	182
2	424	364	364	273	212
3	424	424	333	273	243
4	424	364	333	303	212
5	364	364	333	303	212
6	394	394	364	273	243
7	394	394	364	273	212
8	394	394	333	273	212
9	424	394	333	303	212
10	424	364	364	273	182
11	424	364	303	303	212
12	424	424	364	303	243
13	394	394	303	273	212
14	394	364	364	303	243
15	424	364	333	303	212
16	394	394	333	243	212
17	394	364	364	273	243
18	424	364	333	273	212
19	394	394	333	273	243
20	424	394	364	303	212
21	394	394	333	303	212
22	394	364	333	303	212
23	394	394	333	303	212
24	394	394	333	273	243
25	455	333	333	303	243

	Base	**10%**	**25%**	**50%**	**100%**
Average	407.4	382.0	328.8	287.4	219.5
Standard Dev	19.72	1677.83	18.61	17.76	18.11
Difference	n/a	-25.47	-78.63	-120.05	-187.96
% Difference	n/a	-6.2%	-19.3%	-29.5%	-46.1%

Table 32. Volunteer Hours at the End of Runs (Health Sensitivity Analysis)

Volunteer Hours at Run's End (Calibrated)					
Runs	**Base**	**+10%**	**+25%**	**+50%**	**+100%**
1	999.95	1040.07	1008.09	897.70	566.10
2	1084.67	953.98	1008.96	792.52	712.78
3	1085.12	1131.94	911.28	808.97	823.18
4	1087.39	951.84	905.86	891.13	699.21
5	906.35	949.08	907.36	894.24	700.40
6	991.42	1042.20	997.68	794.51	821.73
7	1001.05	1039.33	1007.27	793.77	706.72
8	998.30	1040.28	911.15	797.39	716.16
9	1076.71	1037.57	909.20	904.46	704.45
10	1079.81	943.67	1015.13	783.54	568.81
11	1079.17	960.38	822.24	899.49	714.27
12	1082.62	1120.64	995.25	902.16	806.34
13	996.96	1040.43	812.76	805.51	702.26
14	998.49	946.59	992.54	906.83	842.03
15	1089.19	940.02	912.50	901.65	688.99
16	996.25	1033.90	918.77	696.81	694.71
17	1008.14	945.75	1012.31	796.51	818.75
18	1075.01	950.68	917.48	791.19	709.80
19	1003.26	1025.74	926.25	792.07	823.18
20	1076.87	1035.46	1006.73	889.84	718.06
21	1000.82	1038.85	926.73	894.54	715.04
22	1001.07	952.86	914.30	891.80	695.08
23	1007.31	1043.41	915.05	888.62	699.96
24	1003.32	1036.19	915.55	801.35	782.18
25	1170.02	879.91	916.56	886.45	816.45

Average	1035.97	1003.23	939.48	844.12	729.87
Standard Dev	54.95	61.01	56.93	58.85	72.29

Table 33. Total Distance in km (Service Area Sensitivity Analysis)

Total Distance in Km (Calibrated)					
Runs	**Base**	**+10%**	**+25%**	**+50%**	**+100%**
1	27725	27738	27960.998	27065	25042
2	29125	28755	28808	26102	29442
3	28551	31456	28505	27973	29430
4	28020	28549	27023	27528	26703
5	26095	28698	26013	28198	27305
6	27186	27655	28168	27782	29318
7	25923	28621	25541	27060	25881
8	27734	28252	28684	27379	27628
9	30107	29318	28058	27050	28182
10	29395	27987	26504	26852	27605
11	28727	26784	28744	27804	30583
12	28384	28710	28450	26141	27905
13	27304	27923	26535	28492	30419
14	26290	28591	26826	28495	27399
15	28647	29020	28467	25218	28075
16	27138	27792	27659	28074	29146
17	27548	27927	27090	27562	28418
18	28984	28263	27467	27867	27202
19	26921	31144	27619	27425	29104
20	28218	28311	28161	27619	28729
21	26764	28150	30113	26495	29207
22	27814	27435	25519	30677	28115
23	26520	26782	29243	27922	28547
24	25953	28889	26484	29129	26526
25	29668	28326	29104	30694	29158

	Base	**+10%**	**+25%**	**+50%**	**+100%**
Mean Dist	27789.6	28443.1	26644.1	27704.1	28202.8
Standard Dev	1189.52	1677.83	1191.38	1232.72	1332.79
Difference	n/a	653.50	-1145.51	-85.52	413.21
% Difference	n/a	2.4%	-4.1%	-0.3%	1.5%

Table 34. Total Number of Drives per Run (Service Area Sensitivity Analysis)

Total Drives per Run (Calibrated)					
Runs	**Base**	**10%**	**25%**	**50%**	**100%**
1	394	364	303	273	182
2	424	394	333	273	212
3	424	394	333	303	212
4	424	364	333	273	212
5	364	364	333	273	212
6	394	364	333	303	243
7	394	364	303	273	212
8	394	364	333	273	212
9	424	394	333	273	243
10	424	364	333	273	212
11	424	364	333	243	212
12	424	394	333	273	212
13	394	364	303	273	212
14	394	394	303	273	212
15	424	394	333	273	212
16	394	333	333	273	212
17	394	364	303	273	212
18	424	394	333	273	212
19	394	424	333	273	212
20	424	364	333	273	212
21	394	364	364	243	212
22	394	364	303	303	212
23	394	364	364	273	252
24	394	394	303	273	182
25	455	364	364	303	212

	Base	10%	25%	50%	100%
Average	407.4	374.7	316.0	275.3	213.8
Standard Dev	19.72	1677.83	18.93	14.95	14.73
Difference	n/a	-32.74	-91.45	-132.18	-193.64
% Difference	n/a	-8.0%	-22.4%	-32.4%	-47.5%

Table 35. Number of Volunteer Hours per Run (Service Area Sensitivity Analysis)

Volunteer Hours for each Run (Calibrated)					
Runs	**Base**	**10%**	**25%**	**50%**	**100%**
1	1000	1008	931	999	832
2	1085	1104	1044	998	993
3	1085	1101	1047	1118	998
4	1087	1009	1035	990	1010
5	906	1009	1040	991	999
6	991	1007	1045	1124	1165
7	1001	1011	939	989	990
8	998	1007	1039	983	1006
9	1077	1097	1041	995	1164
10	1080	1009	1042	1002	1013
11	1079	1005	1044	878	984
12	1083	1098	1039	992	988
13	997	1007	934	1012	1005
14	998	1094	932	992	1002
15	1089	1100	1048	989	1003
16	996	916	1039	1001	994
17	1008	1001	936	993	1005
18	1075	1098	1042	1000	994
19	1003	1191	1042	1005	991
20	1077	1013	1041	1007	998
21	1001	1007	1144	878	1002
22	1001	1006	944	1119	986
23	1007	1004	1135	1004	1014
24	1003	1110	942	994	823
25	1170	1006	1142	1124	995
Average	1036.0	1040.7	984.9	1007.1	998.2
Std Dev	54.95	1677.83	64.16	60.69	69.24
Difference	n/a	4.73	-51.04	-28.83	-37.81
% Difference	n/a	0.5%	-4.9%	-2.8%	-3.7%

Table 36. Average Number of Trips by Purpose (Sensitivity Analysis)

Average Number of Trips by Purpose				
Scenario	**Health**	**Life Maintenance**	**Quality of Life**	**Education/Work**
Base	142	124	115	27
10%	131	113	107	25
25%	115	99	93	22
50%	95	83	78	19
100%	74	64	60	15

Appendix A2: Netlogo Code

The following is a direct copy of the software code written into Netlogo that resulted in the creation of an ABM representative of the NB VDP operations discussed in this thesis. A direct copy of this syntax into the code tab should result in the model with all the operations and features described.

Start of Netlogo Software Code

```
 globals [ridernumbers NumofHDrivers NumofLifeMDrivers NumofQLDrivers
 NumofEduWDrivers looplimit totaldist loopcounter active-list TotalVDrivers  TotalVRiders
CVHoursTotal TotalVHours HDCount HDTotal LMCount LMTotal QLCount QLTotal EDWCount
EDWTotal]
breed [drivers driver]
breed [houses house]
drivers-own [ target avhours cvhours ophours drivedist drivecount drivelim keepdriving? numoriders tpp
atriplim]

to setup-environment

clear-all
 set-default-shape houses "house"

;Driver Waypoint Component
create-houses 1
[setxy  4 34 set color black]
create-houses 1
[setxy 4 6 set color black]
create-houses 1
[setxy 34 6 set color black ]
create-houses 1
[ setxy 34 34 set color black ]

  ; Aesthetic Environment Component – Green Borders
  ask patches [
    if ( pycor > 0 and pxcor < 4 ) ; left side
    [ set pcolor green ]
  if (pycor < 6 and pxcor < 40) ; bottom side
    [ set pcolor green]
  if  ( pycor > 5 and pxcor > 34 ) ; right side
    [ set pcolor green ]
  if ( pycor > 34 and pxcor > 0 ) ; top
    [ set pcolor green ]
]

  ;Health Trip Purpose Icon
  ask patch 1 36 [set pcolor white ]
  ask patch 2 36 [ set pcolor red ]
  ask patch 3 36 [ set pcolor white ]
  ask patch 1 37 [set pcolor white ]
```

```
  ask patch 2 37 [ set pcolor red ]
  ask patch 3 37 [ set pcolor white ]
  ask patch 1 38 [set pcolor white ]
  ask patch 2 38 [ set pcolor red ]
  ask patch 3 38 [ set pcolor white ]

  ;Bottom left Trip Purpose Icon
  ask patch 1 2 [set pcolor 62 ]
  ask patch 2 2 [ set pcolor yellow ]
  ask patch 3 2 [ set pcolor 62 ]
  ask patch 1 3 [set pcolor 62 ]
  ask patch 2 3 [ set pcolor yellow ]
  ask patch 3 3 [ set pcolor 62 ]
  ask patch 1 4 [set pcolor 62 ]
  ask patch 2 4 [ set pcolor yellow ]
  ask patch 3 4 [ set pcolor 62 ]


  ; Bottom right Trip Purpose Icon
  ask patch 35 2 [set pcolor 103 ]
  ask patch 36 2 [ set pcolor white ]
  ask patch 37 2 [ set pcolor 103 ]
  ask patch 35 3 [set pcolor 103 ]
  ask patch 36 3 [ set pcolor white ]
  ask patch 37 3 [ set pcolor 103 ]
  ask patch 35 4 [set pcolor 103 ]
  ask patch 36 4 [ set pcolor white ]
  ask patch 37 4 [ set pcolor 103 ]


  ; Top Right Trip Purpose Icon
  ask patch 35 36 [set pcolor 45 ]
  ask patch 36 36 [ set pcolor blue ]
  ask patch 37 36 [ set pcolor 45 ]
  ask patch 35 37 [set pcolor 45 ]
  ask patch 36 37 [ set pcolor blue ]
  ask patch 37 37 [ set pcolor 45 ]
  ask patch 35 38 [set pcolor 45 ]
  ask patch 36 38 [ set pcolor blue ]
  ask patch 37 38 [ set pcolor 45 ]

; the population density visual
ask n-of (population / 1000) patches with [pcolor = green] [ set pcolor 2  ]

  ask patch 3 39 [set plabel "Healthcare" set plabel-color black ]
  ask patch 38 39 [set plabel "Life Maintenance" set plabel-color black ]
  ask patch 4 1 [set plabel "Quality of Life" set plabel-color black ]
  ask patch 38 1 [set plabel "Education/Work" set plabel-color black ]

  set TotalVHours  ( VolunteerHours * NumberofVDrivers)

  set CVHoursTotal TotalVHours

reset-ticks
end
```

```
to setup-drivers
; driver creation and motion targets set
ask n-of NumberofVDrivers patches with [pcolor = black] [
 sprout-drivers 1 [set color white set shape "car"
   set target one-of houses
   face target
 ]]
 ask drivers [ set avhours  VolunteerHours set ophours 1144 set keepdriving? true ]
 set looplimit  ( NumberofTrips / NumberofVDrivers)

 set active-list ([ keepdriving? ] of drivers )

 set TotalVDrivers TotalVDrivers + NumberofVDrivers

 set HDCount (count drivers with [color = red])
 set LMCount (count drivers with [color = yellow])
 set QLCount (count drivers with [color = green])
 set EDWCount (count drivers with [color = blue])

end

to go
if ticks >= 156600 [stop]
move-drivers
 if count drivers = 0[
 setup-drivers
  trip-assign
 ask drivers [ set CVHoursTotal ( CVHoursTotal - cvhours )]
  ]
tick-advance 60
end

to trip-assign

set loopcounter loopcounter + 1

ask drivers [set atriplim looplimit]

ask drivers [  set keepdriving? true ]

set NumofHDrivers  (( HProb * NumberofVDrivers) / 100 )
set NumofLifeMDrivers   (( LifeMProb * NumberofVDrivers) / 100 )
set NumofQLDrivers   (( QLProb * NumberofVDrivers) / 100 )
set NumofEduWDrivers  (( EduWProb * NumberofVDrivers) / 100 )



 ask drivers[
 ask n-of NumofHDrivers drivers [ set color red set drivelim random-normal chdrivelim h-stdv  set
numoriders one-of ridernumbers set cvhours HTime ]
   ask n-of NumofLifeMDrivers drivers [ set color yellow set drivelim random-normal clmdrivelim lm-stdv
set numoriders one-of ridernumbers set cvhours LMTime]
   ask n-of NumofQLDrivers drivers [ set color green set drivelim random-normal cqldrivelim ql-stdv set
numoriders one-of ridernumbers set cvhours QLTime]
```

```
  ask n-of NumofEduWDrivers drivers [set color blue set drivelim random-normal cedwdrivelim eduw-
stdv set numoriders one-of ridernumbers set cvhours EduTime ]
  ]

 ask drivers [ set TotalVRiders  TotalVriders + numoriders ]



 set HDCount (count drivers with [color = red])
 set LMCount (count drivers with [color = yellow])
 set QLCount (count drivers with [color = green])
 set EDWCount (count drivers with [color = blue])
 set HDTotal HDTotal + HDCount
 set LMTotal LMTotal + LMCount
 set QLTotal QLTotal + QLCount
 set EDWTotal EDWTotal + EDWCount

end

to move-drivers
 ask drivers with [ keepdriving? ] [
  ;; if at target, choose a new random target
  if distance target = 0
   [ set target one-of houses
     face target ]
  ;; move towards target.  once the distance is less than 1,
  ;; use move-to to land exactly on the target.
  ifelse distance target < 1
   [ move-to target ]
   [ fd 1 ]

 set drivedist drivedist + 1     ; distance counter
 set totaldist totaldist + 1

  ifelse show-drivedist?   ; label on/off toggle
 [set label drivedist  ]
 [set label "" ]
  ask drivers[set label-color yellow ]
 ]

 ask drivers [ if drivedist >= drivelim
  [ set keepdriving? false  set drivecount drivecount + 1  die  ]
 ]
end
```

End of Netlogo Software Code

1. Submodel Testing and Analysis

2. Setup-Environment

The setup-environment submodel includes the following lines of code:

```
set-default-shape houses "house"

;Driver Waypoint Component
create-houses 1
[setxy  4 34 set color black]
create-houses 1
[setxy 4 6 set color black]
create-houses 1
[setxy 34 6 set color black ]
create-houses 1
[ setxy 34 34 set color black ]

 ; Aesthetic Environment Component – Green Borders
 ask patches [
   if ( pycor > 0 and pxcor < 4 ) ; left side
   [ set pcolor green ]
 if (pycor < 6 and pxcor < 40) ; bottom side
   [ set pcolor green]
 if  ( pycor > 5 and pxcor > 34 ) ; right side
   [ set pcolor green ]
 if ( pycor > 34 and pxcor > 0 ) ; top
   [ set pcolor green ]
]

 ;Health Trip Purpose Icon
 ask patch 1 36 [set pcolor white ]
 ask patch 2 36 [ set pcolor red ]
 ask patch 3 36 [ set pcolor white ]
 ask patch 1 37 [set pcolor white ]
 ask patch 2 37 [ set pcolor red ]
 ask patch 3 37 [ set pcolor white ]
 ask patch 1 38 [set pcolor white ]
 ask patch 2 38 [ set pcolor red ]
 ask patch 3 38 [ set pcolor white ]

 ;Bottom left Trip Purpose Icon
 ask patch 1 2 [set pcolor 62 ]
 ask patch 2 2 [ set pcolor yellow ]
 ask patch 3 2 [ set pcolor 62 ]
 ask patch 1 3 [set pcolor 62 ]
 ask patch 2 3 [ set pcolor yellow ]
 ask patch 3 3 [ set pcolor 62 ]
 ask patch 1 4 [set pcolor 62 ]
 ask patch 2 4 [ set pcolor yellow ]
 ask patch 3 4 [ set pcolor 62 ]
```

```
 ; Bottom right Trip Purpose Icon
 ask patch 35 2 [set pcolor 103 ]
 ask patch 36 2 [ set pcolor white ]
 ask patch 37 2 [ set pcolor 103 ]
 ask patch 35 3 [set pcolor 103 ]
 ask patch 36 3 [ set pcolor white ]
 ask patch 37 3 [ set pcolor 103 ]
 ask patch 35 4 [set pcolor 103 ]
 ask patch 36 4 [ set pcolor white ]
 ask patch 37 4 [ set pcolor 103 ]


 ; Top Right Trip Purpose Icon
 ask patch 35 36 [set pcolor 45 ]
 ask patch 36 36 [ set pcolor blue ]
 ask patch 37 36 [ set pcolor 45 ]
 ask patch 35 37 [set pcolor 45 ]
 ask patch 36 37 [ set pcolor blue ]
 ask patch 37 37 [ set pcolor 45 ]
 ask patch 35 38 [set pcolor 45 ]
 ask patch 36 38 [ set pcolor blue ]
 ask patch 37 38 [ set pcolor 45 ]

; the population density visual
ask n-of (population / 1000) patches with [pcolor = green] [ set pcolor 2  ]

 ask patch 3 39 [set plabel "Healthcare" set plabel-color black ]
 ask patch 38 39 [set plabel "Life Maintenance" set plabel-color black ]
 ask patch 4 1 [set plabel "Quality of Life" set plabel-color black ]
 ask patch 38 1 [set plabel "Education/Work" set plabel-color black ]

 set TotalVHours  ( VolunteerHours * NumberofVDrivers)

 set CVHoursTotal TotalVHours

reset-ticks
end
```

The lines of software code in this section are responsible for the green and black color of the patches in the ABM and the four trip purpose squares located in each corner. This segment of the code was used to set waypoints that would later be used to control the driving motion of the cars using an arbitrary breed of turtle agents called ‘houses’. Note that a turtle ‘breed’ is just a set of turtles with a specific function or purpose and the same properties. In this case to act as invisible waypoints. Setup-environment also includes a population density visual that sets a certain number of green patches to the color grey to signify the density of the population that is being reflected by the VDP. This has no functional purpose and is purely aesthetic. It also includes the code that is responsible for setting the labels of “Health, Life Maintenance, Quality of Life and Education/Work” around the four trip purpose squares. Lastly, this portion sets up the two global variables of Total Volunteer Hours and Current Volunteer Hours Total. It is easier to ‘test’ this segment as the code has direct visual implications to model. This submodel achieves its purpose in setting up the visual environment within which the VDP operations will be simulated.

3. Setup-Drivers

The second sub-model of the ABM is the Setup-Drivers segment. It includes:

```
; driver creation and motion targets set
ask n-of NumberofVDrivers patches with [pcolor = black] [
  sprout-drivers 1 [set color white set shape "car"
    set target one-of houses
    face target
  ]]
  ask drivers [ set avhours  VolunteerHours set ophours 1582 set keepdriving? true ]
  set looplimit  ( NumberofTrips / NumberofVDrivers)

  set active-list ([ keepdriving? ] of drivers )

  set TotalVDrivers TotalVDrivers + NumberofVDrivers

  set HDCount (count drivers with [color = red])
  set LMCount (count drivers with [color = yellow])
  set QLCount (count drivers with [color = green])
  set EDWCount (count drivers with [color = blue])

end
```

This submodel is responsible for the creation of the number of volunteer drivers that is input in the model. It also sets the waypoint targets for the drivers for when they are given to move. Setup-Drivers then sets the annual volunteer hours, the operational hours, and the driving status for all the driver agents. This portion also controls some of the outputs that are seen in the "Driver Status Overview" monitors such as the number of active drivers, the cumulative total number of volunteer drivers in the model, and a breakdown of the number of volunteer drivers by purpose. This is portion of the code works well as the number of drivers specified in the input is what appears in the model, and the drivers are assigned the requisite variables specified in this portion. The monitors also verify that the status items seen in the driver overview works as intended.

4. Trip-Assign

The following is the trip-assign submodel:

```
set loopcounter loopcounter + 1

ask drivers [set atriplim looplimit]

ask drivers [  set keepdriving? true ]

set NumofHDrivers  (( HProb * NumberofVDrivers) / 100 )
set NumofLifeMDrivers   (( LifeMProb * NumberofVDrivers) / 100 )
set NumofQLDrivers   (( QLProb * NumberofVDrivers) / 100 )
set NumofEduWDrivers  (( EduWProb * NumberofVDrivers) / 100 )



 ask drivers[
 ask n-of NumofHDrivers drivers [ set color red set drivelim random-normal chdrivelim h-stdv  set
numoriders one-of ridernumbers set cvhours HTime ]
   ask n-of NumofLifeMDrivers drivers [ set color yellow set drivelim random-normal clmdrivelim lm-stdv
set numoriders one-of ridernumbers set cvhours LMTime]
   ask n-of NumofQLDrivers drivers [ set color green set drivelim random-normal cqldrivelim ql-stdv set
numoriders one-of ridernumbers set cvhours QLTime]
   ask n-of NumofEduWDrivers drivers [set color blue set drivelim random-normal cedwdrivelim eduw-
stdv set numoriders one-of ridernumbers set cvhours EduTime ]
   ]

  ask drivers [ set TotalVRiders  TotalVriders + numoriders ]



  set HDCount (count drivers with [color = red])
  set LMCount (count drivers with [color = yellow])
  set QLCount (count drivers with [color = green])
```

```
  set EDWCount (count drivers with [color = blue])
  set HDTotal HDTotal + HDCount
  set LMTotal LMTotal + LMCount
  set QLTotal QLTotal + QLCount
  set EDWTotal EDWTotal + EDWCount
```

This submodel is also an important piece of the overall ABM. It contains the code that is responsible for assigning trips to the driver agents. The code starts off by setting a loop counter which is responsible for showing the number of drives recorded. It then sets the status of the drivers to active or not based on a true/false variable called "keepdriving?" The code then assigns trips with a respective purpose to each of the number of drivers in the model according to the probability of each purpose. The equations are seen in the 4th to the 7th line of code. Upon being assigned a trip, the driver agent changes colour to represent each respective purpose, assigns the average trip distance according to a normal distribution and assigns the average trip time for that purpose. The code ends by setting up a counter for the number of drivers according to each purpose and sets up a cumulative count that will record across all iterations of assignments. This code was analyzed by manually checking the number of drivers according to the probability of each purpose based on the total of 44 drivers and also manually counting the number of cars with each respective color across many different runs of this submodel. Their variables assigned such as the trip distance limits and the trip durations were also checked driver by driver. This portion works well and as intended.

5. Move Drivers

The following is the code from the move-drivers submodel:

```
to move-drivers
  ask drivers with [ keepdriving? ] [
    ;; if at target, choose a new random target
```

```
    if distance target = 0
      [ set target one-of houses
        face target ]
    ;; move towards target.  once the distance is less than 1,
    ;; use move-to to land exactly on the target.
    ifelse distance target < 1
      [ move-to target ]
      [ fd 1 ]

  set drivedist drivedist + 1      ; distance counter
  set totaldist totaldist + 1

   ifelse show-drivedist?   ; label on/off toggle
  [set label drivedist  ]
  [set label "" ]
   ask drivers[set label-color yellow ]
  ]

  ask drivers [ if drivedist >= drivelim
   [ set keepdriving? false  set drivecount drivecount + 1  die  ]
  ]
end
```

This portion of code works by asking all the drivers with an active status to set their waypoint to one of the four in the model and move towards it step by step. As they move towards each waypoint, their motion is updated and increase 1km on a step by step basis. The distance counter for each driver is increased and the cumulative distance of all drivers is also recorded. This portion of the code also gives the observer the option to see the distance label for each driver. Finally the code asks the drivers to do a logical comparison of their current drive distance and their assigned drive limits. If the drive distance is equal to the drive limit it will tell them to stop driving and they will be inactive.

6. Go or Run-VDP

The most important submodel. The go procedure, denoted as “Run-VDP” procedure is as follows:

```
if ticks >= 156600 [stop]
move-drivers
 if count drivers = 0[
 setup-drivers
  trip-assign
 ask drivers [ set CVHoursTotal ( CVHoursTotal - cvhours )]
  ]
tick-advance 60
```

This portion of the code is responsible for the running order of the other submodels. It starts off with a conditional statement that is responsible for the temporal extent of the model. The model will have a total of 156600 ticks and when it has achieved that it will stop running. The model assuming the observer has already setup-environment, setup-drivers and trip-assign then executes the move-drivers submodel, and if there are no-active drivers left will loop and do the setup-drivers and trip-assign portion again. This portion also sees the counter for the current volunteer hours being managed. It closes out with tick-advance which shows how much the ticks are updated on every run. This procedure was analyzed by its ability to execute the submodels in the right order and their respective results from each.

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