Overcoming Healthcare Transportation Barriers: A Case Study

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ABSTRACT

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Ehsan Sharifnia

Transportation remains a major barrier in receiving cancer treatment in Canada. The situation is especially alarming for those living in rural areas and in the light of COVID pandemic, poses another risk in the long list of health challenges to patients with pre-existing conditions. In this dissertation we set out find a solution to this problem by providing a framework for a personalized healthcare transportation system tailored to the needs of this population.

A three-step approach is proposed. First, a review of literature and initiatives employed by global transportation providers is conducted to identify major methods used for healthcare industry. Second, a transportation strategy is proposed, and key performance indicators identified through analysis of data and interviews with industry best practices in order to determine key aspects of such operations having the most impact on the overall service level. Finally, a discrete event simulation is provided and tested through various scenarios to understand how such operations would behave in real life and how they react as the environment evolves through time. A case study of a major nonprofit organization for whom this strategy was originally outlined is provided for further context. In the end, the key findings from this research are formulated as a decision-making tool for future guidelines in managing similar operations.

Keywords: Transportation; Strategy; Simulation; Healthcare; Ride Sharing; Breast Cancer

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Glossary

P2P – Peer to peer

Ruban Rose – A.K.A Quebec breast cancer foundation

DAR – Dial-A-Ride

KPI – Key performance indicator

ERP – Enterprise Resource Planning

1. Introduction and problem statement

1.1 Background – Healthcare directions, new horizons and challenges

Cancer is a major cause of death in Canada. According to the Canadian cancer society [1] nearly one in two Canadians are expected to be diagnosed with the disease at some point during their lifetime and even more alarming is the fact that 1 in 4 die from it. Despite the most rapid rate of technological advancements in history, the horizon is not looking good. Although death rates are decreasing, the total number of Canadians diagnosed with cancer has continuously been rising. In 2017, over a span of ~30 years, cancer death rates had decreased by 32% and 17% among men and women, respectively. However, it is projected that by 2030, the number of cancer diagnoses in Canada will be 80% greater than what the number diagnosed in 2005.

This alarming situation has caused immense efforts for cancer control. Fairly consistent progress has been achieved as a result of advances in prevention and screenings that enable earlier detection and treatment (Canadian Cancer society, 2018). The progress is reflected in the consistent decline in mortality rates since the past 30 years. Although trends seem to be variable across genders and cancer types, incidence rates have been constantly decreasing among all cancer types combined.

Although great advancements have been achieved in treatment and reducing fatalities, problems still remain. With the overall number of cancer diagnoses constantly increasing, healthcare infrastructure will naturally have to expand in service offerings to be able to respond to the increasing demand. Obviously, the latter requires considerable costs, time and innovations to maintain on par with the raising standards in healthcare and sustainability. Unfortunately, healthcare and transportation advancements do not seem to be progressing nearly at the same rate as the growing number of diagnosed patients demanding such services. In fact, with more patients vying for fewer resources and increasing personalization trends in treatment, the current healthcare system is at risk of falling short to provide the required patient experience, in the least.

Patients today, similar to their other daily tasks, want a certain degree of comfort and personalization in their treatment process. They can make purchases without having to have their wallets or exchange physical money, or make restaurant reservations instantly without having to line outside the restaurant, or, in the very important area of transportation, today we can have access to on-demand transportation services within the reach of our palms, at roughly any place in the city, any time of the day. This level of gradual but certain transformation in daily activities has brought about a culture to bypass certain logistical barriers allowing us to focus on the task at hand and is expanding to the healthcare industry as well. David Roberts, a global health leader at EY [2], defines this challenge for businesses as the duality of growth; the challenge of strengthening today's core business while preparing to meet the challenges of an increasingly more connected, consumer-centric health ecosystem. Roberts further elaborates on this ”connection” as the main theme spreading across the whole healthcare ecosystem relationships, among consumers, physicians, and health businesses to each other. Examples could include connecting people to goods and services that promote and maintain their health, to physicians when they need clinical intervention; and to each other to stay engaged in the trends and best practices. The benefits of this connected vision of the health ecosystem becomes especially important as the North American average population age increases, and logistical barriers of distance and time show themselves with a clearer image.

The promise of a connected ecosystem in the healthcare sector has emerged, like other sectors, with the advancements in digital technologies. Data analytics and machine learning techniques have been few of the driving forces allowing insights into how this future can be shaped. Using survey data gathered from several countries enabled decision makers to gain a holistic big picture of customer and physician expectations and to lay out those expectations in a digitally connected ecosystem [2]. That being said, there still seems to be a gap between those expectations and implementation to this date [2]. Unprecedented problems arise when strategies are moved into implementation phases. Problems such as financial hardships and lack of appropriate infrastructure are among the greatest hurdles for implementing digital strategies in healthcare [3,4,5].

Based on a demographic analysis of breast cancer patients' overhead costs during treatment [3] and the Quebec Breast Cancer Foundation's patient data, we know that in Canada, transportation counts as one of the major hurdles for breast cancer patients receiving treatment both in terms of overhead costs and accessibility. According to a study conducted in 2011 on out of pocket costs imposed to 800 Canadian women with breast cancer while receiving adjuvant radiotherapy [4], within total net costs after receiving assistance, transportation approximately comprised about 93% for home living patients and 40% for patients lodging away from home. The numbers become more extreme for the suburban population. Taxi and public transportation become expensive and inaccessible as the travel distances increase. As we move away from metropolitan areas holding the majority of these cancer treatment centers, regular commuting becomes more difficult. In fact, based on the same study [3], the average breast cancer patient in Quebec will have to travel ~20 km for an average of ~23 days to receive treatment – which given the physical and emotional state such patients already hold (especially for those in shock of early stages of cancer), will undoubtedly result in deteriorating the treatment experience for both patients and those involved.

Transportation hurdles also act as one of the top 3 major reasons for cancer treatment non receipt, according to a research conducted in Ontario in 2017 [4]. According to a survey on that study, ~20% of patients identified transportation as the major reason why they could not attend their treatment appointments. The situation becomes worse for rural patients, comprising 46% of the national patient population, as they are typically more distanced from specialized healthcare facilities. In fact, according to the same study, 20% of rural patients travel above 200km to see a doctor. In some cases, travel barriers prevent individuals from attending their jobs. Up until the time these lines are being written, we know the need for transportation is growing. We personally interviewed several nonprofit executives who seeked out to offer transportation services within Quebec. Our overall findings from those interviews [6], indicate that in the light of the COVID-19 pandemic, traditional means of transportation are riskier for this already vulnerable population and the number of people vying for a more secure, stable and accessible means of transportation is increasing.

In short, there seems to be a need for an appropriate means of transportation for breast cancer patients during the treatment period throughout Canada. One that not only helps reduce the already huge imposed costs (~$435 and ~$376 per month on average for living-away and home-living patients respectively [4]), but also makes this experience more accessible through a more seamless and personal process.

1.2. Problem Statement

Based on a real case study, this research aims to develop and discuss a novel operational strategy for a tailored on-demand transportations system to improve the breast cancer treatment process. Since 2018, we partnered with a major non profit organization, Quebec Breast Cancer Foundation (Ruban Rose), as part of their research and development program for the same purpose. On a high level, the main focus area of this particular project is to reduce the barrier of transportation for breast cancer patients for receiving therapy and those barriers, based on the foundations previously conducted market research and as our literature review confirms, have been defined as economical and accessibility barriers. In order to tackle those barriers, we focused broadly on three main areas–minimizing patient out of pocket costs during treatment and logistic barriers, while ensuring required health and safety conditions are maintained to make sure the service is tailored to the specific needs of this patient segment, among other services that are already out there.

There are a range of existing business models to choose for this purpose. In the following lines, we identified a list of potential models and will then highlight the model we will be considering for this project and the reasons behind that. Today, when it comes to transportation, there is a range of potential solutions available in order to accommodate different customer segments. Operational models are made subsequently differently. At the time this research was done, some available examples within the region include the following:

- Local carpooling services (e.g. Netlift)
- On-demand transportation services (e.g. Uber)
- Volunteer based operating models
- Public transportation system
- Ride sharing models

We had to choose the operating model that is an appropriate balance between the client's capabilities and also, being effective enough to tackle the problem and be able answer to the unique problems of the patient population. Based on the client's capabilities for the starting phase of this project, a volunteer based operating model was selected with the following attributes: The service would be 1 on 1 (1 driver per patient). Second, based on the types of patients and their treatment plans, it was decided that patients could book rides between a day to 6 hours in advance of the ride time. Therefore, ample time would be given to coordinate administrative operations prior to the ride, such as selecting an available driver and connecting them with the patient requesting the ride. We will talk about further assumptions in the Methodology section.

1.3. Thesis Contribution

In summary, the following dissertation presents a novel healthcare transportation strategy in the region of Quebec tailored to the unmet needs of a specific patient segment (breast cancer) in order to improve accessibility for that population and have a positive social and economic impact. This would be the initial phase of our case study client Ruban Rose's long-term project that will set out to use this strategy to develop a digital offering including a mobile application for this service.

1.4. Outline of the Thesis

In the next chapter we will study the previous work within this field and identify where the gaps are and where our research sits in this context. In the following chapters, we will introduce our methodology in detail with the main objective of increased accessibility in mind. We will introduce a diagnostic simulation model of business operations as our methodology to forecast variabilities in the system and how resources should be coordinated to respond to those variabilities in the best way possible, in the form of potential recommendations. We will then assess the feasibility and impact of each recommendation to best achieve the client's goals. We will finish by additional material used for our case study to hopefully inspire future researchers or business leaders to pursue similar actions to leave a positive social impact in their geographical region.

2. Literature Review

2.1 Introduction

Various mathematical and simulation models have been developed to model transportation systems throughout the world. In context of healthcare industry in Canada and specifically in the

Quebec region, however, further research and solution development are required to address various practical issues that have long been present. We will study current transportation models and methods used to study them. Then we dig deeper into the simulation method and how it has been used in literature for this context. We will finish with touching upon the pricing methods used in transportation for healthcare.

2.2 Transportation models

Transportation nourishes economic and social activity and is one of the most research topics in management and operations research [7]. There are various transportation models practiced in today's world and they are evolving to solve different transportation problems. Overall, it appears that transportation is moving towards decentralization allowing both servers and user to enjoy more flexibility and more control over all aspects such as timing, costs, locations, etc.

Transportation models are contextual in nature and were evolved in order to solve specific problems revolving around transportation. Berger et al [8] combine simulation and dynamic pricing to reach the optimum seat allocation mixture in order to maximize revenue. Friesz et al [9] use dynamic game theory modeling and dynamic pricing to determine the behavior of uncertain ad stochastic demand for urban freight development.

Another problem commonly faced in transportation is cost minimization. This is also relatable in our own case. Researchers look into what factors of costs are most important in a specific transportation problem. For instance, Zheng, Geroliminis 2015 [10], in a study to investigate the impact of parking limitations and costs on mobility seek out to identify novel parking policies with the goal of cost minimization. In another example, Melachrinoudis et al [11] provide a dial a ride (DAR) model with flexible time windows and apply it in the healthcare industry with the objective of minimizing cost and achieving the most time efficiency.

2.2.1 Ride Sharing

Ride sharing is a transportation model that has gained special popularity. Along with the decentralization trend that was visible in other industries as well, such as housing and TV broadcast, this also came along as a new trend that has so far, been growing in popularity because it allows in many cases for both servers and user to enjoy more flexibility and more control over all aspects such as timing, costs, locations, etc.

Ride sharing also helps with solving other transportation problems. For instance, Xu. H et el [12], discuss the relationship between ride sharing models and traffic congestion, explaining how the model helps reducing the congestion and improving the flow of urban mobility.

Having less cars on the ground, this also has environmental benefits. This is studied in a case study by Caulfield et al [13], where they conducted an experiment in Dublin to estimate the environmental benefits and reduction go greenhouse gas emissions and how it falls along the lines of future mobility and increased sustainability. Fagnant et al [14], confirms that by studying fleet size comparisons using simulations. Agatz et al [15] also certify how ride sharing transportation models provide significant societal and environmental benefits by reducing the number of cars needed for personal travel and improving utilization of seat space.

2.3 Transportation in healthcare industry

Transportation is one of the major elements in healthcare delivery. It is perhaps one the most important kinds of transportation as the nature of the job is within the process of healing or receiving treatment. Therefore, in case where the patient is involved in the transportation process, it requires the utmost care in patient experience to make sure the situation fits the needs. Those needs can be safety, reliable accessibility, manageable cost, speed of travel and many other features depending on the context.

Accessibility can be referred to as the larger umbrella definition covering components such as time flexibility, costs, etc. Melachrinoudis et al [11] study a dial-a-ride model with flexible time windows and its application to their case study, the CAB Health and Recovery Services, Inc., a non-profit organization, with the objective of minimizing transportation costs and clients' inconvenience time. They use Mathematical modeling to test and verify their findings. Using LINGO modeling language and using the Branch and Bound (B&B) algorithm they certify dial a ride model to be an useful and promising model of healthcare transportation.

In terms of safety, it may be required that healthcare transportation would have some differences with regular personal use. Sometimes it may be required for the patient to have access to emergency or relatable help en route. O'Neil et al [16] provide a plan to provide the most current and proper support to children with special transportation needs to be developed by the Individualized Education Program team, including the parent, school transportation director, and school nurse, in conjunction with physician orders and recommendations. Using Qualitative data, surveys, historical references, they Provided basis for a comprehensive guidance for implementation inclusive of staff training, provision of nurses or aides if needed, and establishment of a written emergency evacuation plan as well as an infection control program. Zhang Z. et al, study a practical patient transportation problem provided by Hong Kong Hospital Authority. Their methodology includes Mathematical modeling, memetic algorithm, a customized crossover operator in order to Model the problem as a multi-trip dial-a-ride problem (MTDARP), which requires designing several routes for each ambulance. Novel crossover operator customized and tailor fitted to the problem, use of real world data that were specifically used for this problem.

Speed of travel is not the most crucial factor in nonmedical healthcare transportation, and the other aspects become more important and seems to be not as well researched as other types of healthcare transportation. Wallace et al [18] Address the gap that is the access to non-emergency medical transportation, characteristics of the problem and the population that experiences those accessibility issues. They conduct National level demographic case study and surveys (U.S.) and provide recommendations to address issues focused on social benefits and quality of life. They link their findings across different demographics across the country and matching with appropriate opportunities to respond to these shortcomings. The research gap in non medical healthcare transportation lays the ground open for emergence of innovative solutions and technologies. For instance, Boulos et al [19] gives us an overview of GeoAI technologies (methods, tools and softwares), and their current and potential applications in several disciplines within public health, precision medicine, and Internet of Things-powered smart healthy cities.

They posit clear explanation of potential opportunities for GeoAI technologies to step into in different industries, especially healthcare research, linkages to applications in healthcare.

A common service in Canada is volunteer driver transportation assistance for people with cancer and is offering from various foundations for a variety of clientele such as elder adults, handicaps, cancer patients, and patients with other different pre existing conditions. Each of these groups have their own specific characteristics that affect coordination and scheduling of the services from the management point of view. For instance, cancer patients usually have regular appointments while elder adults might have occasional requests for commute to far less frequent doctor visits. According to our research [1], the average projected growth of senior population in Canada can be one of the need more attention. As much as this proves to be a crucial subject to improve, there appears to be a lack of research considering optimization methodologies for volunteer ride systems. Similarly, organization and usage data among rural volunteer driving programs do not appear to have been previously systematically collected and analyzed [21].

Another promising method in healthcare seems to be the Dial-A-Ride model. According to the literature [21], in customized transportation services where customers call in requests to a call center and the transportation is carried out from door to door is called Dial-A-Ride (DAR) service. This method of can be designed in various ways depending on the purpose and level of service. Two relatable and key components could be service level and operational costs. Due to their rather inexpensive nature, there are various applications for DAR services and this is particularly a reason it has gained attention in the non-profit sector and for the elderly and disabled people. Tailored transportation for seniors or injured passengers are among another examples. Another application is for healthcare including external and internal hospital transportation. According to the application, the structure of service provider organization and their vehicle type would vary. It also affects the objectives and constraints in simulation and optimization models. Ride and waiting time, pickup/delivery time-windows, and vehicle capacity are some of the considerable elements of these systems [22]. DAR systems often have multiple (and sometimes conflicting) goals, necessitating multi-criteria. An emerging application area is in public transportation. There are similarities between the volunteer ride system for patients and the usual DAR services while there are differences as well. In DAR systems considered in the literature usually, the vehicle is shared while in the volunteer-based system the priority is to service the clientele and sharing might come in the future potential consideration. DAR systems own the fleet of vehicles while in volunteer-based works the driver owns the vehicle. The existing work also does not have a considerable variety of availability of staff while it is a very important constraint for volunteer-based ones.

2.3.1 Regions

There seems to be a gap for sufficient studies in the area of nonmedical healthcare transportation in Canada. Specifically, in Quebec, we did not find related work and seeing as there is a significantly large transportation problem occurring, we became inspired to help contribute to solving this socioeconomical issue.

Among the rest of the world, there are numerous case studies in Asia and U.S. For instance, Zhang et al provided promising results for their healthcare transportation solution in Hong Kong.

In another example, Mao et al [20], measures special accessibility for healthcare in Florida, U.S. in order to provide guidance for policy makers to mitigate health inequity issues.

2.4 Simulation

Simulation methods such as system dynamics, discrete event simulation and agent-based modeling have been increasingly used to analyze healthcare systems and find solutions for problems around both the world and also in this area [23]. Simulation has been used to evaluate the important aspects and factors and for modeling of worst-case scenarios in DAR services [22, 23, 24, 25, 26]. The purpose of simulation might not be necessarily finding exact values for the variables, but rather showing the parameters that have a significant effect on KPIs, the way they affect the process, and providing a combination of what-if scenarios. For example [21] studied the trade-off between customer service level (waiting times, maximum allowed ride times or deviations from desired departure and arrival times) and vehicle costs in the scheduling and assigning time windows. They considered the time window of pick-up at the exact requested time and another one while the driver makes some delay to share a vehicle with another customer requested service from a nearby area. They concluded that before making any changes in scheduling policies, the service level or cost of customer should be analyzed to not be decreased drastically.

Simulation is a useful tool to help decision-makers by providing various scenarios and analysis. Nevertheless, it does not necessarily provide the optimum solution. The objective of the problem depends on the application. The basic mathematic model provided by [27] has formed a basic and expanded by some other researchers in their models. According to [28] in the optimization models for DAR problem typically the features such as vehicle capacity, ride time, route duration, and selective visits are considered. Other elements include the number of vehicles used, the number of objective functions considered, and numbers of trips allowed in a] single day. In a survey of DAR problems [28], presented models are categorized into four groups according to the modeling methodology. Majority of models are static and deterministic [ex. 29,20] which is based on previous data and the uncertainty is not considered. Some static models also considered uncertainty like [31]. Much fewer studies modeled the problem as dynamic and deterministic [21] and fewer are considered uncertainty in dynamic models similar to [32].

2.5. Pricing

As we mentioned, one major factor in healthcare transportation accessibility is financial planning and pricing aspects. Although pricing is not covered as a part of the present thesis research, we felt this might become useful for future research. There are some budgets based on charity while the pricing and financial management is still an issue. The questions are if the hosting organizations were to charge the clients, how should they charge? – per ride or ask for an annual subscription fee. One method could be to charge the clients per ride and based on the characteristics such as distance. As an example, we noticed some researchers [33] proposed a dynamic pricing and optimization model to make an equilibrium between social impact and profit-maximization for the host organization. Based on the price quoted by the system, an arriving customer will join the queue if and only if the benefit is greater than the expected waiting cost. They also analyzed the effect of different strategies on the pricing equilibrium.

Another highly relatable method to model pricing is dynamic pricing. This is a demand-based approach that serves as solutions to equip businesses to optimize pricing by detecting and responding to changes in demand. The logic behind this has been the norm for most of human history as traditionally it was referred to as price negotiation. The two parties would negotiate on what the price would be by taking into account a number of factors affecting it, which is exactly what variable pricing does and how it is set. Throughout time, the basic logic still remained true and evolved to respond to the requirements of time. As retail industry expanded in the industrial revolution, business owners were facing challenges with scaling the traditional haggling system over the price of each product. One could argue that economies of scale caused corporations to think of a time efficient system to set prices. That led to the invention of price tag; a fixed price for everyone [5], with the idea behind as being fair to all regardless of wealth and smoothing their retail experience by being time and cost efficient in the back end for the corporation. Of course, one thing this approach did not consider among many others, was the variability of demand. Although, what was interesting was this fixed price approach would go on to rule the retail business for many years. Dynamic pricing as we know it today was only re-introduced during the 1980s with the help of technological advances, which makes sense since it would not have been possible to deploy without having access to strong data processing tools used today without much hassle.

The approach was created with a mission to empower firms to grow revenue without sacrificing customers' loyalty and without giving up control of pricing strategy. By enabling companies to develop their own customized solutions that fit their market position dynamic prices is flexible enough to respect the limitations of a business, allowing for ample customization to fit specific objectives and business characteristics in high detail [34].

Although, it should be mentioned that this technique is highly proprietary and works best if certain conditions hold.

2.5.1 Fixed Pricing vs Dynamic Pricing

More often than not, in real life situations, the demand level for a product or service varies throughout time. Consumer behavior, economic changes and technological advances are to name a few reasons. Fixed pricing, as the name suggests, us keeping the price of an attraction fixed throughout a certain time. Although this approach has shown good responses in some real life cases (some commodities), essentially, that is equivalent to some-what ignoring the demand changes in the course of time all together [34]. Dygonex, a pricing firm descirbes this situation as in this case, "the pricing would not be "demand-based" and is merely a product of taking into account the costs that went through to create that attraction and possibly an initial analysis of the market at the time this price was being set." The point being, once the business is facing a relatively high variability in demand, naturally, there will be periods of lower demand where the value of the product/service produced are not regarded by the market's eyes quite as high as in other periods or at least not as much as the corporate initially intended it to be. Likewise, on the flip side, there could also be periods in which the demand will be higher, and the value of the product/service will be regarded higher than other times, i.e. the product/service is in high demand. In both of the mentioned situation, charging a single flat price could mean leaving a huge amount of possible revenues on the table.

One might argue that the solution to such an issue would be to identify a few periods in which we expect the demand to be higher or lower than usual and charge accordingly with a discount or surge. You might have witnessed examples of this approach in local bars or restaurants putting up discounted offers for certain days of the week (ex. Taco Tuesday discounts) or certain hours of the day (ex. Happy Hour). However, we will discuss in the following section in detail how these discount programs alone would not be able to capture the full potential to respond to high or low demand periods in cases where the demand in more variable and the stakes are higher for the corporation.

3. Solution Approach

Let us remind ourselves once again of the problem we are setting out to find a solution for. This research aims to evaluate various patient transportation operational coordinations and seeks out for techniques to optimize and/or refine those operations for both sides of the equation; the patients and the serving organizations. By "optimize", we mean to understand and identify the best operational strategies and coordination of resources as the different variabilities occur throughout the system. And by "best" we mean the highest impact, highest feasibility solutions for the current environment.

As for the overall research methodology structure, the overall solution roadmap of this project was created around answering the following three questions:

1. **What should the overall transportation process look like?**
2. **How to ensure it works as the environment evolves?**

3. **How can we implement this strategy and what risks should we consider?**

Let us go through each of these buckets and explain what they mean for this project and how we went through them.

To answer the first question, the overall transportation system, we will introduce supply chain process maps for ERP (Enterprise Resource Management), keeping in mind that they were designed in a way to be used by the future developers for continuing phases of the project. To answer the second question, how to test and make sure the process can work, with the main objective of increased accessibility in mind, we will introduce a diagnostic simulation model of such business operations to forecast variabilities in the system. By doing so, we will make an effort to answer the third question, how the client's resources should be coordinated to respond to those variabilities in the best way possible, in the form of potential recommendations. We will then assess the feasibility and impact of each recommendation to best achieve the client's goals. It is noteworthy to mention this research acts as the infant stage of a long term project. Therefore, answering the third question on implementation issues requires more information on the clients capabilities and more trial and testing over time, and counts as an unavoidable limitation at this stage of this project and the present research. That being said, we tried our best to paint a picture for the client through testing a wide range of variabilities and resource patterns, along with interviewing executives who had run similar initiatives within the region of Quebec.

Now that we know the overall road map taken for the solution approach, we present below (Figure 1) a general scope of the process. This will allow us to gain an understanding of the simulation model in a simplified manner, understanding only the main steps to be taken throughout a typical transportation journey.

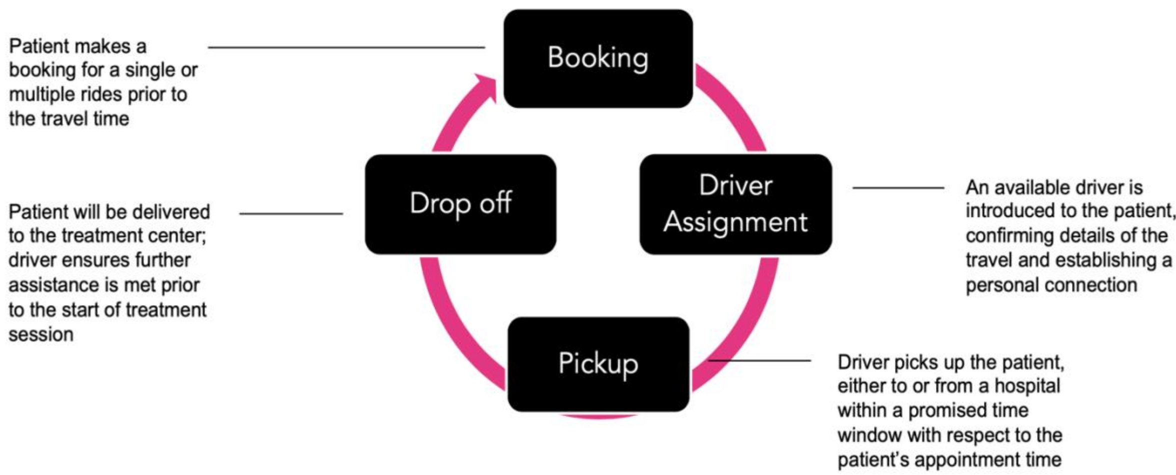


Figure 1 – High level scope of identified transportation process

In order to understand the figure, let us explain the process briefly and why we came to choose this among other alternatives. First, in order to answer the question of why we came to design such process, let us remind ourselves once again of the problem statement. As mentioned in that section, we researched and proposed a range of tried and tested operational models available in the region (including but not limited to ride sharing, public transportation, etc.). We had to choose the operating model that is an appropriate balance between the client's capabilities and also, being effective enough to tackle the problem and be able answer to the unique problems of the patient population. Based on the client's capabilities for the starting phase of this project, a volunteer based operating model was selected with the following attributes: the service would be

1 on 1 (1 driver per patient). Second, based on the types of patients and their treatment plans, it was decided that patients could book rides between a day to 6 hours in advance of the ride time.

In short, the methodology of this project is to create a simulation model to model the system and test possible scenarios. The first step is to gather data about the system. Majority of simulation models imitate a real existing situation. In this case, the system (volunteer ride service to breast cancer patients) is not implemented yet. However, information of clienteles, their addresses, and their treatment destination can be extracted. Information about potential volunteer drivers can be assumed based on assumptions from literature and interviews with industry best practices and benchmark with other operating systems. Various numbers of volunteers and their related attributes can be assumed, tested and analyzed. Based on the results, decision-makers would be able to anticipate the outcomes and effects of each combination. After creation of the model, the next steps are model verification and validation. Verification can be achieved by correcting any syntax error in programming and testing the model in various situations. Validation could be achieved by comparing the results of the model with a sample that contains all the details of the system. Moreover, the model can be tested with an existing close system. After assuring the validation, various scenarios would be tested.

In the following section, we dig deeper in the process model, introducing the generic model used to create the diagnostic operational simulation model which will be rich in more detailed than the process we just introduced and then introduce the input parameters for the model.

3.1. Input Modeling & Scope

In this section we will study the simulation model deeper, explaining the input variables and parameters. First, starting with a more detailed look of the simulation model. Figure 2 shows a generic version of the previously introduced model in more detail. The process works in the same main steps that we explained previously in figure 1 along with some added features and inputs that will be the topic of this section.

These parameters were deemed relevant according to the needs of the needs of the client within the space of breast cancer in Quebec along with what we found out to be critical in the literature review and market research. Let us address the parameters used as follows:

- **Type of booking:**
    - Scheduled: refers to patients who would be more interested to book their trip in advanced (at least a day prior)
    - On-the-spot: refers to patients who would need to be served on the same day

- **Type of patients:**
    - Radiotherapy: will typically need more than one regular bookings in a given week
    - Chemotherapy: will typically need 1-2 bookings in a given week

- **Type of service:**

  It was decided for to run the service initially as a one-on-one serving type. Meaning that 1 driver will be connected to 1 patient for each request, as opposed to a driver picking up multiple patient at a time. The reasons behind this decision were as follows:

1. It would fit the client's capabilities at the initial phase. Setting up a ride sharing system poses heavier coordination weight on the hosting organization and the client that we did the project with did not intend to make such an investment at least in the earliest phases.

2. There are health limitations toward this specific demographic at this specific time for the foreseeable future. The breast cancer population typically require some degree of physical and/or mental health sensitivity. Specifically, at a time of COVID this becomes even more critical to serve them with the utmost care and make sure the process runs as smooth as possible, cutting away any extra delays or bottlenecks, as it was the very intention of this project which would differentiate it from existing transportation models.

Also, in terms of timing, with respect to the difference between the types of patients and how the treatment plans and need for transportation would differ according to that, the client's executive team decided they will be able to handle booking requests at least 6 hours in advance for Chemotherapy patients and at least 1 day in advance for Radiotherapy patients to the day of travel. This decision was incorporated in the simulation to test for the extreme conditions and study the results.

- **Drivers:**

As explained above, due to the client's initial investment decisions and the intended type of service, it was decided for the service to be volunteer run at this stage. Meaning that drivers would be volunteers for specific locations at the start of this project which would be in line with the client's ability to acquire a sufficient number of them. The sufficient number to run the system would obviously depend on how many patients are to be served in a given day and is something that we tested for different scenarios in the next sections. Based on the interviews we held with industry experts and firms who had done similar volunteer run projects in Quebec, we decided to give every volunteer one ride job per day.

- **Simulation Method & Strategy:**

  We developed a diagnostic discrete event simulation using AnyLogic simulation software in order to model the operations and help with the strategic decision making down the line. The reasons behind choosing that type of simulation was made because it would fit the ultimate diagnostic goals we had in mind better, as opposed to the other relevant types of simulations because. For instance, we did not have an extensive amount of agent individual decision making in this business model and almost everything will go on as a chain of procedures in advance. If any step fails, the system either iterates to redo the step or stops for that agent completely. We also decided to use AnyLogic as it is one the most powerful simulation tools on the market right now and has proven time and again to provide accurate and reliable results for such purposes.

  The simulation is based on a set number of scenarios to be tested, all agreed upon and discussed with the client executives, in order to paint a picture of how such operational model would behave as the environment around it evolves, and as variabilities affect it.

We defined 4 main buckets of simulation that portray the key needs of the client, explained with detail later on in the next section.

- **Bookings:**

  In order to simplify the process as much as possible for the patient and make similar to the current existing type of bookings they already are familiar with, we decided to create bookings on a time slot basis. Basically, patients will be promised a time window to be served within, according to their own schedule and how early they will want to be at the treatment center. The reason for this is very important to understand first how patients want to be served, then come up with the plan to best serve them, as was the main goal of this research. We noticed through interviews with the client and literature review that breast cancer treatment transportation consists of at times a stressful mental state for the patient, causing them to try to make sure no other source of stress is present, for example, being late to the appointment. Therefore, a good number of these patients actually try to eliminate that by being a bit early to the appointment, while some don't. In choosing a timeslot-based booking model, wanted to respect that flexibility by letting the patient choose a timeslot that is appropriate for them according to their appointment with their cancer center. Now in a real world condition, there may be delays causing a driver not to reach a patient in time. Regardless of how large of a threshold that should be (discussed in a specific scenario), based on the client data, we found out that 40% of patients would agree to be picked up at a later time than their initial pick up time expectation, and we incorporated that through the simulation. The remaining 60% are modeled to reject and will therefore exit the model upon that situation.

Hours of operation were set at 7:30 AM through 5:30 PM where most appointments usually take place within Quebec. Length of each timeslot was set at 90 minutes in the base model, happening throughout the day every 30 minutes. Length of timeslot was calculated as follows. While of course this is not constant, we wanted to gain an understanding of how long every ride should take on average. This depends on a lot of things, but two key variables is the average distance to be traveled and the speed at which the travel is taking place. Seeing as this service was expected to serve the Island of Montreal, we aimed to calculate for that region taking into account a central driver dispatcher in downtown, patients randomly scattered throughout the island (collectively, and separately tested for each side of the island, Montreal North, South, and center), and an expected number of cancer treatment centers within the island and Laval and Longueil (as expected from the client). Now as we mentioned, there are other variables affecting how long it takes to travel to such areas, one being traffic level, so we took that into consideration and reduced speed travel to ~30 KM/Hour on average. Using mapping tools of Google and Microsoft Excel, we iteratively calculated such scenario for 15000 times, and reach 90 minutes on average. Again, since this was only an average and that we noticed in a real world condition,1 there may be other variables affecting this, such as time of day and the traffic or any other barriers that are present at some specific times of day and not present in others, we took this number as a base model and created a simulation scenario only around that, which will be explained in the following section along with other scenarios.

In order to make sure patients will not experience delays, we had to make sure drivers will get to them in time, as promised in the booking timeslot. Therefore, we defined driver shifts 30 minutes longer than the timeslot, 2 hours. This was tested in Anylogic within the validation phase of the simulation for 5000 patients and proved to be the least amount of time a driver has to start driving earlier than the timeslot in order to make it in time within the Island of Montreal region, in order to be 100% successful. Therefore, driver shifts were defined in 2-hour slots. Also seeing as they are volunteers, we did want to consider that to be attractive for numerous profiles in order to want to take part in this project. Making a volunteer shift too long for a working-class profile would be making it difficult to attract them. Making it too short would risk not being fully utilized in certain hours were patient demands were not as high. 2-hour shifts proved to respond well to both situations.

In this section we explained the assumptions and input parameters used to create and validate the simulation model to give logical results. In the following section we study the simulation model deeper and how it was tested.

3.2. Simulation Model Design

In this chapter we will further investigate the simulation model and explain how it was used. After that we introduce each scenario and why they were deemed critical, and also what each of them will test. Then we will finish off with the simulation results for the baseline scenario which was used as a point of reference to compare with the results of each scenario.

An overall scheme of the model is presented once again in the figure below. This is the generic process map that we designed in order to create an equivalent model in Anylogic, with the idea in mind that it would be able to serve all scenarios, with minimal change. In Figure 3 you can see a snapshot of the same model in Anylogic language.

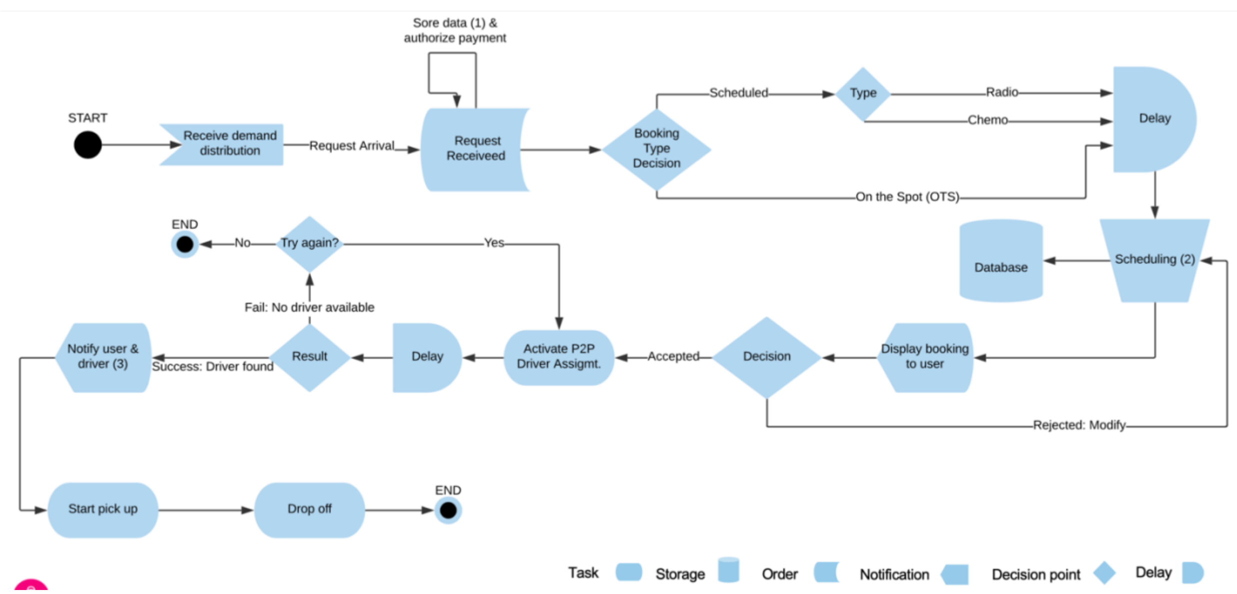


Figure 2 – Generic simulation model process map

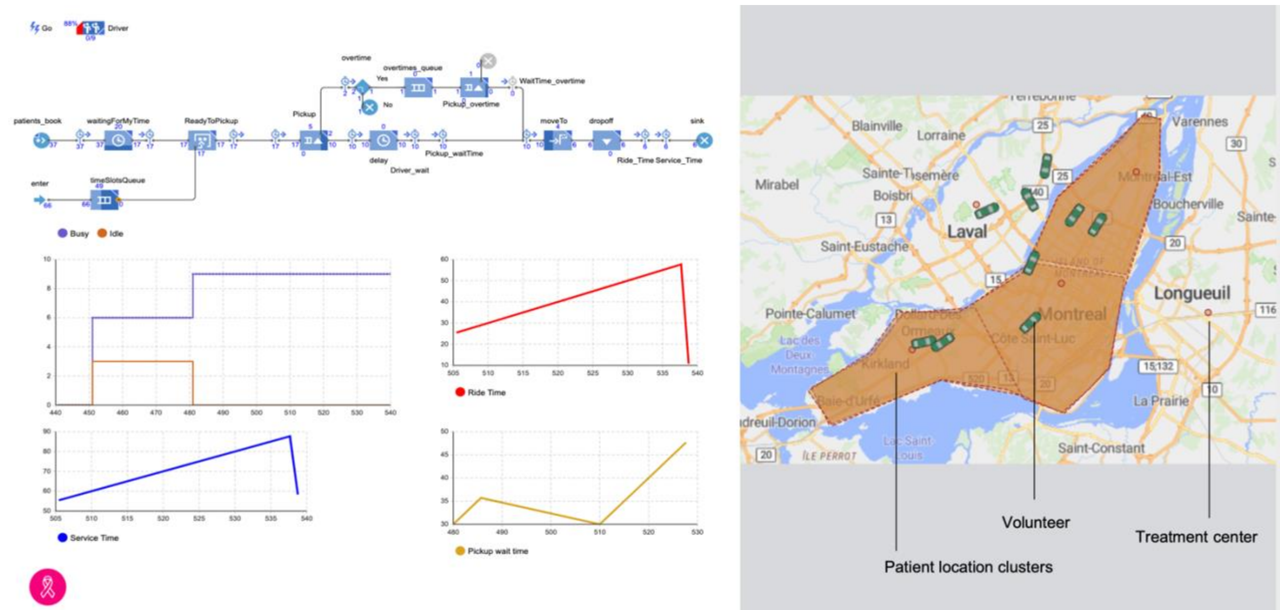


Figure 3 – Simulation model in Anylogic software space

As we mentioned, the aim of the simulation is to create preliminary guidelines as to how the model can be created in real life, and how the change of the internal or external variables will result the outcome. For that we have to first define what we mean by “outcome” and then what are the key variables, and how should they be varied. Once we find out of the overall situation, we will go ahead with testing the simulation for the baseline scenario in order to use as a point of reference for every other scenario and drive useful insights.

First, let us start by defining the desired outcome of the simulation. From the point of view of an executive, the key objectives behind a simulation of business operations is seeing how important performance factors will look like, the desired output. And then there are two questions that comes to mind,

1. What structure of inputs will give the system the desired output?

2. How does change in those inputs affect the output, and what can we do to make sure the output remains desirable?

Answering these two core questions is the fundamental reason behind the simulation, along with the fact that this service within this region was not done before. So, no valid data that would be applicable to this situation was available, hence we turned into the simulation method.

Now, what is the output? After studying relevant literature and interviewing the client executives and industry best practices within this region, we came up with a set of key performance indicators (KPI) that will directly impact the overall decision criteria. The decision criteria are made up of the most important set of factors impacting key stakeholders in this system, from patients, to drivers, to the hosting organization. They are; resource constraint, time horizon to implement changes, patient impact and appreciation. The KPIs we chose that will directly affect the decision criteria break up into two main categories are listed and defined as follows:

1. Time KPIs

- **Service time** = Drop off time – slot start time

  How long will the service take for the patient, from the start time of their booked timeslot to the time they are actually dropped off safely at their destination.

- **Ride time** = Drop off time – Pick up time

  The duration of the ride for the patient

- **Pick up wait time** = Pick up – Slot start time

  The duration a patient has to wait to be picked up, starting from the slot start time

- **Driver wait time:** in case a driver reaches early to the patient, how they have to wait for the patient (assumed patients are ready at their booked slot start time)

- **Driver ride time:** Duration of the work for the driver, from the time they start driving to pick up to the time they drop off the patient

2. Service level KPIs:

- **Total patients served**
- **Total patients served within promised time limit**
- **Capacity utilization:** Real time capacity being defined as number of drivers available multiplied by the number of hours they are expected to work.
- **Number of delayed patients**
- **Number of patient refusals:** Number of patients who will choose to cancel the service in case the pick up wait time passes their expected pick up time window.

Now that we know the output KPIs we will introduce a baseline scenario that will be used a point of comparison to the upcoming scenarios to ultimately help us draw insights from the scenarios. From this point forward, the data is generated to simulate a realistic situation. We were not able to find sufficient existing data to support our simulation thus we generated the data using the interviews we conducted with industry experts and literature review. The outline parameters of the base level scenario is shown below.

Base level scenario

Parameters	Values
• Booking rate	~5 / hour
• Patient distribution	Poisson, peaking at ~8 AM
• Slots available	54
• No. of patients	20
• Choice of slot	Random
• Travel speed	30 km/hour
• Expected avg service time	1.4 hour (84m)
• Patient location	Entire greater Montreal area
• Driver distribution	Level 3

Figure 4 – Baseline scenario parameters

Let us explain how each value parameter was chosen. Booking rate was generated as the average volume of requests for treatment visits in the patient data at Ruban Rose, taking into account the current volume of their patients who the expected would want to opt in for this service. Patient distribution was also set as a Poisson distribution peaking at 8 am due to the way cancer treatment centers operate in Quebec. We started with 54 slots available per day as we calculated the hours of operations to be from 7:30 AM to around 5 PM, judging again by the way hours of treatment work for cancer treatment centers and to fit the expected profile of working volunteers, making sure we can attract as most volunteers as we can. We started with 20 patients because we were identified by the client this will be the amount that will fall in balance with how many patients they could attract to use this service initially per day, and also what their capacity can handle. Choice of slot has been identified as random to give the most flexibility to patients to pick the desired timeslot, making the simulation more realistic. Travel speed was set as 30 KM/hour, lower than usual travel speed within the city in order to take into account the speed limiting factors such as construction and traffic. Expected average service time was set as a baseline level of 84 minutes, as we mentioned in the previous section, this was set taking into account the amount of time it will take on average for a patient to go to one of the cancer treatment centers around Montreal, with the speed that we set. The distance was set on average 20 KM, using the data we gathered from literature [3], which was confirmed by the client and their current data. Patient location was set as Greater Montreal area in general, randomly scattered, as this will be where the client will start the service. In terms of driver distribution, we generated different levels of distributions, based on the profile of volunteers we gathered from the volunteers industry practices within this region [3]. We generated one of the most fitting distributions to the realistic situation of current volunteers in Quebec as we identified from our findings which we named level 3. Details of the levels will follow in Figure 8 and in the verification section.

Now we will show the simulation output values, which will be the KPIs that we introduced in

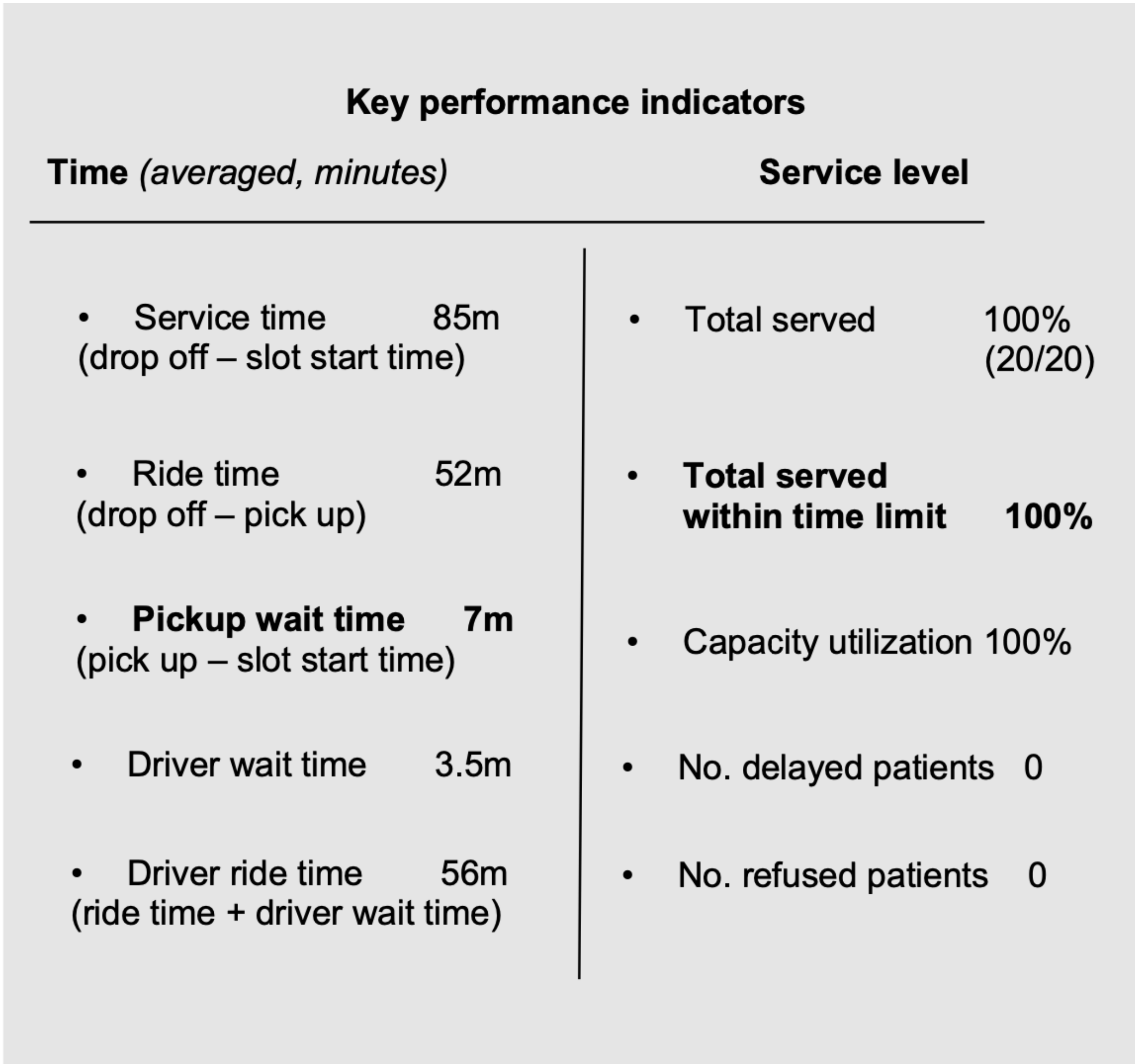


Figure 5 – Output of baseline scenario

The numbers for time KPIs are averages. We will show ranges and standard deviations in appendix section. As is visible we can see the pick up wait time is manageable and within standards of today's on demand transportation services, and also everyone was served with no delays. That is due to two main reasons, one the demand was within expected capacity and second, in our validation, we made sure of reducing the risks of drivers reaching patients later than the promised time window as much as possible. We achieved that by extending the driver's shifts by 30 minutes more than the timeslot they would be serving at. Having that as a unified recommendation results in all drivers being able to start driving to the patients a bit earlier in order to take into account the reduced speed that may be caused by various factors en route, e.g. traffic, construction, etc. This will also have another benefit and that is enabling drivers to fill in for each other, because each one of them will be available for 30 minutes longer than the rate the slots will be filling in at. This will result in increasing driver utilization in potential situations when if a driver may not be matched with a patient within 1.5 hours, thus improving the service level KPIs. This was one of our main recommendations to the client as well, to make it mandatory for driver shifts to be slightly extended over the timeslots.

Next we finally study the scenarios and what they will test, and how that matters in order to impact the mentioned KPIs. Scenarios test four key parts of this system that could change within time in a real life situation. Our hypothesis was to see the impact of their variations on the major KPIs we just mentioned, to measure their impact and propose recommendations for running this operation in the present and future. Variations will broadly test 2 situations, one having less extensive load on the system than the base level scenario, and the other one pushing more load on the system. We are hopeful our insights will be helpful for future researchers and business strategists in following similar efforts within transportation services.

List of Scenarios:

1. Demand

2. Capacity

3. Pick up time window

4. Timeslot Length

We will explain each scenario in the following points:

1. Demand

We will test how changes in patient demand characteristics impact our service level and time KPIs. We will test changes in volume of patient demand, locations they come from, and the distribution at which they enter the system, throughout the cycle of the simulation. We hope this scenario would help ease future decision makings by providing senior management with insights on the effect of an increased daily booking requests on the organization's operations. The detailed values for demand levels are as follows, having the baseline levels as a reference.

- Location (see Figure 7)
  - Montreal East
  - Montreal West
  - Centreville

- Distribution

  - Single mode Poisson, peaking at ~8 AM
  - Bi modal Poisson, peaking both at ~8 AM & ~1 PM

- Volume
  - Low capacity, 10 patients per day
  - High capacity, 50 patients per day

2. System Capacity

As we mentioned there are a number of components forming up capacity. Volume, time worked and distributions. We are not testing variations in time worked, which will translate into the length of driver shifts due to, as we mentioned, our findings from industry experts experiences with volunteers working in transportation in the region of Quebec. We will test the other two components, that are changes in volume and distribution of drivers in each day. Our goal would be to see how they will impact our KPIs, specially time KPIs such as driver response rates and patient wait times that are critical in this context.

- Volume
  - Low capacity, 10 drivers per day
  - High capacity, 40 drivers per day
- Distribution (see Figure 8)
  - Level 1
  - Level 2

- Level 3

3. Pick up time window

We will analyze changes in patient time sensitivities, specifically for pick up, which will be critical in determining the success level of such transportation services, and is most in control. Once the patient is picked up, there is not much in control of the driver in terms of timing of drop off, as long as they do their best in setting a balance between driving safely and with an acceptable speed. Our goal for this scenario is to find optimized time windows we expect and propose to patients in advance of the ride in order to maintain acceptable service levels (whatever level they may be, based on a transportation provider preferences).

- Time sensitive profile: 30 min
- 1 hour
- 1.5 hour (or equal to timeslot length)

4. Timeslot length

We tested changes in length of expected service times, in order to make sure we propose the right amount of timeslots to the patients for booking. This is the backbone of our system, since this will affect everything else: such as how long a service should take, and how should every driver shift be set accordingly. The reason we decide to make such scenario was in a response to the location scenario. In reality service times would be different naturally according to the locations and distances. Therefore, we expect to see different regions of Montreal area to have different expected service times, and therefore timeslot lengths. Our goal in this scenario is to coordinate guidelines to choose the best estimations of service times under different conditions, one of the most important ones being the patient locations.

- 1.5 hour (normal)
- 1 hour (short)

We should mention again that all the numeric values for scenarios were generated in comparison to the referenced base level scenario to see how the system would react in heavier and more flexible conditions. In the following sections we will verify some of the parameters and explain the results of our tests.

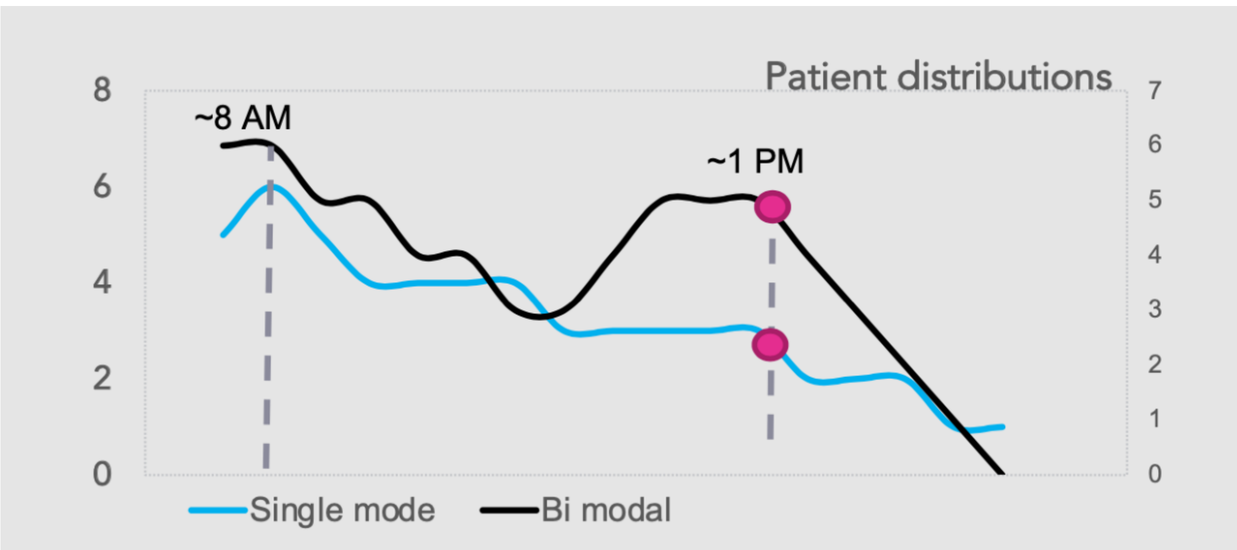


Figure 6 – Generated patient distributions (based on patient data observations)

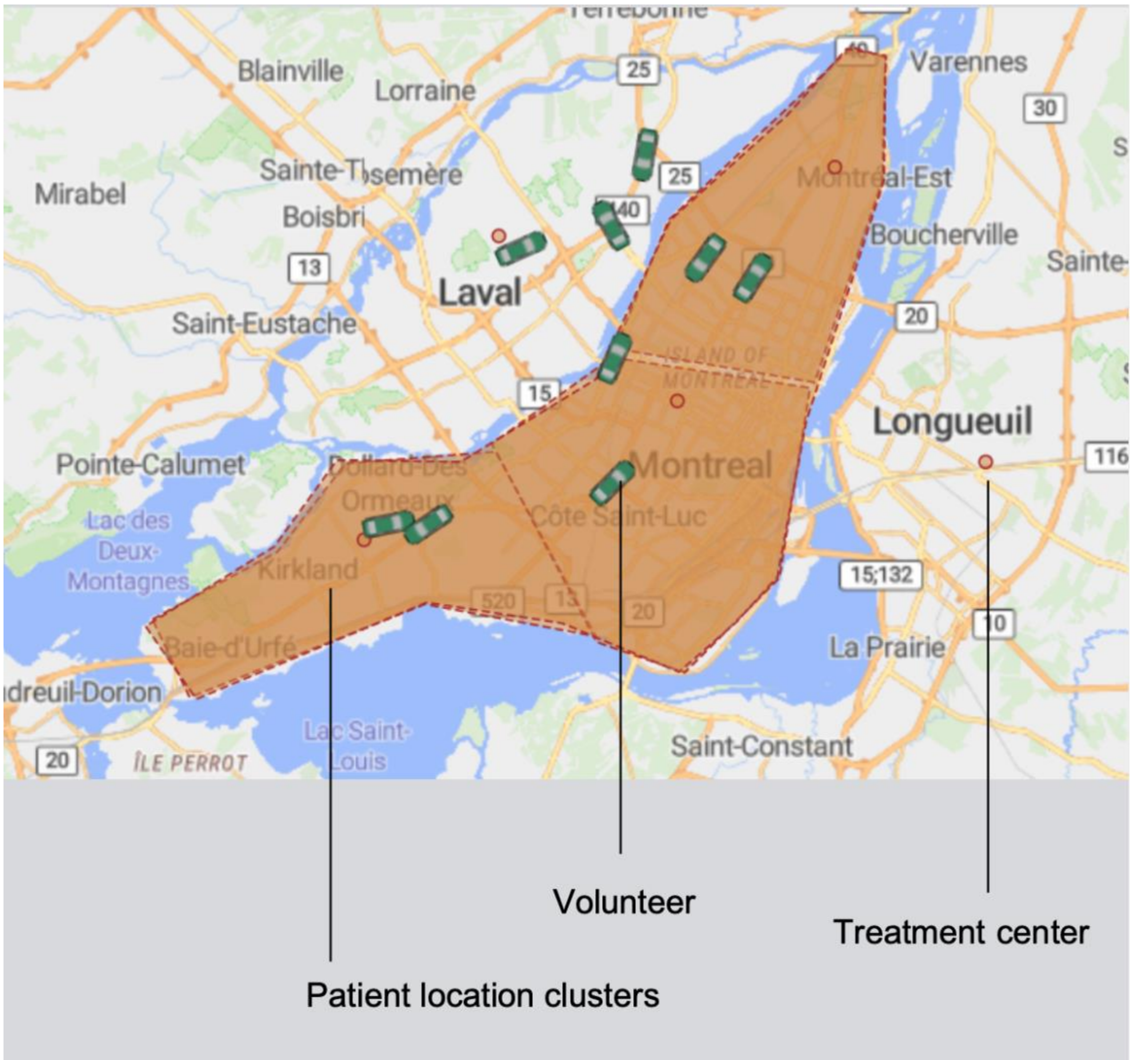


Figure 7 – Simulation map, animation screenshot, introducing legends

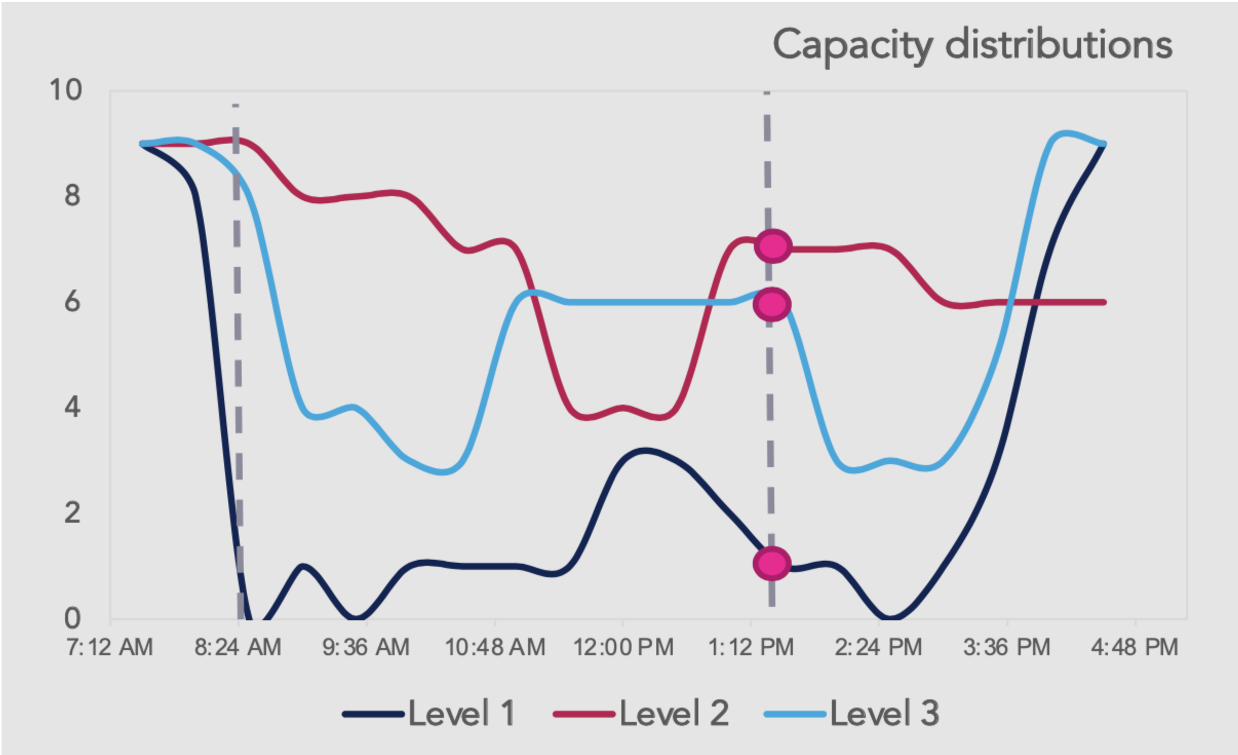


Figure 8 – Proposed capacity distributions across time

3.2.1. Verification & Validation

In the previous section, we provided a description of the paramters used and how they were validated to maintain realistic, relevant and logical. Here we will provide the list of the parameters we validated and how they were validated.

Service time / timeslot length: As mentioned, there are other variables affecting how long it takes to travel to such areas, one being traffic level, so we took that into consideration and reduced speed travel to ~30 KM/Hour on average. Using mapping tools of Google and Microsoft Excel, we iteratively calculated such scenario for 15000 times, and reach 90 minutes on average. Again, since this was only an average and that we noticed in a real world condition,1 there may be other variables affecting this, such as time of day and the traffic or any other barriers that are present at some specific times of day and not present in others, we took this number as a base model and created a simulation scenario only around that, which will be explained in the following section along with other scenarios.

Number of patients: In the base level scenario, we started with 20 patients because we were identified by the client this will be the amount that will fall in balance with how many patients they could attract to use this service initially per day, and also what their capacity can handle. In order to consider other variations across time as the service grows, we tested a situation for almost double the amount (50 per day) and also, one for potential easier days (10 per day) to see how the organization has to coordinate its resources in both conditions, which may most likely happen more often than other values in between this range.

Demand distributions: We identified from our client patient information that the patient distribution would closely follow a Poisson distribution throughout the hours of 7:30 am to around 5 pm. The peak however would be variable but mostly happens either during the morning or at noon, then falling down for the rest of the evening. We matched that distribution with our proposed volumes. This however might not be entirely accurate for other regions or other treatments but according to our source of information, was correct.

Capacity distributions: We studied volunteer profiles from different non profits in Montreal and Quebec, and proposed 3 distributions to match different individual profiles to show how busy or available they would be depending on their free time. For instance, level 1 could fit a working class profile how would not be available for volunteer work during business hours. Level 2 would be a different profile, resembling the profile of a student or someone more flexible (students are one major population of volunteers in Canada) and level 3 would be another profile, a mixture of the two.

Hours of operation: We started with 54 slots available per day as we calculated the hours of operations to be from 7:30 AM to around 5 PM, judging again by the way hours of treatment work for cancer treatment centers in the Montreal area and to fit the expected profile of working volunteers, making sure we can attract as most volunteers as we can

Treatment centers (number and location): At the time this project was done, our client had or was in the process of setting up agreements to work with 5 treatment centers within the Montreal region, and asked to have one in each region as specified in figure (?).

Driver dispatcher (no, and location): At the time this project was done, our client had or was in the process of setting up agreements to work with one central third party driver dispatcher within the Montreal region, and asked to have one in each region as specified in figure (?).

Speed of travel: Travel speed was set as 30 KM/hour, lower than usual travel speed within the city in order to take into account the speed limiting factors such as construction and traffic.

Patient time sensitivity: In a survey identified by the client, we came to an understanding on what will be the most viable number on pick up time window, and we reached the number of 30 minutes. Also, based on the client data, we found out that 40% of patients would agree to be picked up at equally a later time than their initial pick up time expectation, and we incorporated that through the simulation.

Time of bookings: with respect to the difference between the types of patients and how the treatment plans and need for transportation would differ according to that, the client's executive team decided they will be able to handle booking requests at least 6 hours in advance for Chemotherapy patients and at least 1 day in advance for Radiotherapy patients to the day of travel. This decision was incorporated in the simulation to test for the extreme conditions and study the results.

3.3. Output Analysis

In this section we synthesize the outputs of the simulation model and the insights we gathered from the results of the scenarios. We will prioritize scenarios based on the impact they had on the set performance KPIs and talk about the most interesting results that led to our final recommendations and guidelines for managing such operations. The full details of all scenario results are presented in Appendix sections.

The two most impactful scenarios were related to demand (scenario 1) and pick up wait time (scenario 3). Let us dig deeper into each of them and explain our takeaways from the results.

A. Scenario 1.1.

Demand Location – Montreal East and West sections

These configurations gave highly similar results that can be talked about in a cluster. The greatest observations we saw for these regions was represented in service time and pick up wait time. Comparing to the base level scenario, average service time increased by 8% to 92 minutes and pick up wait time on average increase 43% with a range of 0 – 37 minutes. This means patient location greatly impacts our time KPIs and overall patient experience and we need to adjust either resources or system configurations accordingly. In terms of service level, results were not optimistic as well. We noticed 10% decrease in service level (90%) and in a sample size of 20 patients in a day, 2 patients were lost due to longer wait times than their expected wait time. Since increasing resources (drivers) to service patients would be cost extensive and the obvious solution, the key takeaway that we got from this section of the demand scenario was that expected duration of service should be adjusted based on area to prevent potential delays.

B. Scenario 1.2.

Demand Distribution – Bi modal demand distribution matched with level 3 capacity distribution

For this specific configuration we noticed interesting results that we deemed crucial for mentioning in order to make sure senior management is prepared to face potential delay risks. In terms of time KPIs, we noticed service time decreased by 14%, down to 73 minutes on average, and patient wait time increased by 10%, up to average 7.7 minutes, holding a range of 0-90 minutes. You can see that although the average is relatively low, the range can at times get increasingly higher. If we want to maintain high service levels we need to make sure we address such discrepancies as well.

In terms of service level KPIs, we noticed service level on average decreased by 5% (95%) and we lost 2 patients out of 20 in a typical day due to long delays in pick up. The key takeaway we got from this part of the simulation was that variabilities in patient arrival distribution require adjustments in capacity distribution mix in order to match the right distributions together and ensure timely matching of the two stakeholders.

B. Scenario 3.

Pick up wait time – 30-minute threshold

In this scenario we tried different patient time sensitivities because in reality possibly not every patient has the same expectations. In terms of time KPIs, we noticed that while service time and pick up wait time remained stable at respectively, 84 minutes and 7.7 minutes on average, pick up wait time stretched its range to 124 minutes in rare cases of overtime pick-ups (up by 148%).

This was alarming to us if the organization wants to set a value proposition to serve every patient. Also, in terms of service level KPIs, we saw negative results. Number of served patients fell by 30% from 100% base level, and number of delayed patients increased to 6 out of 20 comprising 30% of total daily commuters. The key takeaway that we got from this part of the simulation was that the estimated average patient pick up wait time, with current resources should be greater than 30 minutes if we are considering the entire Montreal island area.

Now that we explained the most critical and impactful scenarios, we will work to explain our key recommendations and guidelines to cover all the mentioned situations. It is noteworthy to mention while other scenarios also had changes to the KPIs, they were not as impactful (refer to Appendix for full result tables). Nonetheless, we will include their results in the guidelines that we set for future decision makings.

In order to improve the system results, there are numerous potential actions to take. Figure below charts some of those actions in terms of their potential impact versus their feasibility for the hosting corporation. The definitions of impact and feasibility can take many translations depending on the type of resources an organization will spend and the types of results they or the patients as clients, deem important. What we offered is only an example to what we thought would be some of the most important definitions for these two terms.

As we identified and matched the following actions with our client and industry experts, we found out that putting efforts into two parameters would have the most impact and would be most feasible for similar clients to our own. They are, adjusting time of pick up and communicating a realistic pick up time window to the patients, depending on what segment they come from. Let us walk our readers through both and explain what specific recommendations we came through for this project.

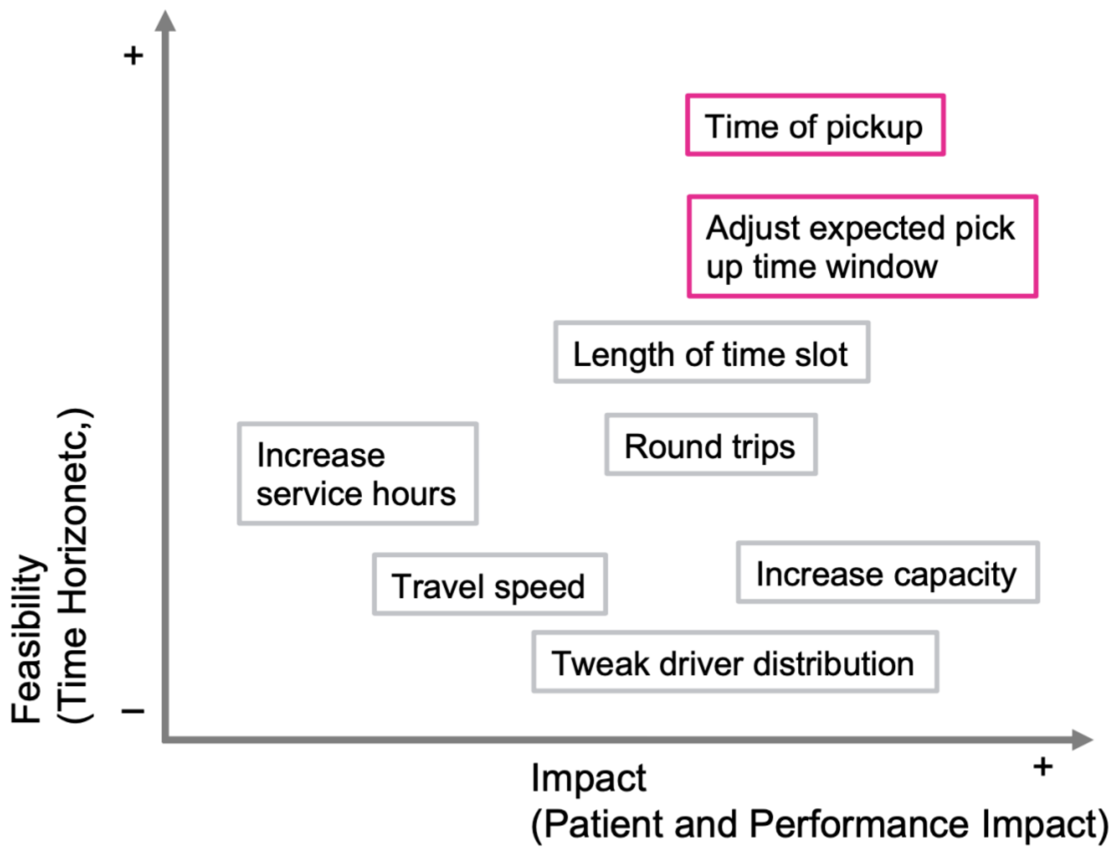


Figure 9 – Identified potential actions and parameters to improve performance

Our recommendations to improve the performance of such system based on the capabilities of our client for this project, and without considering obvious choices like increasing capacity, would be within two main buckets;

1. To urge all drivers to ensure pick up at the start of timeslots

2. To actively adjust the pick up time window

To explain the first one, in order to maintain consistent performance, this simple rule of ensuring pick ups are occurring at the beginning of timeslot as much as possible, if followed throughout the day will make a considerable difference. The reason for that follows within the lines that we previously mentioned: it makes more sense all the delay factors that are easily within control, before trying to change more difficult exterior delay factors that are mostly uncontrollable and sometimes even a surprise.

In order to explain the second recommendation, we noticed how different variabilities can cause patient delays. We think the organization should actively communicate tailored expected wait times at least with respect to the patients clustered geographical area prior to the time of the ride. That is if the system would be expected to operate with the current settings of limited volunteer resources. Our results show the following brackets to be promising and safe; 1-1.5 hour seems to be the safe zone for all regions within Montreal island without any delays. 30 minutes or less would risk ~25-30% of patients to be delayed and could increase wait times by ~x2.5 on average.

The two recommendations we mentioned are generalized, in the next steps we will consider them for more specific situations, taking into account more data we gathered from the simulations. The approximate outcome of such recommendations based on our calculations will result in service levels above 95%, pick up wait times less than 15 minutes and no delays in drop off.

3.4. Alternative Configurations

In this section we will take our simulation insights further to provide guidelines for future strategic decision making under different configurations. We came up with the following numbers (presented in the following page) by iterating variables as explained above in order to reach the desired outcome. Needless to say, the desired outcome is subjective to different business expectations but what we provide here can be easily adjusted to different needs.

Potential Situation	Suggested Course of Action	Expected Outcome
Patient distribution: single peaked (morning) **Volume:** 20-50 / day 55-70 / day	**Suggested driver distribution mix** 50% level 2, 50% level 1 60% level 2, 40% level 1	**>95% service level** **10m or less pick up wait time** **No delays in drop off**
Patient distribution: double peaked (morning & afternoon) **Volume:** 20-50 / day 55-70 / day	**Suggested driver distribution mix** 50% level 2, 50% level 1 60% level 2, 40% level 1	**>95% service level** **10m or less pick up wait time** **No delays in drop off**
Patient location cluster • Greater Montreal area • Centre & downtown area • Montreal East & Ouest area	**Suggested pick up time window** Use 1–1.5h window Use 1–0.5h window Use 1–1.5h window	**>95% service level** **15m or less pick up wait time** **No delays in drop off**

4. Limitations, Risks & Future Outlook

This project was the initiation phase of a larger projected expected to maintain for the next two years with our client. Therefore, we only set out to lay out the bedrock for future researchers to follow and improve. There are naturally some limitations to what we set out to solve. We will explain them by structuring them within 4 main components of that will be our sources of risks:

1. Drivers

Our main operators in this system were set to be volunteers doing one job per day according to our client's preferences. This will make the results more susceptible showing delay risks or lowering the response rates. The good news is our recommendations were suggested to a tighter situation which could make them more reliable in a real life situation were there are added sources of risks. Also, the data we used for driver distributions were generated by our own observations from similar volunteers within this region. We tried to make it more realistic by breaking them down into three different types to fit different volunteer profiles (working class, flexible, students, etc.) The accuracy of their detailed distribution is also a source of risk, but with the current simulation, it is very well adjustable. Hopefully that will be a way to mitigate this risk as we gather more confident data and feed it to the simulation. The future outlook for this section could show different coordination for drivers such as working more shifts per day, or doing multiple pick ups similar to current ride sharing business models. The location of drivers could in that case, also be decentralized and scattered across the city, as they will be self-employed.

2. Methodology

We chose to use simulation because this was a novel strategy that was not done before in this context in Quebec. We did not have reliable data to test this strategy with. Although we took the effort to minimize the risks of our results being inaccurate through testing different configurations and scenarios, along with choosing one of the best in the market simulation tools at the moment (Anylogic software) that chance still remains.

3. Patients

Patients will have more characteristics in real life and therefore, making more decisions individually. While we did try to consider the most common ones, like different expectations in windows of wait time, it is possible we did not take into account enough alternatives. Also, we did not consider patients changing their minds and making cancellations prior to the day of travel. Patients might also ask for the volunteer driver to do more than driving and perhaps help them with taking them outside their residence or folding a wheelchair before starting the pick up, or ask for a volunteer to wait at the treatment center for the return trip. This might take a few minutes and add to the service time. We did not consider this and assumed their impact will be negligible according to the patient profiles we currently saw from the client's data. But this may very well change in future.

4. Environment

There numerous external sources of risks in real life. We will mention a few that relate most to the choices we made and the context of our project. One of them could be the number of cancer treatment centers, we used 3 as per our client's preferences. Adding more or placing them in locations that are further away from the central driver dispatcher will undoubtedly add more delay risks for the patients. In that case it is recommended that the senior management work with more than one driver dispatcher or change their policies in how the drivers operate, for instance, using local volunteers without the need for a centralized dispatcher location. As mentioned there may very well be other external sources of risks such as uncontrollable risks of constructions in certain roads that will cause the drivers to take another route, heavier than calculated traffic, etc.

5. Case Study

Since August 2018, we partnered with a major non profit organization in Quebec, the Quebec Breast Cancer Foundation (Ruban Rose), as part of their research and development program for the same purpose that will continue for at least the next two years. We were on the start of the initiation phase at the time this research was conducted. On a high level, the main focus area of this particular project is to reduce the barrier of transportation for breast cancer patients for receiving therapy and those barriers, based on the foundations previously conducted market research and as our literature review confirms, have been defined as economical and accessibility barriers. In order to tackle those barriers, we focused broadly on three main areas–minimizing patient out of pocket costs during treatment and logistic barriers, while ensuring required health and safety conditions are maintained to make sure the service is tailored to the specific needs of this patient segment, among other services that are already out there.

The Quebec Breast Cancer Foundation (Ruban Rose), based in Montreal, is the only non-profit charitable organization dedicated to investments for the benefit of the province’s breast cancer patients in the region of Quebec. For over 25 years, they have been committed to defending the interests and well-being of people affected by breast cancer and their loved ones. The contribution is especially noteworthy in the area of medical and scientific advances. Also, they invest in innovation and cutting-edge research and in patient-support programs, ranging from prevention to cure [24]. Currently, one of Ruban Rose's main operation consists of supporting its clientele with allowances for their transportation costs. They are planning to implement a system of applying volunteer or paid drivers to service breast cancer patients. As the future phases of this project, they also consider offering managing the lodging services to the patients coming from other areas of the province who need accommodation. They believe that offering this service does not only provide transportation service but also some comfort of being accompanied by another human being who is willing to help.

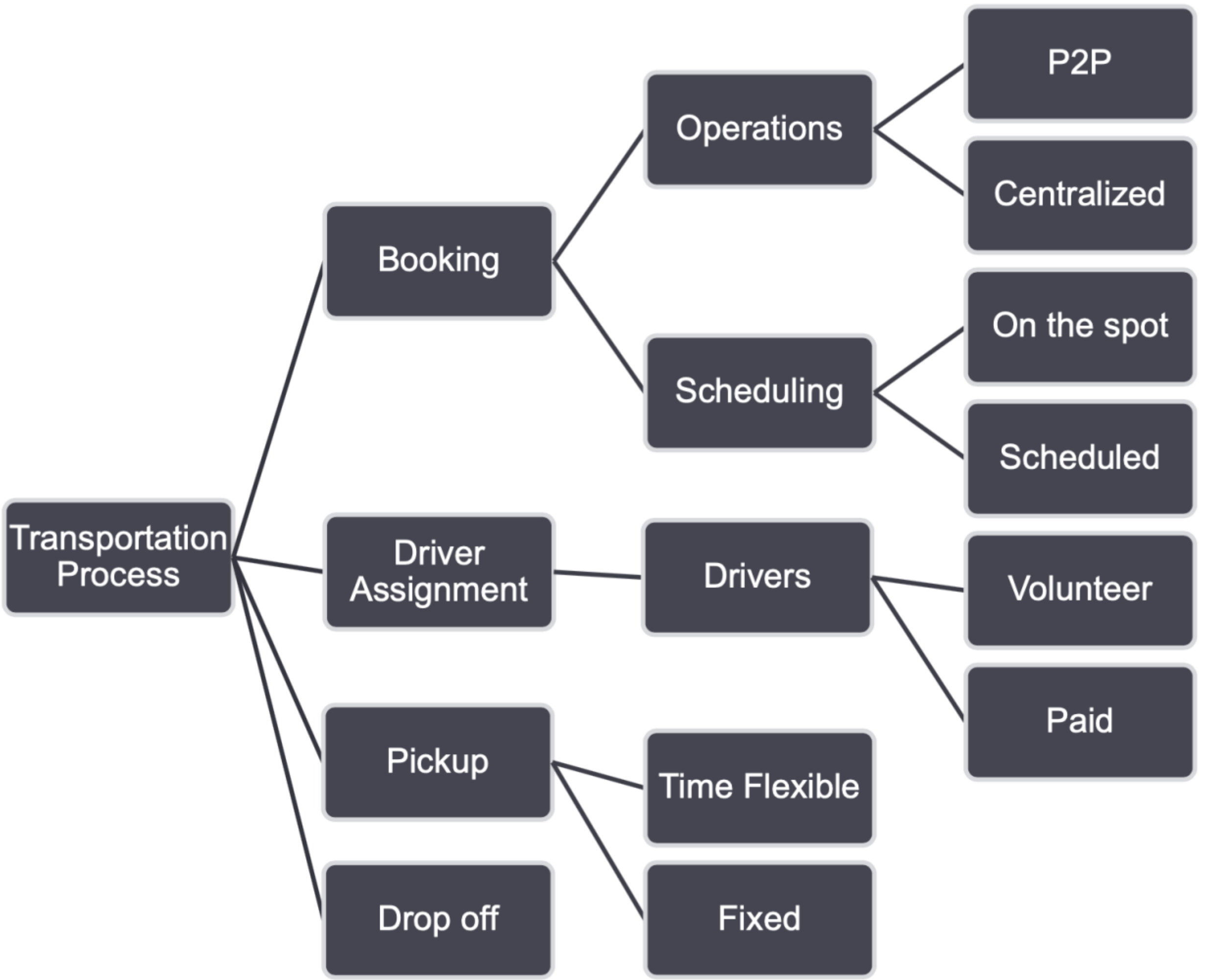


Figure 10 – Issue tree structure of proposed operations

Ruban Rose is interested in considering both strategic and operational issues before and during implementing the desired service. Issues such as pricing, capacity planning, scheduling, lodging, data management, service level and many other details. According to [21], the drive attribute data typically included: drive ID, volunteer ID, start time, volunteer hours, travel distance (client travel only), client ID(s), presence of companion/helper, origin/destination, stop purposes and number of stops (including whether they returned home), and other groups specific information (e.g., fee per ride). All these details should be taken into account at the operational level. Our proposed research aims to address the aforementioned issues in several collaborative projects and provide an integrated decision-making solution.

We also provided UML diagrams to chart process maps for making clear enterprise resource management (ERP) roadmaps for future steps of this service that include making a mobile application to allow patients to book their rides. (Figure 11)

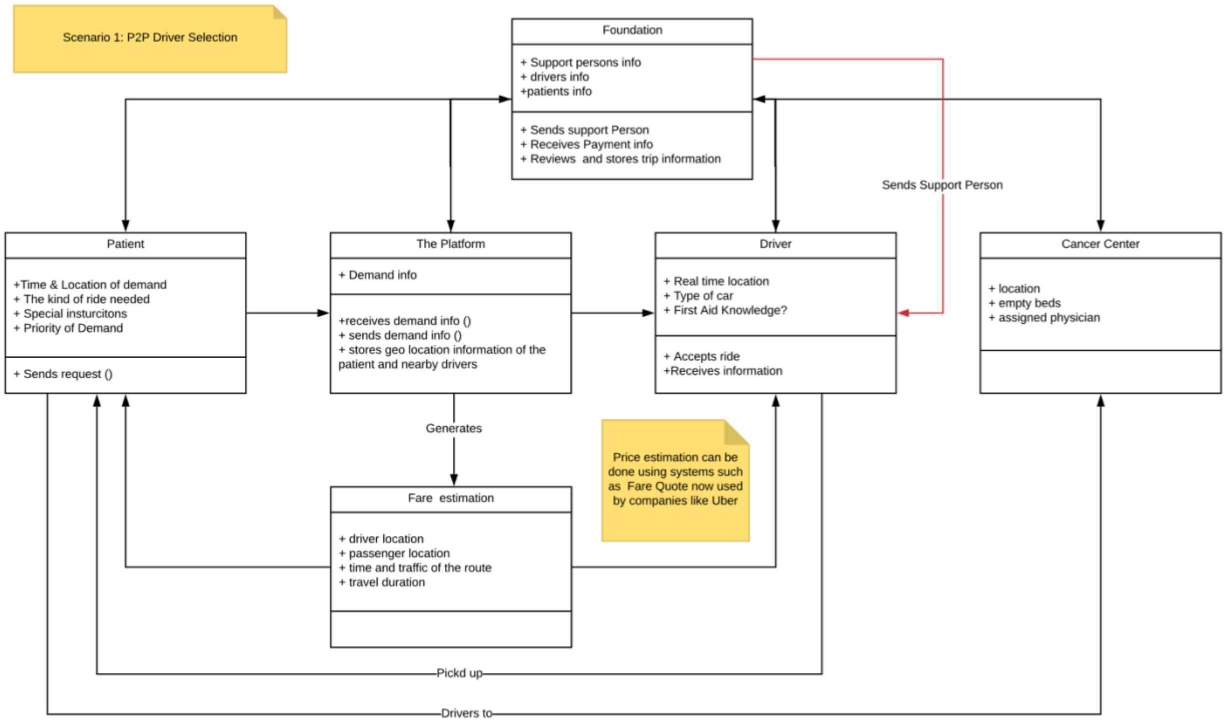


Figure 11 – Preliminary UML class diagram of P2P transportation business operation

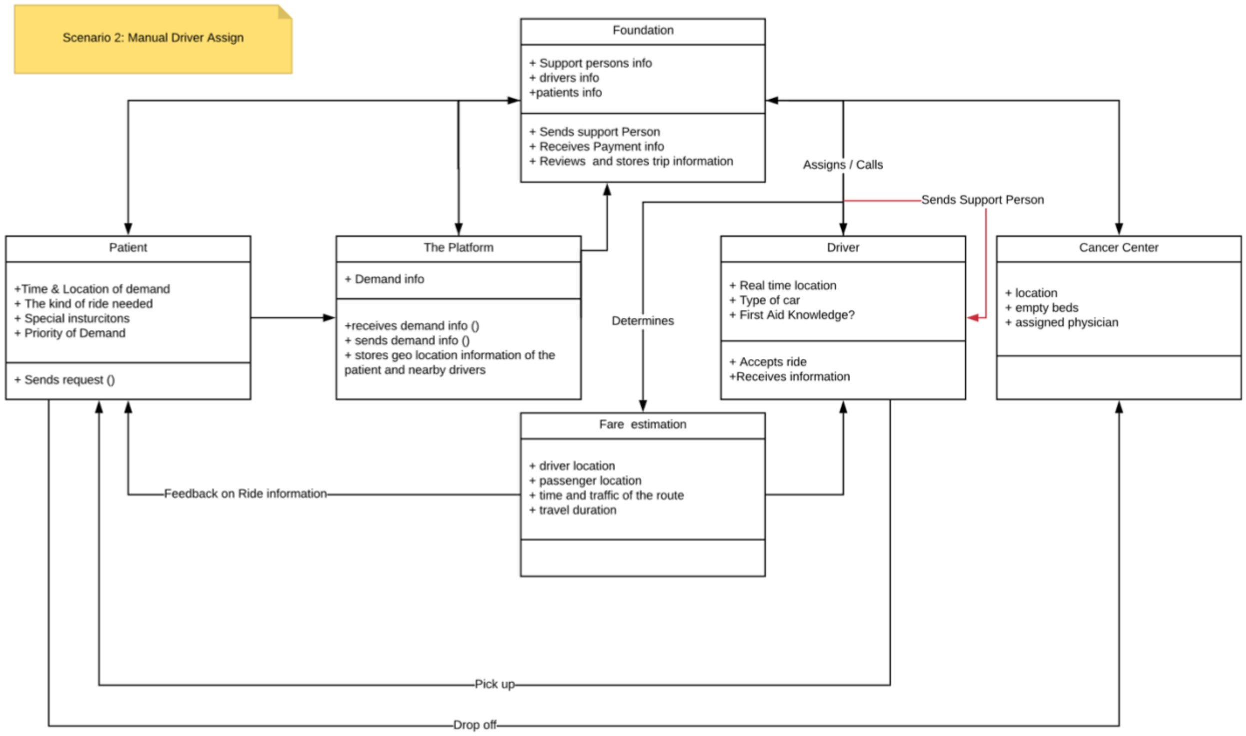


Figure 12 – Preliminary UML class diagram of manual matching transportation operations

5. Conclusions

This research addresses the problem on transportation accessibility for patients with pre-existing conditions in the Montreal area. We set out to offer a transportation strategy with the goal of making transportation more accessible for breast cancer patients residing in Quebec. Our definitions of accessibility were set around overhead costs imposed to the patients and ease of service according to the specific needs of this population. First, we reviewed the literature and initiatives employed by global transportation providers and identified major methods used for healthcare industry. Second, an overall transportation strategy was proposed, and key performance indicators were identified through our analysis of data and interviews with industry best practices in order to determine key aspects of such operations having the most impact on the overall service level. Finally, a discrete event simulation was provided and tested through 3 main scenarios to understand how such operations would behave in real life and how they react as the environment evolves through time. Next we analyzed the limitations and risks associated with our method to hopefully lay a bedrock for future work. A case study of a major nonprofit organization for whom this strategy was originally outlined was provided. On a high level, the main focus area of this particular project is to reduce the barrier of transportation for breast cancer patients for receiving therapy and those barriers, based on the foundations previously conducted market research and as our literature review confirms, have been defined as economical and accessibility barriers. In order to tackle those barriers, we proposed a discrete event simulation method, focused broadly on three main areas–minimizing patient out of pocket costs during treatment and logistic barriers, while ensuring required health and safety conditions are maintained to make sure the service is tailored to the specific needs of this patient segment.

This research is naturally built around the case study we offered, our we partnership with a major non profit organization in Quebec, the Quebec Breast Cancer Foundation (Ruban Rose), as part of their research and development program for the same purpose that will continue for at least the next two years. We were on the start of the initiation phase at the time this research was conducted. Based on literature and our client's key preferences, we coordinated specific KPIs and tested different scenarios in our simulation of these operations. Test data results show promising outcomes within our recommendations and the boundaries the simulations were tested within. Our recommendations to improve the performance of such system based on the capabilities of our client for this project, and without considering obvious choices like increasing capacity, would be within two main buckets; 1. To urge all drivers to ensure pick up at the start of timeslot and 2. To actively adjust the pick up time window. We proposed different configurations as guidelines for future decision making to maintain the desired KPIs.

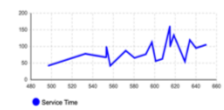
Because this was the preliminary phase of this project, our results are subject to inaccuracies as the project and the environment around it evolves. We explained the risks and mitigations in a specific section within this research thesis. In the same section, we talked about how future work can add on to our work to address more relatable situations and consider more realistic data. We will generally mention here that future efforts could build on giving each stakeholder of our system more characteristics and more individual decision-making abilities, and also to expand this work to larger regions with heavier loads of service. We hope our work would be a bedrock of inspiration to future researchers and leaders within the healthcare space at this critical time of COVID crisis in order to leave a greater social impact on our world.

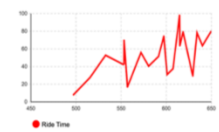
6. Appendix

A. Simulation Results

Scenario 1.1. Demand distribution

S 1.1.1 BASE MODEL - patient arrival distribution - Medium - Rate: poisson (lambda 5) / hour						
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	84	42	159	31	Total Served (%)	100%
Ride time (Dropoff - pickup)	52	8	97	23	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	55.5	8	113	21	Driver utlization	100%%
Pickup wait time (pickup time - slot start time)	7	0	37	10	Capacity utlization	37%
Driver wait time	3.5	0	16	5	Number of delayed patients	0
					no. of Patients refused	0
					No. of patients served	20





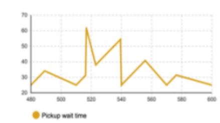
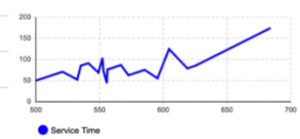
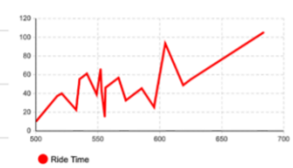


Table 1 – Base level scenario (reference)

S 1.1.2 patient arrival distribution - High - Rate: poisson (lambda 7) / hour						
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	85	45	173	28.7	Total Served (%)	100%
Ride time (Dropoff - pickup)	43	10.6	105	23	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	52.3	10.6	126.5	23.2	Capacity utlization	37%
Pickup wait time (pickup time - slot start time)	3	0	38.59	8.8	Number of delayed patients	0
Driver wait time	9.3	0	21.5	7.6	no. of Patients refused	0
					No. of patients served	20





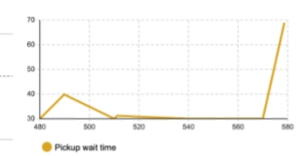


Table 2 – Scenario 1.1 High demand distribution

S 1.1.3 patient arrival distribution - Low - Rate: poisson (lambda 2) / hour						
Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	83	47	133.6	21	Total Served (%)	100%
Ride time (Dropoff - pickup)	50	10.5	79	18.5	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	59.2	10.5	103	18	Driver utlization	37%
Pickup wait time (pickup time - slot start time)	2.7	0	24.4	6.1	Number of delayed patients	0
Driver wait time	9.2	0	24	8	no. of Patients refused	0
					No. of patients served	20

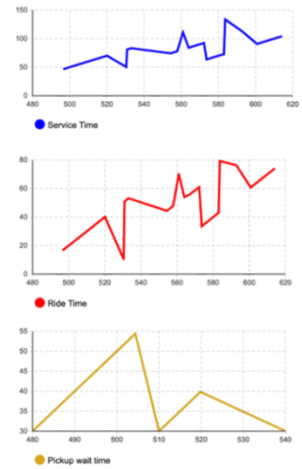


Table 3 – Scenario 1.2 Low demand distribution

Scenario 1.2 Demand Volume

1.2.1 Medium 20 patients						
Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	84	42	159	31	Total Served (%)	100%
Ride time (Dropoff - pickup)	52	8	97	23	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	55.5	8	113	28	Capacity utlization	37%
Pickup wait time (pickup time - slot start time)	7	0	37	10	Number of delayed patients	0
Driver wait time	3.5	0	16	5	no. of Patients refused	0
					No. of patients served	20

Table 4 – Low demand volume

1.2.2 High 50 patients						
Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	75	43	159	21	Total Served (%)	100%
Ride time (Dropoff - pickup)	47	5.5	98	23	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	53.3	5.5	119.4	23.5	Capacity utlization	93%
Pickup wait time (pickup time - slot start time)	3	0	37	7.2	Number of delayed patients	0
Driver wait time	6.3	0	21.4	6.4	no. of Patients refused	0
					No. of patients served	50

Table 5 – High demand volume

Scenario 2.1. Capacity volume

2.1.1 Half 10 Drivers

Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	94	42	149	32	Total Served (%)	100%
Ride time (Dropoff - pickup)	53	8	87	11	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	54	8	97	13.5	Capacity utlization	41%
Pickup wait time (pickup time - slot start time)	14	0	30	15	Driver utlization	100%
Driver wait time	1	0	10	2.5	Number of delayed patients	0
					no. of Patients refused	0
					No. of patients served	20

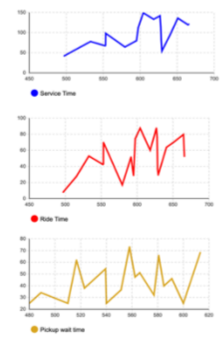


Table 6 – Low capacity volume

2.1.2 Double 40 Drivers

Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	84	41	160	31	Total Served (%)	100%
Ride time (Dropoff - pickup)	52	8	98	24	Total served within desired time limit (%)	100%
Driver Ride time (Ride time + driver wait time)	55.5	8	114	24	Capacity utlization	11%
Pickup wait time (pickup time - slot start time)	6	0	37		Driver utlization	100%
Driver wait time	3.5	0	16	5	Number of delayed patients	0
					no. of Patients refused	0
					No. of patients served	20

Table 7 – High capacity volume

At capacity	54 patients with 54 capacity					
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	73	40	149	25	Total Served (%)	100%
Ride time (Dropoff - pickup)	45	12	93	21	Total served within desired time limit (%)	
Driver Ride time (Ride time + driver wait time)	52	12	114	22	Capacity utlization	100%
Pickup wait time (pickup time - slot start time)	8.5	0	30	13.5	Driver utlization	100%
Driver wait time	7	0	21	6.4	Number of delayed patients	0
					no. of Patients refused	0
					No. of patients served	54

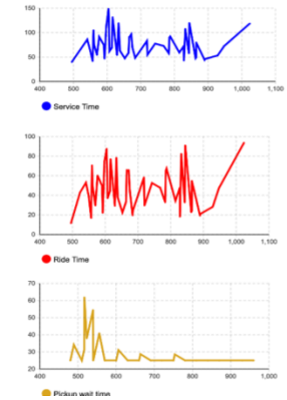


Table 8 – At capacity volume

Scenario 2.2 Capacity distribution

2.2.1 Level 1						
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	77	47	113	18	Total Served (%)	100% (20/20)
Ride time (Dropoff - pickup)	44	15	76	17.2	Total served within desired time limit (%)	100% (20/20)
Driver Ride time (Ride time + driver wait time)	52.5	15	100.37	16	Driver utlization	100%
Pickup wait time (pickup time - slot start time)	8	0	29	6	Number of delayed patients	0%
Driver wait time	8.5	0	24.37	8	no. of Patients refused	0%
					No. of patients served	20
					Capacity utlization	51%

Table 9 – Capacity distribution level 1

2.2.2 Level 2

Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	77	47	113	18	Total Served (%)	100% (20/20)
Ride time (Dropoff - pickup)	44	14.7	76	17.2	Total served within desired time limit (%)	100% (20/20)
Driver Ride time (Ride time + driver wait time)	53.2	14.7	100.37	16	Driver utlization	100%
Pickup wait time (pickup time - slot start time)	2	0	24	6.1	Number of delayed patients	0%
Driver wait time	9.2	0	24.37	8	no. of Patients refused	0%
					No. of patients served	20
					Capacity utlization	18%

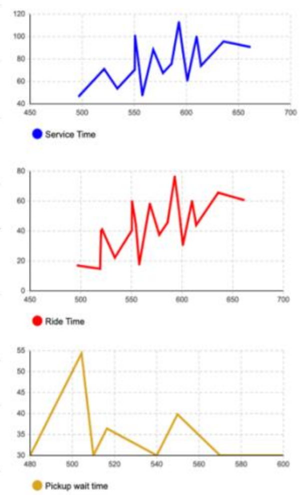


Table 10 – Capacity distribution level 2

Scenario 3. Pick up wait time

3.1 .5h threshold and 1h overtime threshold

Time Results (m)	mean	min	max	dev	Service level results	Amount
Service time (dropoff - slot start time)	84	35	163	34.65	Total Served (%)	90% (18/20)
Ride time (Dropoff - pickup)	45	5.6	79	17.4	Total served within desired time limit (%)	70% (7/10)
Driver Ride time (Ride time + driver wait time)	58	11	103.37	23.1	Driver utlization	100%
Pickup wait time (pickup time - slot start time)	15.44 **	0	84*	14	Number of delayed patients	30% (6/20)
Driver wait time	13	5.4	24.37	5.7	no. of Patients refused	10% (2/20)
					No. of patients served	18
					Capacity utlization	20%

*over time wait stats

avg 40m
max 54
min 31

** Disregarded those who refused overtime service.
(Refused population included: 17.44m)

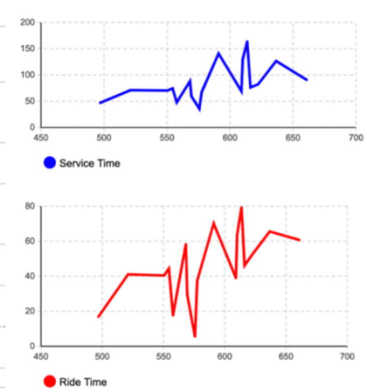
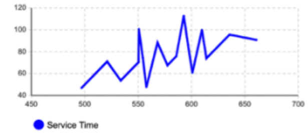
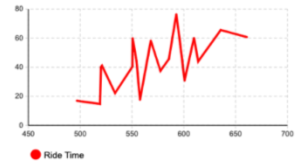


Table 11 – 30 minutes threshold

3.2 1h threshold and .5h overtime threshold						
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	76	46	112	34.65	Total Served (%)	100% (20/20)
Ride time (Dropoff - pickup)	44	15	76	17.25	Total served within desired time limit (%)	100% (20/20)
Driver Ride time (Ride time + driver wait time)	53	15	100	18	Driver utlization	100%
Pickup wait time (pickup time - slot start time)	7	0	29	6	Number of delayed patients	0
Driver wait time	9	0	24	8	no. of Patients refused	0
					No. of patients served	20
					Capacity utlization	22%





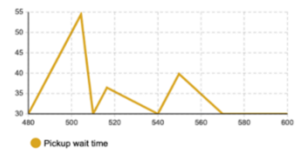
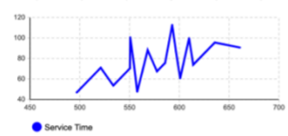
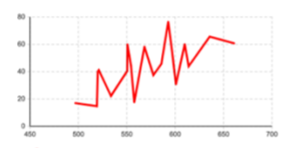


Table 12 – 60 minutes threshold

Scenario 4. Timeslot length

4.1: Timeslot & wait threshold = 1h						
Time Results (m)	**mean**	**min**	**max**	**dev**	**Service level results**	**Amount**
Service time (dropoff - slot start time)	76.6	45	112	18	Total Served (%)	100% (20/20)
Ride time (Dropoff - pickup)	44	15	76	17.2	Total served within desired time limit (%)	100% (20/20)
Driver Ride time (Ride time + driver wait time)	53	15	100.37	18	Driver utlization	100%
Pickup wait time (pickup time - slot start time)	2	0	24.4	6	Number of delayed patients	0%
Driver wait time	9	0	24.37	8	no. of Patients refused	0%
					No. of patients served	20
					Capacity utlization	22%





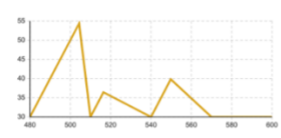


Table 13 – 60 minutes time slot

B. Simulation Model Documentation

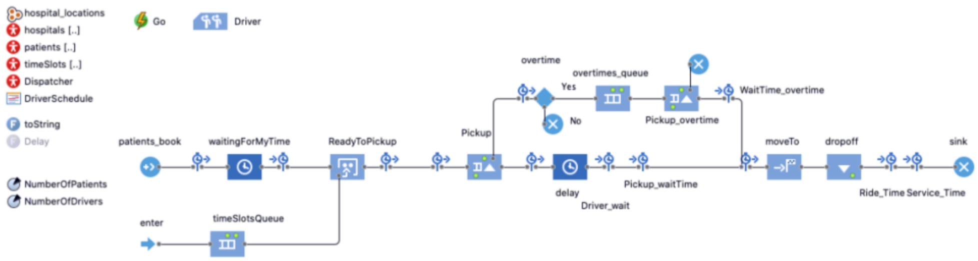
Name	Value
General	
Model time units	minutes
Numerical methods	
Differention Equations Method	Euler
Algebraic Equations Method	Modified Newton
Mixed Equations Method	RK45+Newton
Absolute accuracy	1.0E-5
Time accuracy	1.0E-5
Relative accuracy	1.0E-5
Fixed time step	0.001
Advanced	
Java package name	time_slots_demo
File Name	/Users/ehsansharif/Models/Transportation Simulation Model/Time Slots Demo v6.alp

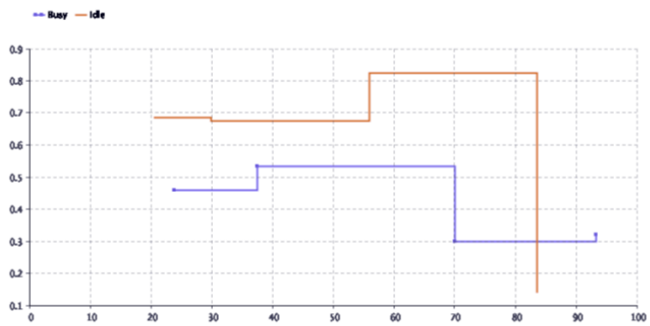
Agent Type: Main

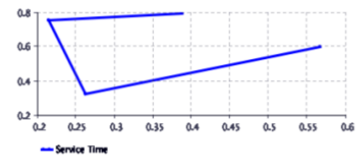
Name	Value
Agent actions	

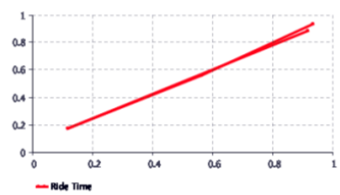
Startup code	List<Tuple> rows = selectFrom(schedule).list();
	for (Tuple row : rows) {
	int tsn = row.get(schedule.timeslots);
	for(int i=0; i<tsn; i++){
	TimeSlot ts = add_timeSlots(row.get(schedule.start_of_shift),
	 row.get(schedule.end_of_shift),
	 false, null);
	enter.take(ts);
	}
	}

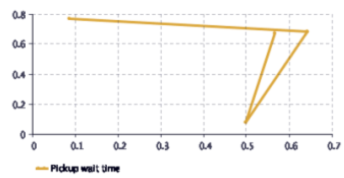
Agent in flowcharts	
Use in flowcharts as	Agent
Dimensions and movement	
Speed	(10 : MPS)
Rotate animation towards movement	true
Rotate vertically as well (along Z-axis)	false
Space and network	
Enable steps	false
Advanced Java	
Import	import org.eclipse.jetty.websocket.api.SuspendToken; import org.eclipse.jetty.websocket.api.SuspendToken; import java.util.concurrent.DelayQueue;
Generic	false
Advanced	
Logging	true
Auto-create datasets	true
AOC_DATASETS_UPDATE_TIME_PROPERTIES	- Recurring Event Properties
Limit the number of data samples	false

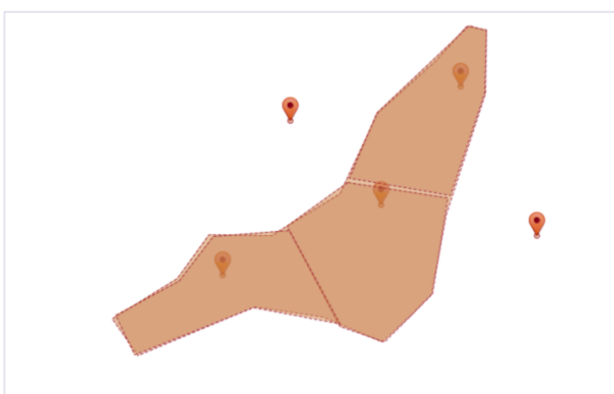












Scale: scale

Name	Value
General	
Unit	meters
Scale	10.0
Type	Defined graphically

Name	Value
Length, pixels	100.0
Show at runtime	false
Lock	false
Public	false
Position and size	
x	0.0
y	-150.0
Rotation	0.0

Parameter: NumberOfPatients

Name	Value
General	
Array	false
Default value	0
Type	int
Show at runtime	true
Show name	true
Value editor	
Label	NumberOfPatients
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Parameter: NumberOfDrivers

Name	Value
General	
Array	false
Default value	0
Type	int
Show at runtime	true
Show name	true
Value editor	
Editor control	Text
Advanced	
System dynamics units	false
Save in snapshot	true

Dynamic Event: Go

Name	Value
General	
Logging	true
Show at runtime	true
Show name	true
Action	
Action	waitingForMyTime.stopDelay(patient);

Parameters:

Name	Type
patient	Patient

Function: toString

Name	Value
General	
Return type	String
Return type:	Returns value
Show at runtime	true
Show name	true
Function body	
Body	return "hospital_locations = " + hospital_locations;
Advanced	
Access type	public
System dynamics units	false

Schedule: DriverSchedule

Name	Value
General	
Show at runtime	true
Show name	true
Data	
Value type	integer
The schedule defines	Intervals (Start, End)
Representation type	Days/Weeks
Repeat time	1
Repeat time interval	days
Is snapped to date	false
Default value	0
Load From Database	true
Intervals Query	- Database Schedule Interval Query
Action	
Action	Driver.set_capacity(Driver.capacity + value);
Preview	
SCHEDULE_PREVIEW_START_DATE	1604971110762
Advanced	
System dynamics units	false

Collection: hospital_locations

Name	Value
General	
Initial contents	{ gisPoint1, gisPoint2, gisPoint3, gisPoint4 }
Initial contents	{ gisPoint1, gisPoint2, gisPoint3, gisPoint4 }
Element class	GISPoint
Collection class	ArrayList

Name	Value
Show at runtime	true
Show name	true
Advanced	
Access type	public
Save in snapshot	true

Enter: enter

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: TimeSlot]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: TimeSlot]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
New location	self.LOCATION_NOT_SPECIFIED
Change dimensions	false
Add newborns to:	false
Forced pushing	true

Queue: timeSlotsQueue

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: TimeSlot]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: TimeSlot]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Capacity	100
Maximum capacity	false

Agent Parameters:

Name	Value
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

TimeSlot: timeSlots

Name	Value
General	
Initialization Type	Initially empty
Population of agents	true
Initialization Type	Initially empty
Population of agents	true
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

Source: patients_book

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Arrivals defined by	self.RATE
Arrival rate	poisson(5)
Set agent parameters from DB	false
Multiple agents per arrival	false
Limited number of arrivals	true

Agent Parameters:

Name	Value
Maximum number of arrivals	NumberOfPatients
Location of arrival	self.LOCATION_NODE
Node	East
Speed	1
New agent	new time_slots_demo.Patient()
Change dimensions	false
Custom time of start	false
Add agents to:	true
Population	patients
Forced pushing	true

On at exit	TimeSlot ts = findFirst(timeSlotsQueue, t -> !t.isBooked);
	if(ts != null){
	ts.isBooked = true;
	ts.bookedBy = agent;
	agent.slot = ts;
	}

Patient: patients

Name	Value
General	
Replication	NumberOfPatients
Initialization Type	Contains a given number of agents
Population of agents	true
Replication	NumberOfPatients
Initialization Type	Contains a given number of agents
Population of agents	true
Show name	true
Dimensions and movement	
Speed	(1 : MPS)
Initial location	
Place agent(s)	in the node
Node	Montreal
Node	Montreal
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

Sink: sink

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false

Name	Value
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Type	self.MANUAL
Maximum capacity	true
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

On enter	double s = dateToTime(agent.slot.start);
	double dt = s - 30 - time();
	create_Go(dt, agent);

TimeMeasureStart: timeMeasureStart

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureEnd: timeMeasureEnd

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart }

Agent Parameters:

Name	Value
Dataset capacity	100

ResourcePool: Driver

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Resource type	self.RESOURCE_MOVING
Capacity defined	self.CAPACITY_DIRECT
Capacity	NumberOfDrivers
When capacity decreases	false
New resource unit	new time_slots_demo.Driver()
Speed	30
Home location is	self.HOME_SINGLE_NODE
Home location (nodes)	{ dispatcher }
Specified by	self.DOWNTIME_RESOURCE_POOL_PROPERTIES
Maintenance	false
Failures / repairs	false
Breaks	false
Custom tasks	false
'End of shift' priority	1
'End of shift' may preempt	false
'End of shift' preemption policy	self.PP_NO_PREEMPTION
Customize request choice	false
Add units to:	false
Force statistics collection	false

MoveTo: moveTo

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false

Name	Value
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Agent	self.MODE_MOVE_TO
Destination:	self.DEST_AGENT
Agent	hospitals.random()
... with offset	false
Straight movement	false
Movement is defined by:	self.MOVE_SPEED
Set agent's speed	true
Speed	30

Release: dropoff

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Release	self.ALL
Moving resources	false
Wrap-up (e.g. move home)	self.WRAP_UP_ALWAYS
'Wrap-up' usage statistics are:	self.USAGE_BUSY

hospital: hospitals

Name	Value
General	
Replication	hospital_locations.size()
Initialization Type	Contains a given number of agents

Name	Value
Population of agents	true
Replication	hospital_locations.size()
Initialization Type	Contains a given number of agents
Population of agents	true
Show name	true
Dimensions and movement	
Speed	(0 : MPS)
Initial location	
Place agent(s)	in the node
Node	hospital_locations.get(index)
Node	hospital_locations.get(index)
Statistics	
Statistics	[]
Advanced	
Show at runtime	true
Public	false
Embedded object collection type	Access by index (ArrayList)
Logging	true

Dispatcher: Dispatcher

Name	Value
General	
Population of agents	false
Population of agents	false
Show name	true
Dimensions and movement	
Speed	(0 : MPS)
Initial location	
Place agent(s)	in the node
Node	dispatcher
Node	dispatcher
Advanced	
Show at runtime	true
Public	false
Logging	true

Seize: Pickup

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	

Name	Value
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Seize	false
Resource sets	{ { Driver } }
Seize policy	self.SEIZE_UNITS_ONE_BY_ONE
Maximum queue capacity	true
Send seized resources	true
Destination is	self.DEST_ENTITY
Attach seized resources	true
Task priority	0
Task may preempt	false
Task preemption policy	self.PP_NO_PREEMPTION
Customize resource choice	false
Resource selection	self.RESOURCE_SELECTION_NEAREST_BY_ROUTE
Define preparation tasks by	false
Enable exit on timeout	true
Timeout	60
Enable preemption	false
Canceled units:	self.CANCELED_UNITS_RETURN_TO_HOME_LOCATION
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	true
"agent1 is preferred to agent2"	false

TimeMeasureStart: timeMeasureStart1

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureEnd: Pickup_waitTime

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart1 }
Dataset capacity	100

SelectOutput: overtime

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Select True output	true
Probability	0.5

Sink: sink1

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	

Name	Value
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Queue: overtimes_queue

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Maximum capacity	true
Queuing	self.QUEUING_FIFO
Enable exit on timeout	false
Enable preemption	false
Restore agent location on exit	true
Force statistics collection	false

Delay: delay

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false

Name	Value
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Pickup: ReadyToPickup

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: , Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Pickup	self.BY_CONDITION
Condition	container.slot == agent
Pick from	true
Forced pushing	false
On exit	traceln(date()+": slot start - "+container.slot.start);

Delay: waitingForMyTime

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	

TimeMeasureStart: timeMeasureStart3

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureEnd: Service_Time

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Patient]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Patient]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart3 }
Dataset capacity	1000

TimeMeasureEnd: Ride_Time

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Patient]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute: Patient]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false

Name	Value
Logging	true

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart2 }
Dataset capacity	100

TimeMeasureStart: timeMeasureStart2

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

TimeMeasureStart: timeMeasureStart5

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Seize: Pickup_overtime

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	

Name	Value
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Seize	false
Resource sets	{ { Driver } }
Seize policy	self.SEIZE_UNITS_ONE_BY_ONE
Maximum queue capacity	true
Send seized resources	true
Destination is	self.DEST_ENTITY
Attach seized resources	true
Task priority	0
Task may preempt	false
Task preemption policy	self.PP_NO_PREEMPTION
Customize resource choice	false
Resource selection	self.RESOURCE_SELECTION_NEAREST_BY_ROUTE
Define preparation tasks by	false
Enable exit on timeout	true
Timeout	30
Enable preemption	false
Canceled units:	self.CANCELED_UNITS_RETURN_TO_HOME_LOCATION
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	true
"agent1 is preferred to agent2"	false

TimeMeasureEnd: WaitTime_overtime

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart5 }
Dataset capacity	100

Sink: sink2

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
Destroy policy:	com.anylogic.libraries.processmodeling.Sink.DESTROY_ONLY_CREATED_IN_SOURCE

Plot: plot1

Name	Value
General	
Lock	false
Public	true
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Interpolation	Linear
Position and size	
x	810.0
Width	440.0
y	370.0
Height	210.0

Name	Value
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	360.0
Chart Area: Y Offset	30.0
Chart Area: Height	120.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Plot Items:

		Dataset						
Title	Type	X Axis Value	Y Axis Value	Point Style	Color	Line	Width	Interpolation
Service Time	dataset	Service_Time.dataset		CIRCLE	blue	true	3.0	LINEAR

Plot: plot2

Name	Value
General	
Lock	false
Public	true
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Interpolation	Linear
Position and size	
x	810.0
Width	430.0
y	820.0
Height	230.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	

Name	Value
Chart Area: X Offset	50.0
Chart Area: Width	350.0
Chart Area: Y Offset	30.0
Chart Area: Height	140.0
Chart Area: Background Color	white
Chart area border color	black
Advanced	
Show name	false
Logging	true

Plot Items:

Title	Type	Dataset		Point Style	Color	Line	Width	Interpolation
		X Axis Value	Y Axis Value					
Pickup wait time	dataset	Pickup_waitTime.dataset		CIRCLE	goldenRod	true	3.0	LINEAR

Plot: plot3

Name	Value
General	
Lock	false
Public	true
Data update	
Analysis auto update	false
Dataset Samples To Keep	100
Scale	
Horizontal scale	Auto
Vertical scale	Auto
Appearance	
Labels horizontal position	DEFAULT
Labels vertical position	DEFAULT
Labels Text Color	darkGray
Chart Area Grid Color	darkGray
Draw line	true
Interpolation	Linear
Position and size	
x	810.0
Width	430.0
y	580.0
Height	250.0
Legend	
Show legend	true
Legend size	30.0
Legend text color	black
Chart area	
Chart Area: X Offset	50.0
Chart Area: Width	350.0
Chart Area: Y Offset	30.0
Chart Area: Height	160.0
Chart Area: Background Color	white

Name	Value
Logging	true

Agent Parameters:

Name	Value
Type	self.TIMEOUT
Delay time	dateToTime(agent.slot.start) - time();
Maximum capacity	true
Agent location	Montreal
Forced pushing	false
Restore agent location on exit	true
Force statistics collection	false

TimeMeasureEnd: Driver_wait

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	true
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

Agent Parameters:

Name	Value
TimeMeasureStart blocks	{ timeMeasureStart4 }
Dataset capacity	100

TimeMeasureStart: timeMeasureStart4

Name	Value
General	
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Population of agents	false
Generic Parameters Substitutes	[Generic Parameter Substitute:]
Show name	false
Initial location	
Place agent(s)	at the agent animation location
Advanced	
Show at runtime	true
Public	false
Logging	true

C. Comparable Analysis

OVPAC Volunteer program was a similar program done in 2014-2015 in Montreal with the purpose of offering transportation services to seniors.

Scope:

1. 525 volunteers – duties:
    - Driving senior patients to their treatment centers
    - Mentoring
2. Equipment loans (wheelchairs, walkers, etc.)
3. Emotional support program
    - Conferences
    - Follow up with people affected through confidential system, allowing meetings or telephone interviews with personalized follow-ups as needed.

Goals:

1. Social inclusion of patients and those affected, particularly seniors (66% > 65 y/o)
2. Make transportation more accessible (one of the biggest hurdles in the treatment process, costly and inaccessible)
3. Train potential future professional staff (drivers and attendants)

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