The Distribution of Blood for a Stat Order in Northern Health Authority of British Columbia

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1 Introduction

Donated blood is a valuable resource. Its uses vary, but in all cases it can be a lifesaving component of planned and emergency healthcare. This utility is challenged by three fundamental problems: The limited supply of blood, the precise conditions needed to store it, and its limited shelf life even when stored properly. Throughout Canada, the Canadian Blood Services (CBS) handles the supply of donated blood and the distribution of that blood to the hospitals within the provincial authorities (Dhahan et al., 2025). Our client is the BC Provincial Blood Coordinating Office (PBCO), which oversees the distribution of blood throughout BC.

Red Blood Cells (RBC) are often the most vital component of blood to save lives in emergencies. However, with a shelf life of 42 days, supply is a consistent problem, especially in regions that are more difficult to access regularly. In remote regions and on islands, particularly, emergency supplies of blood take more time to reach the hospitals and patients that need them. This is further complicated by the need to minimize waste, which results in redistribution between hospitals carrying supplies of RBC (Dhahan et al., 2025). To combat these transportation issues, we believe it is possible to optimize the distribution and redistribution of blood, which will create a better model for supply in remote areas.

1.1 Problem:

In the BC blood distribution network, an emergency (stat) order can come at any time at any location. The speed with which this order can be fulfilled is vital in ensuring the best care. A stat order can be needed in any location, so determining the fastest and most optimal distribution is important. When a smaller site needs a lot of blood and they cannot wait a day for a CBS order, they will rely on redistribution by ground transport within the health authority. We will determine where a hospital site should draw from when they need blood redistributed to them as fast as possible in an emergency.

1.2 Background:

We will focus on the BC health authority of Northern Health (NH). We spoke with Kylah Sorenson (personal communication, February 18, 2025) a Medical Laboratory Technologist from the University Hospital of Northern BC to gain insight into NH and how blood products are distributed. NH is the largest health authority in the province in terms of geographical area. Much of this area is sparsely populated with large distances between each hospital. With limited infrastructure, challenging terrain, and more severe winter weather, air transport is not always possible. Compounded with limited number of flights, airports, and staff, ground transport is often utilized instead of air. Ground transport is usually not affected by snow storms and NH has a reliable internal courier for their region. The Northern Health Courier (NHC) services NH for much of their normal distribution and redistribution. The NHC transports goods throughout the region including blood products, testing samples, pharmaceuticals, and equipment. It is often faster and more reliable than CBS. During a stat order, if the NHC is not positioned correctly, NH will rely on taxi or even RCMP to transport blood products. Speed is prioritized over financial cost in an emergency when saving lives is at stake.

Historically, most sites in NH do not use much inventory, so do not keep much on hand. Further, blood products have a shelf-life, so stockpiling for emergency situations is not possible. Distribution deliveries to NH from CBS can be as few as once per week for small remote sites and only 2-3 times per week for medium. Any additional orders from CBS directly would come at a large financial cost for NH. For all of these reasons, redistribution between sites is vital in an emergency situation.

Blood group O negative is a particularly precious resources because it is the universal blood type and is compatible for all recipients. Only 6-7% of the general population has O negative blood type; however, it is utilized in 12% of transfusions. With a lack of blood testing in remote areas, it is the main blood type used for stat orders. Many remote and smaller sites only carry O negative blood group, if they have any inventory at all (Dhahan et al., 2025). Redistribution is key in emergency situations to ensure that the O negative units are not expired.

We gained further information from Sorenson (personal communication, February 18, 2025) about inventory levels of the hospital sites of NH. Like all BC health authorities, NH relies on a min-max inventory system for RBC ordering from CBS. An order is prompted when the inventory of a site reaches its minimum (min) level and is then replenished up to the maximum (max) inventory target. Historical use of blood products, particularly O negative RBC, is used when determining the min-max inventory level for each site. These numbers are reevaluated regularly and NH is consistently one of the better health authorities in limiting product expiry. Consistent min-max levels will help ensure any model being effective.

2 Methodology:

2.1 Literature Review:

Linear programming models are used in the allocation of resources to optimize the cost of the supply chain network. Cost can come in several forms including financial cost or time cost. Transportation problems are a generalized form of an assignment problem where goods are transported from an origin to a destination. The objective function is a linear function that determines the maximum or minimum cost while staying within a set of constraints. There are several solutions to the transportation problem, known as feasible solutions, where all variables are met within the constraints. The optimal solution is when the objective function takes it's maximum or minimum value, depending on the problem (Strayer, 1989).

A stat order for RBC can be compared to the transport of goods under an emergency situation.

Our problem is similar to that of Parwanto, et al. (2015) who used network flow optimization techniques to improve the transportation of goods during natural disasters. Immediate action is required during an emergency and speed is prioritized over financial cost. They employ a transportation algorithm for their multi-objective function to minimize the transportation time to fulfill the demand at each location. With multiple supply locations and multiple demand locations, the optimal solution to the linear program will provide the fastest routing for each supply of goods. Road infrastructure may be damaged during an emergency, so Parwanto, et al. (2015) factor in the probability of a broken or damaged road segment when constructing their constraints of their linear program. We can employ this strategy since a damaged road is similar to one that is impacted by a storm, a common occurrence in NH. We will use real-time traffic data in our updated model to account for this.

Transportation time can be optimized using linear programming. A linear program is constructed to minimize an objective function under certain variable constraints. Khan (2014) uses the built in Solver in Microsoft Excel to solve a transportation problem. This solver uses the simplex algorithm to find the optimal solution under the given constraints. In this linear program, warehouses send supply to markets to meet demand, with a cost associated with sending a supply along a given route (Khan, 2014). We can employ this type of mathematical model to our problem to provide a simple and robust optimization. To make the problem balanced where the supply is equal to demand, we will use a dummy market. Any extra supply can be connected to this dummy market at no cost. Any supply that is sent to the dummy market is said to remain at the warehouse (Strayer, 1989).

In the distribution of RBC, we will also consider Sustainable Supply Chain and Logistics Modeling (SSCLM). SSCLM is a complicated process which focuses on optimizing multiple objectives at the same time, such as economic, environmental and social factors (Jayarathna et al., 2021). Researchers have proposed different optimization methods including mixed-integer programming (MIP), multi-objective optimization (MOO), and metaheuristic algorithms (Trisna et al., 2016). Optimization for multiple objective functions can be solved using the Pareto principle of optimality to find an efficient solution, known as Pareto-optimal. These efficient solutions are called nondominated points, where no other feasible solution can improve one objective without worsening another. As compared to a single objective where there is one optimal solution, the multi-objective aims to find the set of all nondominated points where each solution contributes to an efficient solution. Each solution determines the weighting of objectives which leads to a better decision making process (Bazgan et al., 2022). The study of Hosseini, et al. (2022) analyzes crisis-prone regions and uses MOO to optimize blood distribution by minimizing the total distance and time. The study of Entezari, et al. (2024) uses a classical method to solve the MOO problem which highlights the two objectives that must be addressed simultaneously: minimizing distance and time while ensuring blood delivery in order to meet the demand of patients in a crisis. MOO is also used to find the best solutions while maintaining the suppliers' existing constraints (Rezapour et al., 2017). The constraints are used to maintain the units of blood within the minimum and maximum inventory levels.

Many studies in literature show how hard it is to solve multi-objective optimization problems (Ehrgott, 2000). Multi-objective optimization can be simplified into a single optimization by using a scaler, α, as a weighting of parameters. This α is given a value between 0 and 1. Solutions are obtained by using the Pareto principle of optimality (Bazgan et al., 2022). The most common scalarization technique is the weighted sum scalarization (Ehrgott, 2008). The study uses the weighted sum scalarization to find the set of efficient solutions; however, not all efficient solutions are considered as supported solutions, some are considered unsupported (Bazgan et al., 2022). Research by Neis and Zipf (2008) considers the solutions when $\alpha = 0, 0.5$, or 1 to make decisions based on factors such as traffic, emergency deliveries, or closed highways. The study uses real-time traffic integration by fetching real-time data from open location services (OpenLS) with an API key. This real-time data plays a vital role in optimizing the problem by improving route selection (Neis & Zipf, 2008). Traffic data is a powerful tool for analyzing the road conditions in a crisis (Choosumrong et al., 2012). Using real-time data will help make better decisions and reshape the supply chain.

2.2 Data:

Data for min, max, and average daily inventory levels for O negative type RBC were received from Kylah Sorenson and Jasdeep Dhahan (personal communication, March 20, 2025). These estimate numbers are shown in Table 1. These values are reevaluated on a regular basis so will likely need to be updated. Google Maps was used to map location and give coordinates of hospital sites based on the NH Northern BC Communities Map (Northern Health, 2011). From this, we can obtain estimate travel times between hospital sites.

Northern Health Hospital O Negative RBC Inventory				
Index	Hospital	Max	Min	Average Daily
1	Atlin	0	0	0
2	Dease Lake	4	2	4
3	Hazelton - Wrinch Memorial	4	2	4
4	Houston	0	0	0
5	Kitimat General	10	2	7
6	Masset Northern Haida Gwaii	3	1	3
7	Prince Rupert General	11	2	8
8	Queen Charlotte - Haida Gwaii	2	1	2
9	Smithers - Buckley Valley District	9	2	7
10	Stewart	0	0	0
11	Terrace Mills	10	2	6
12	Burns Lake - Lakes District	2	1	2
13	Fort St James - Stuart Lake	2	1	2
14	Fraser Lake	0	0	0
15	Mackenzie and District	2	1	2
16	McBride	2	1	2
17	Prince George - UHNBC	29	10	20
18	Quesnel G.R. Baker	7	2	5
19	Vanderhoof - St John	5	2	4
20	Chetwynd	2	1	2
21	Dawson Creek and District	17	4	10
22	Fort Nelson General	3	2	7
23	Fort St John	13	2	7
24	Hudson's Hope - Gething	0	0	0
25	Tumbler Ridge	2	1	2

Table 1: Estimate NH O Negative RBC Inventory

To improve the route selection, an update to the model will use real-time data for distance and travel times between the hospital sites. We obtained accurate latitude and longitude of all NH hospital sites and used Open Routing Services (ORS) with a free API key to fetch real-time data. ORS API delivers real-time traffic for accurate distance and travel times between hospitals.

A python script was written to fetch the real-time data while handling API rate limits and missing data scenarios. The model uses the free API key of ORS, so it comes with a limited number of requests accepted per minute.

To optimize route selection, the model follows steps of of processing, collecting, and saving data. First, the hospital locations and valid routes are loaded from a comma-separated values (CSV) file into Pandas Data Frames using the Pandas library in Python. The sites are then mapped from their latitude and longitude using dictionary structures for instant lookup. The ORS API fetches the two key metrics: distance between hospitals and estimated travel time based on current road conditions. In the case of request failures, API errors were managed with automatic retries. Before retrying, rate limits were handled by waiting progressively longer to avoid requesting over the limit per minute. The calculated distance and times are then stores in a new CSV file and labeled by their time of day. We will compare morning and evening. Using this processed data will improve the runtime efficiency.

2.3 Assumptions:

For the sake of clarity, we have made several assumptions during construction of our mathematical model. For one, we will assume the packing of blood products can be done at any time and always takes a set amount of time. This packing time will not be factored into our model. We will also assume all stat orders of RBC use O negative blood type. This is a safe assumption, as this is usually the case, particularly in emergencies where blood type of the patient may not be readily known. We will also assume that the inventory of O negative RBC is at the estimated average daily inventory level for each site at any given time. This allows for a simplification of the model. If needed, the inventory numbers can be manually changed. We have also removed the Haida Gwaii island sites of NH from the initial model. Ground travel to both Haida Gwaii hospitals from mainland BC requires an eight-hour ferry, so this form of transport is not feasible in an emergency.

2.4 Model Description:

The objective is to minimize the transportation time to meet the demand from a stat order. A balanced transportation problem is set up as follows:

Stat Order Transportation Problem Objective Function:

$$
\begin{aligned}
Minimize \sum_{i=1}^{n}\sum_{j=1}^{m} C_{i,j}x_{i,j} \\
subject\, to \sum_{i=1}^{n} x_{i,j} = s_i \ (i = 1, 2, \ldots n) \\
\sum_{j=1}^{m} x_{i,j} = d_j \ (j = 1, 2, \ldots m) \\
such\, that \sum_{i=1}^{n} s_i = \sum_{j=1}^{m} d_j
\end{aligned}
$$

$$\begin{aligned} where\ m &= \text{number of supply sources} \\ n &= \text{number of demand destinations} \\ s_i &= \text{number of units from supply source} \\ d_j &= \text{number of units required at demand destination} \\ x_{i,j} &= \text{number of units transported} \\ C_{i,j} &= \text{cost of units transported} \end{aligned}$$

Output / Input	M_1	M_2	M_3	M_4	M_{dummy}	$Supply_i$
W_1	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$x_{1,5}$	s_1
W_2	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$x_{2,5}$	s_2
W_3	$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$x_{3,5}$	s_3
W_4	$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$x_{4,5}$	s_4
$Demand_j$	d_1	d_2	d_3	d_4	d_5	C_{Total}

Table 2: Example Transportation Matrix

For a balanced transportation problem, the total units available to be supplied by all source locations are equal to the total demand (Strayer, 1989). To balance our transportation problem, a dummy warehouse was created to show when a unit remained at its source location and was not shipped. To represent this, the dummy warehouse is given a travel cost of zero.

Table 2 is an example transportation matrix where W_i represents the warehouses that provide supply, s_i, to meet the demand, d_j, of each of the markets, M_j. The cost of transporting a supply unit $x_{i,j}$ from warehouse W_i to market M_j is given by $C_{i,j}$. In our case, the warehouses and markets are the same hospital when $i = j$ and the cost to transport to themselves is given a value of zero. An additional dummy market, M_{dummy}, with zero cost of transporting is added to the network to balance the total demand, $\sum d_j$, with the total supply, $\sum s_i$. Total hospital supply is assumed to be greater than demand. If this is not the case, a supply order would be required from CBS. The demand for this dummy market is the difference between the total hospital supply and the total hospital demand. C_{Total} is the total cost to transport the total supply needed to meet the total demand.

Supply levels for each hospital indicates the number of O negative blood units available for redistribution. This is calculated by the difference between the estimated average daily supply level minus the min supply level for each hospital. All demands will initially be set to zero to indicate normal conditions with no redistribution needed. Cost for transporting each supply is represented by the travel time between each hospital. Travel time is used instead of travel distance since time is the most important factor in an emergency situation. Financial cost is rarely considered in an emergency. These travel times are representative of average travel time between locations from Google Maps data. It does not take into account delays due to weather or traffic. To simulate a stat order, demand will be set to a large value for one hospital with other demands equal to zero. The optimal solution of the linear program will indicate the fastest way to provide the blood units needed for a stat order and which hospitals provide the units.

When all values are input into this matrix, the simplex algorithm is employed to solve this linear program. This algorithm iteratively moves along the edge of the matrix to find the optimal solution by performing pivots to the columns and rows. The objective function will be improved after each step until the optimal solution is reached. We will set up and solve this linear program using Microsoft (MS) Excel Solver tool. This simple design requires manual inputs for each supply, demand, and transportation cost; however, is efficient and easy to understand.

2.5 Model Update:

The updated model optimizes the blood distribution using ground transportation. Real-time traffic data is added to make the model more applicable to a real world situation. The main objective is to minimize both transportation distance and delivery time while considering inventory constraints of different hospital sites. It is a multi-objective optimization problem which is solved using a Pareto front approach by varying the weight α for distance in the combined objective function. The model will output the optimized routing for a general distribution and redistribution between hospital sites depending on traffic and inventory levels.

Pareto Front Optimization - Weighted Cost Objective Function:

$$
\begin{aligned}
Minimize \sum_{i \neq j} & y_{i,j}(\alpha \cdot CD_{i,j} + (1-\alpha) \cdot CT_{i,j}) \\
subject\,to \sum_{i \neq j} & y_{i,j} = 1 \; (outgoingflow) \\
\sum_{i \neq j} & y_{j,i} = 1 \; (incomingflow) \\
I_i \geq \sum_{i \neq j} & y_{i,j} \cdot d_j \\
I_i \geq & Imin_i \\
I_i \leq & Imax_i
\end{aligned}
$$

$$\begin{aligned} where\ CD_{i,j} &= \text{distance cost of unit transported} \\ CT_{i,j} &= \text{time cost of unit transported} \\ y_{i,j} &= \text{binary variable for blood transportation from } i \text{ to } j \\ \alpha &= \text{weighting constant} \\ d_j &= \text{number of units required at demand destination} \\ I_i &= \text{inventory level} \\ Imin_i &= \text{minimum inventory level} \\ Imax_i &= \text{maximum inventory level} \end{aligned}$$

The decision variable are based on route selection and inventory levels. As indicated, the variable $y_{i,j}$ is a binary variable that is given a value of 1 if blood is transported from i to j along this route and 0 if not. α is the weight assigned to the cost variables and ranges between 0 and 1 to generate Pareto solutions.

The model follows constraints of flow conservation to ensure each site has exactly one incoming route and one outgoing route. However, it does not limit a site to only having one incoming route from one other site. A hospital can receive blood from multiple locations provided those routes are selected by the decision variables.

The system will need to be modified to ensure inventory constraints, blood transfer requirements, and other constraints in order to make it work for multiple outgoing routes. Inventory and blood transfer constraints will also need to be adjusted to account for the possibility that a site may be involved in several blood transfers at the same time.

Each hospital's inventory I_i is maintained at or above the min inventory level $Imin_i$. This ensures that no hospital runs out of blood. In addition, the model ensures that each hospital's inventory does not exceed the max inventory level $Imax_i$. This is useful to prevent overstocking, which could lead to wastage or logistical problems.

The inventory of each hospital is sufficient to meet the blood requirements for outgoing transfers. The blood required for a route $i \to j$ is specified in the blood supply and demand matrix. For each hospital i, these constraints ensure that inventory is sufficient to cover the amount of blood required for demand at j. This is calculated based on the routes selected and the amount of blood needed. Traffic conditions and route availability can change in real time using API data. If a route is blocked or time becomes excessive due to traffic, the model can be adapted to consider these new values using real-time data. This requires periodically updating the distance_data and time_data matrices to reflect real-time changes.

3 Results:

3.1 Simplex Algorithm using MS Excel Solver for Stat Orders:

The transportation problem using manual inputs in the MS Excel Solver helped show where blood products should be redistributed from in an emergency when a stat order is required. The general results showed that the closest site should redistribute to the neighbouring site in an emergency for the fastest response. Results were similar when comparing the size of the site requesting the stat order. A small site is one that normally has no O negative units on hand, a medium site is one that has a max inventory ranging from 1-4, and a large site is one with 5 or more. In general, a small site is typically one that is very remote with a small population and large distance from the next closest hospital. A medium site is still rural but relatively closer to other sites. A large site is one with a larger population and more infrastructure. This allows the larger sites to be better equipped for redistribution with more staff.

According to our model, when a small site needs a large amount for a stat order the majority comes from the closest large site with the remainder coming from the closer small and medium sites. As an example, if we assume Atlin needs 7 units it has drawn 2 units each from the closest medium site of Dease Lake and Hazelton then the remainder coming from the larger site of Terrace Mills. This solution and network flow is shown in Table 3 and Figure 1. This would provide a few units quickly and then a larger amount from the bigger site after a longer time period. We see a similar pattern when a medium site needs a large amount in a stat order. The main difference is that a medium site can first exhaust units from their own storage. The remainder is provided by nearby medium sites with the majority coming from the closest large sites. As an example, lets assume the medium site of Burns Lake needs 12 units of blood. Firstly, they deplete their own storage. Then the remainder comes from the nearby medium sites Vanderhoof and Fort St James with the majority coming from the large site of Prince George. When a large site needs an emergency stat order most of the supply comes from themselves with a secondary supply coming from the nearest medium or large sites. If our model was given the manual input of 22 units of blood needed in Prince George, most of the supply would come from Prince George with the few remaining coming from nearby Vanderhoof.

The results show that in an emergency, a site should draw RBC from a nearby site to meet the demands. Even if this nearby site does not have sufficient supply to meet the total demand, it will allow for a buffer before the remainder of the demand can be received. In general, a stat orders differ depending on the size of the site. Since small sites do not have any initial supply, they rely entirely on nearby sites. The nearest sites to a small site with available inventory are usually medium sites, since they are in more remote areas. Since medium sites do not carry much inventory and we cannot deplete them below their min level, a stat order for a small or medium site relies on deliveries from many different sites. This differs from large sites who will rely heavily on their existing supply to fulfill a stat order. The remainder is filled by any nearby site, typically only needing fewer sites to fulfill the total order.

Our model can also be easily set up to simulate when multiple sites need a stat order. With a slightly more complex problem, the results are still similar. Small sites rely on nearby medium sites for the quick initial supply but are still heavily reliant on the larger sites for the bulk of the order. Large sites rely heavily on their own supply and then other nearby medium and large sites. The model efficiently optimizes the shortest time to fulfill multiple orders at the same time.

Output / Input	*Atlin*	*Dease Lake*	*Hazelton*	*Terrace Mills*	*Extra*	$Supply_i$
Atlin	0	0	0	0	0	0
Dease Lake	2	0	0	0	0	2
Hazelton	2	0	0	0	0	2
Terrace Mills	3	0	0	0	1	4
$Demand_j$	7	0	0	0	1	5304

Table 3: Transportation Matrix of Stat Order of 7 for Atlin

In Table 3, the Cost C_{Total} in the lower right corner is the optimal solution to the objective function of minimizing total travel time. This number indicates the sum of transportation time over all units of blood, so is not indicative of actual time. Actual time would be the travel time between the hospitals, since transporting one unit would take the same amount of time as several units. The model outputs the optimal routes to take and the number of units provided by each site. The numbers within the matrix indicate how many units are transported between each location, matching the column to the row. All other locations did not contribute to the supplying the demand, so were left out of the matrix.

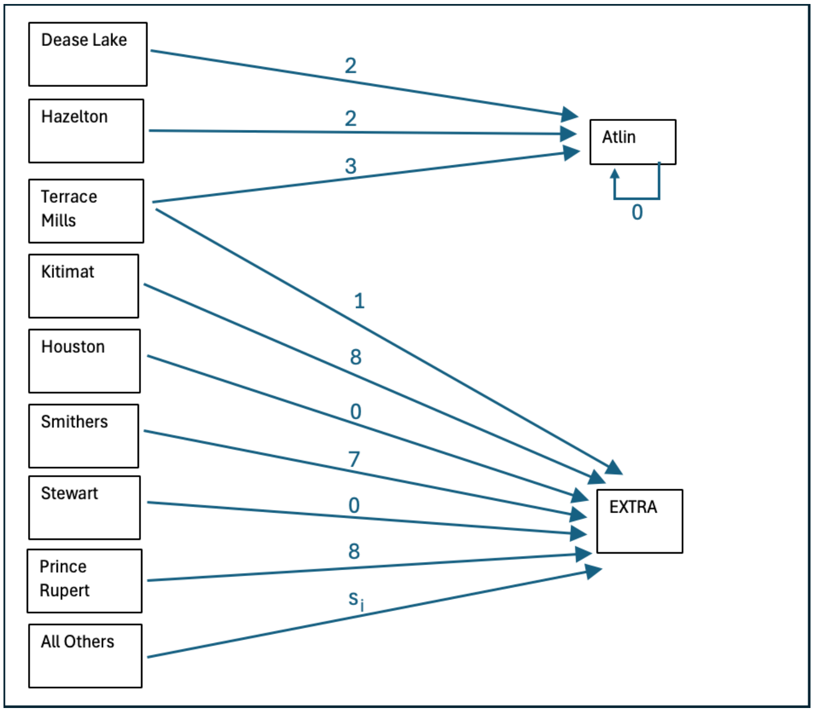

Figure 1: Example Network Flow of Stat Order of 7 for Atlin

Figure 1 shows the network flow of our same example. The 7 units Atlin requires for this stat order are provided by Dease Lake, Hazelton, and Terrace Mills. The remainder of Terrace Mills along with the supply from every other site is sent to the *Extra* or *dummy* site. The supply connected to this dummy site remains at its original location. Atlin itself has no supply, which is indicated by the arrow connected to itself.

Input \ Output	*Atlin*	*Dease Lake*	*Kitimat General*	*Prince Rupert*	*Hazelton*	*Terrace Mills*	*Smithers Buckley*	*Extra*	$Supply_i$
Atlin	0	0	0	0	0	0	0	0	0
Dease Lake	2	0	0	0	0	0	0	0	2
Kitimat General	0	0	5	0	0	0	0	0	5
Prince Rupert	1	0	1	0	0	0	0	4	6
Hazelton	2	0	0	0	0	0	0	0	2
Terrace Mills	0	0	4	0	0	0	0	0	4
Smithers Buckley	5	0	0	0	0	0	0	0	5
$Demand_j$	10	0	10	0	0	0	0	4	8445

Table 4: Transportation Matrix for Multiple Stat Orders of 10 for Atlin and 10 for Kitimat General

A more complicated example is when more than one site needs a large amount delivered in multiple stat orders at the same time. This is indicated in Table 4, with Atlin and Kitimat General both requiring 10 units. This optimal solution minimizes the travel time to fulfill both stat orders and indicates which sites provide the supply to meet this demand.

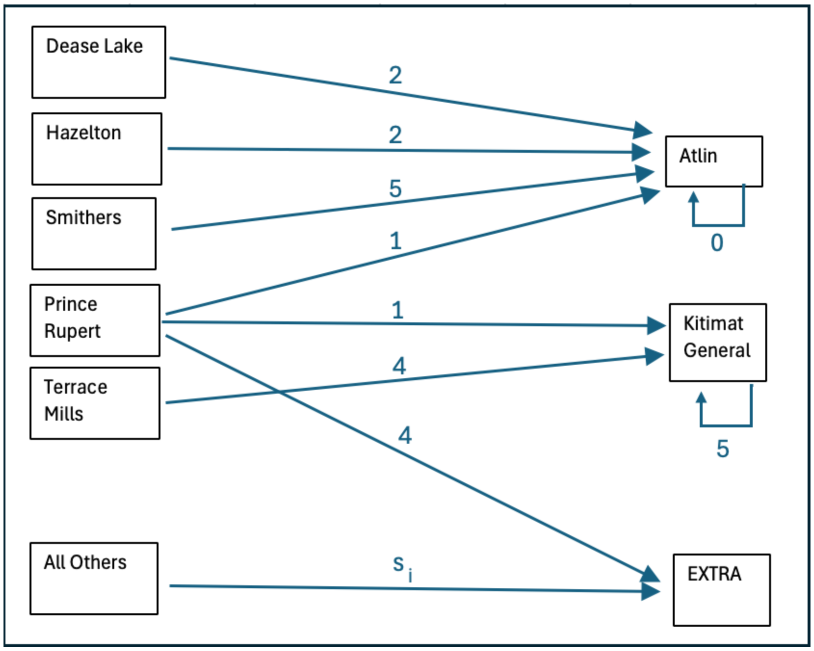

Figure 2: Network Flow for Multiple Stat Orders of 10 for Atlin and 10 for Kitimat General

Figure 2 shows a more complicated example of a network flow when there are multiple stat orders. It differs significantly from the single stat order case seen in Figure 1. Atlin no longer receives the majority from Terrace Mills as this is now rerouted to Kitimat. Atlin receives the majority from Smithers. Prince Rupert provides some supply to both Atlin and Kitimat. This solution minimizes the total travel time to fulfill both stat orders as efficiently as possible.

While using the MS Excel Solver is efficient and does not require much computing power or an internet connection, it has its limitations. On top of needing manual inputs for all variables, it also does not consider traffic delays due to weather or accidents. Also, the MS Excel Solver is limited to 200 decision variables for the matrix, so can only solve up to a 14 x 14 square matrix. Since we have 25 distinct sites, we had to separate these into sub-regions so the solver could be used. In updating the model, we will consider these factors.

3.2 Weighted Cost Pareto Solutions for Distribution:

The updated model can be applied to stat orders while including real-time data. It also gives a general redistribution model for the NH hospitals. In the routing of RBC, we have simplified it by using the one-to-one method. This indicates that one hospital site can only send supply to one other site and receive supply from one other site. The receiving and supplier sites do not necessarily need to be the same. This will help determine the first site to reach out to in an emergency.

The model solves the optimization using a coin-or branch and cut (CBC) solver, an open source optimization solver. The solutions are shown in Figure 3 for multiple values of α from 0 to 1 with steps of 0.1. All α values represent efficient solutions. At $\alpha = 0$, the objective focuses on only minimizing time while at $\alpha = 1$ the objective only minimizes the distance. At $\alpha = 0.5$, the objective is a weighted balanced sum of both conditions.

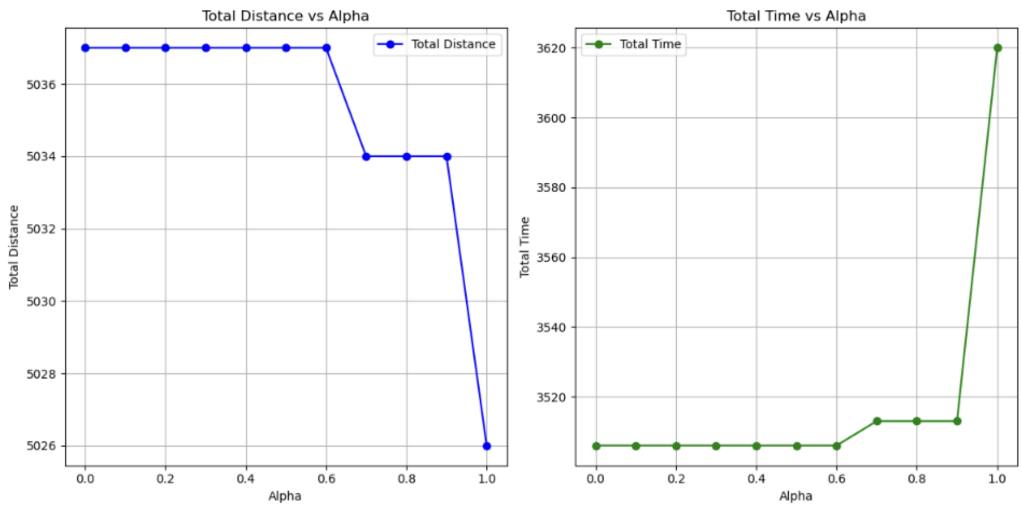

Figure 3: Total Distance vs Alpha and Total Time vs Alpha

The map shown in Figure 4 shows a balanced weighting using $\alpha = 0.5$ paired with offline data collected from Google Maps. The hospital sites are labeled with the index matching those of the Inventory Table 1. The map in Figure 5 can be compared to this. It uses the real-time data collected using ORS API at the same time of day. There are slight changes in the routing based on traffic or weather delays. This could indicate that real-time data should be considered when determining optimal routing.

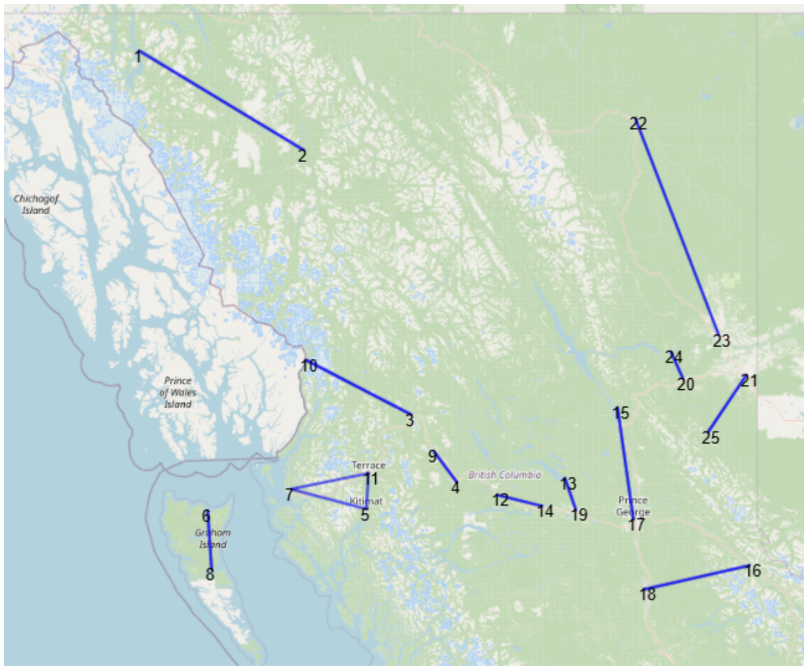

Figure 4: Offline Data Routing Map using One-to-One Method $\alpha = 0.5$

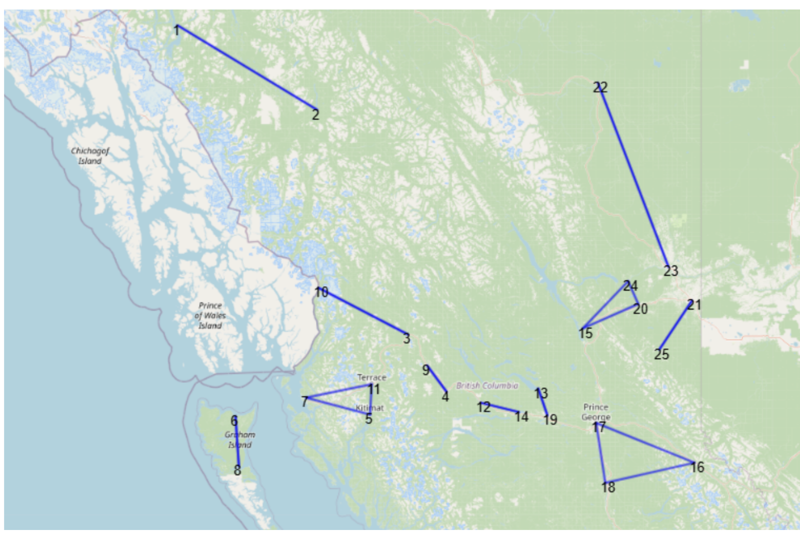

Figure 5: Example Real-time Routing Map of One-to-One Method $\alpha = 0.5$

Figure 6 shows the redistribution of RBC using a one-to-one method. This map indicates where a supply should be redistributed to avoid expiry of the O negative RBCs. These results are based off of the inventory numbers of Table 1. As an example of this, we chose 5 sites with varying average daily inventory levels, ranging from small, medium, and large as before. The small site Atlin receives redistribution from a medium site Dease Lake while Dease Lake recieves from a large site, Kitimat General. This shows that the model manages blood supply by redistributing between hospital sites while still maintaining the objective and minimizing cost and time. The model works to keep sites above their min inventory while not going over the max.

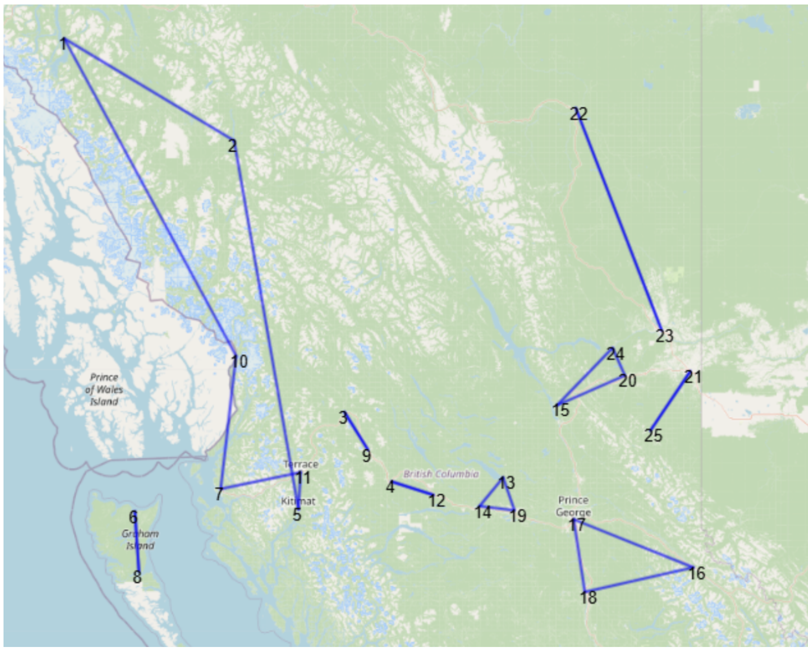

Figure 6: Optimizing Redistribution Using One-to-One Method

3.3 Applications and Limitations:

Our model is designed to be simple and robust. The stat order objective function employs MS Excel, a widely used software that can be operated by all health clinics. The model is efficient with a short solve time so does not require extensive computing power or even a reliable internet connection. Manual inputs of inventory levels make it easy for the user or the model. However, these manual inputs will need to be reliably maintained for each location. The min, max, and average inventory levels are simple to change using the software, which is positive since these values are reevaluated on a regular basis by every BC health authority.

The update to the model helps indicate the first site one should reach out to in an emergency. This is indicated by the one-to-one connection. We can update this to be a one-to-many relationship, where we can have multiple branches going to and coming from each hospital site. This would give a more thorough understanding of the network.

The model is limited in a few ways. Our model is optimizing ground transportation and does not consider other modes of transport. While ground is usually faster than air travel over short distances, there may be some cases where air is a more efficient option. Further, inventory numbers must be reliably kept up to date for each location. Our model only uses estimate inventory amounts so do not necessarily reflect actual data. It was also assumed that redistribution can occur at any time from any site. This is often not the case, particularly at small and medium sites where staffing is limited and 24-hour support is not always available. In particular, not everyone on staff may be able to package RBC products.

Our real-time data was collected over a short time period without natural disasters or heavy snowstorms in the region. This makes it difficult to understand the full extent of which travel time is affected by traffic or weather delays. Even as such, we see small changes in optimal routing when comparing real-time data to offline data, indicating this should be considered in the future.

3.4 Moving Forward and Improvements:

The model can be easily applied to other health authorities within BC. In particular, both Island Health and Interior Health are similar to NH in having many rural communities and large geographical areas, albeit not as large geographically as NH. Both of these BC health authorities also have strong internal courier systems. By updating the travel times between health clinics and min-max inventory levels, we can apply our model effectively.

The same model can be modified for the most cost effective redistribution after a stat order. In our initial problem of an emergency order, cost is not a factor and the priority is speed. This will deplete the resources from a number of nearby hospitals to ensure that the stat order is received quickly. These depleted hospitals will need inventory brought back above their min supply level. Our model can be modified to minimize the cost of redistributing small amounts to multiple sites to replenish inventory. Manual inputs would be required on a case-by-case basis by changing the demand for multiple sites. This would be relatively straight forward in MS Excel.

Further, the model can be applied to any permutation of redistribution needed. If multiple sites need higher inventory and do not want to order from CBS directly, the model can find them which sites to draw this inventory from. Given any manual inputs for inventory needed and correct inventory numbers, the optimal routing for a cost effective redistribution can be found.

The one-to-one method can be updated to include multiple inflows or outflows to each hospital site. This would give a further understanding of the network flow. We could also consider using a different API other than ORS. ORS is limited to requesting data 40 times per minute and 2500 requests per day, which limited the scope of our findings. A different API could be used which allows more requests per minute.

A further improvement could be to implement machine learning to simulate the distribution between hospital sites. This would help to improve the decision making during an emergency situation. This MOO approach can be compared to other MOO methods to see if there is a better Pareto front.

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