Route Optimization for Blood Bank Visits in Tacloban City Using the Traveling Salesman Problem

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ABSTRACT

Efficient access to blood banks is critical for patient care in regions experiencing persistent shortages of blood supply. This study applies the Traveling Salesman Problem (TSP) framework to optimize travel routes among eight major blood banks in Tacloban City, Philippines. Using data on distance, time, and fare collected through field observations, Google Maps, and local fare matrices, weighted graphs were constructed to represent inter-hospital connectivity. The Greedy Algorithm was employed to generate heuristic solutions for minimizing total travel burdens from multiple starting points. Results showed that optimal paths varied depending on the choice of starting facility, with centrally located hospitals such as Mother of Mercy Hospital and Divine Word Hospital producing shorter routes in terms of both time and cost. By contrast, the Eastern Visayas Medical Center, being geographically isolated, consistently resulted in higher travel distances. Findings demonstrate that heuristic approaches can effectively support healthcare logistics by reducing cost and time for patients' families during emergencies. This research contributes to the growing body of work integrating combinatorial optimization into public health logistics, offering insights for planners, administrators, and policymakers.

Keywords: Traveling Salesman Problem, healthcare logistics, greedy algorithm, Tacloban City, blood bank access

Blood availability represents one of the most critical determinants of a functional healthcare system globally. As a unique medical resource, blood cannot be artificially synthesized, has a limited shelf life, and is indispensable across numerous clinical procedures. It plays a life-saving role in trauma care, maternal emergencies, surgical operations, treatment of hematological disorders, and management of cancers requiring transfusion support. The World Health Organization (WHO) underscores that consistent and safe blood supply is a cornerstone of modern health services, yet significant disparities persist between high- and low-income regions. Globally, nearly 120 million units of blood are donated annually, but this remains insufficient to meet demand, particularly in resource-limited settings where infrastructure and healthcare access are unevenly distributed. Of these donations, 40% are collected in high-income countries, which house only 16% of the world's population, highlighting a profound inequity in resource distribution. In low-income countries, up to 54% of transfusions are administered to children under five years old, whereas in high-income countries, the most frequently transfused group is patients over 60 years of age, accounting for up to 76% of all transfusions. These disparities are further exacerbated by challenges in blood screening, processing, and storage, with only 56 of 171 reporting countries producing plasma-derived medicinal products domestically (Pop, 2024).

The Philippines, and specifically the Eastern Visayas region, provides a compelling case study for examining blood supply logistics in resource-constrained environments. The Department of Health (2020) reported that Eastern Visayas requires approximately 30,000 units of blood annually, but actual collections consistently fall short of this target. This gap between supply and demand intensifies during periods of increased medical need, such as the dengue outbreak of 2024, which led to a 314% surge in cases compared to the previous year. This resulted in an overwhelming demand for blood and platelet concentrates, particularly at tertiary hospitals like the Eastern Visayas Medical Center (EVMC). Despite intensified donation campaigns, hospitals reported critical shortages (Leyte Samar Daily News, 2024), forcing families of patients to take on the burden of searching for blood supplies themselves, often traveling across multiple facilities without guarantee of availability.

This situation highlights an often-overlooked dimension of healthcare logistics: the socio-economic burden placed on patients' families. When shortages occur, hospitals often require relatives to secure replacement donations or locate blood units from other institutions. Without centralized information systems, families resort to physically visiting different blood banks across Tacloban City, a process that is time-consuming, resource-draining, and psychologically taxing. For families already under stress due to medical emergencies, this additional burden translates to wasted effort, time, and money, potentially exacerbating health inequities (Raykar et al., 2021).

Consider a typical scenario: a relative of a patient requiring an urgent transfusion starts at EVMC, the primary referral hospital in the region. After being informed that the blood type is unavailable, the relative must visit other facilities such as the Philippine Red Cross, Divine Word Hospital, or Mother of Mercy Hospital. Each trip entails transportation costs, waiting times, and uncertainty. If the relative travels inefficiently—backtracking across distant hospitals or missing nearby facilities—they may spend hours and significant financial resources without securing the needed blood. In critical cases, this inefficiency can be life-threatening. Thus, the problem is not solely one of supply shortage but also of access optimization and resource allocation.

This study proposes that mathematical optimization, specifically through the Traveling Salesman Problem (TSP), offers a systematic approach to reducing wasted resources in this context. The TSP is one of the most well-known NP-hard problems in combinatorial optimization, asking: given a set of locations and pairwise distances, what is the shortest possible route that visits each location exactly once and returns to the starting point? It has been widely applied in logistics, manufacturing, and healthcare, including ambulance routing, vaccination distribution, and patient scheduling (Liu et al., 2022). Recent advancements in heuristic algorithms, such as those applied in home care scheduling and blood supply chain management, demonstrate the potential for TSP-based solutions to address real-world logistics challenges (Teng et al., 2022). For instance, studies have shown that heuristic algorithms can optimize routes for healthcare workers serving patients in dispersed locations, reducing travel time and costs while improving service delivery (Pop, 2024).

The appeal of using the TSP in Tacloban's blood bank network lies in its ability to model the search process of families. Each hospital with a blood bank can be represented as a "node," and the travel distance, time, or fare between hospitals serves as the "weight" of the connecting edge. Solving the TSP allows for the identification of routes that minimize the total burden of visiting all potential facilities. While families may not need to visit all hospitals in practice, the principle of route minimization ensures that any truncated journey follows an efficient sequence, making the model highly applicable to real-time decision-making.

Various methods exist for solving the TSP. Exact algorithms like Branch-and-Bound (Little et al., 1963) and Cutting Plane approaches (Dantzig et al., 1954) guarantee optimality but are computationally demanding for real-time applications. Metaheuristics such as Genetic Algorithms (Holland, 1992) and Ant Colony Optimization (Dorigo & Gambardella, 1997) provide near-optimal solutions but require specialized implementation resources (Teng et al., 2022). In contrast, the Greedy Algorithm offers a balance of simplicity and utility, making it suitable for resource-constrained settings. The Greedy Algorithm follows a straightforward nearest-neighbor strategy, selecting the closest unvisited location at each step until all are visited (Cormen et al., 2009). Although it does not guarantee global optimality, it often produces near-optimal solutions for small networks and aligns with human decision-making under stress (Pop., 2024).

One critical advantage of the Greedy Algorithm in this context is its flexibility for route truncation. Since each step selects the nearest unvisited hospital, families can stop the route at any point once blood is secured, confident that the sequence was efficient up to that point. This property distinguishes it from other heuristics that may require complete route execution for efficiency. Moreover, the algorithm's simplicity allows for easy integration into mobile applications or printed guides, providing practical solutions for families in crisis.

From a policy perspective, this approach offers actionable insights. Healthcare administrators could provide pre-computed efficient routes from each hospital, tailored to distance, time, or fare metrics. Local government units could integrate such models into digital platforms, reducing the informational burden on patients. Additionally, recognizing that efficiency metrics may not always align—e.g., shortest distance versus lowest fare—decision-makers can offer multiple route options based on family priorities (e.g., cost minimization versus time urgency).

This study situates itself at the intersection of healthcare logistics, computational optimization, and equity in access. By applying the TSP framework and Greedy Algorithm to Tacloban's blood bank network, it addresses both theoretical and practical concerns: how to model an NP-hard problem in a constrained environment, and how to reduce the socio-economic burden on families during medical emergencies. In doing so, it contributes to ongoing discussions in operations research, healthcare access, and local health policy, while highlighting the need for innovative solutions in resource-limited settings.

The objectives of this paper are threefold: (1) to construct weighted graphs representing distances, times, and fares among major blood banks in Tacloban City; (2) to apply the Greedy Algorithm in generating minimized travel routes; and (3) to evaluate the relative efficiency of different starting points. By demonstrating the utility of heuristic optimization in a pressing public health context, this research aims to bridge the gap between abstract mathematical models and the lived experiences of patients and families in resource-limited settings.

MATERIALS AND METHODS

Study Locale

This study was conducted in Tacloban City, Leyte, Philippines, the regional hub of Eastern Visayas. Tacloban serves as the primary access point for healthcare services in the region and hosts several public and private hospitals that maintain blood banks. The city is geographically compact but characterized by uneven clustering of medical facilities: while some hospitals are located within short walking distance of one another in the city center, others such as the Eastern Visayas Medical Center (EVMC) are situated in relatively isolated areas. This uneven distribution provides a natural case study for route optimization problems in healthcare access.

Eight major hospitals and blood banks were included in the study, with each facility assigned a letter code to represent its corresponding node in the graph: (A) Eastern Visayas Medical Center (EVMC), (B) Divine Word Hospital, (C) Philippine Red Cross – Leyte Chapter, (D) Mother of Mercy Hospital, (E) United Shalom Hospital, (F) Remedios Trinidad Romualdez (RTR) Hospital, (G) ACE Medical Center Tacloban, and (H) Tacloban City Hospital. These coded nodes form the network of primary blood supply sources for patients in Tacloban and its neighboring municipalities.

Data Collection

Data on travel distance, travel time, and transportation fare between each hospital pair were collected using a combination of direct observation and digital mapping. Distances were measured using Google Maps, ensuring that the shortest practical road routes were selected**.** Travel times were recorded through actual trips using public transportation under normal traffic condition. Fares were documented based on fare matrices for local jeepney and tricycle services, validated through actual commutes between facilities.

Data collection was conducted between October 2024 and January 2025, a period representative of typical city traffic but excluding extraordinary disruptions (e.g., typhoon aftermath). Each route was measured at least twice to account for variability in traffic, and average values were used in subsequent analyses.

Graph Construction

The collected data were used to construct weighted, undirected graphs where: the vertices (nodes) represent the blood banks, the edges represent the connections between facilities, and the weights correspond to one of three metrics: distance (kilometers), time (minutes), or fare (Philippine pesos). Separate graphs were generated for each metric to allow for independent analysis of travel efficiency depending on the constraint considered.

Algorithmic Approach

The study employed the Greedy Algorithm as a heuristic solver for the Traveling Salesman Problem (TSP). The algorithm proceeds as follows:

1. Initialization: Select a starting vertex (hospital).
2. Selection rule: From the current vertex, choose the nearest unvisited vertex based on the chosen weight (distance, time, or fare).
3. Iteration: Mark the chosen vertex as visited and repeat the selection rule until all vertices have been visited.
4. Completion: Return to the starting vertex, forming a Hamiltonian cycle.

This process was repeated for each of the eight hospitals as starting points, generating a set of candidate routes. The algorithm was implemented manually using recorded data and systematically checked for accuracy.

Although the Greedy Algorithm does not guarantee an optimal global solution, its computational simplicity and interpretability make it a suitable heuristic for small-to-medium problem instances, such as the eight-vertex case in this study.

Ethical Considerations

As this study involved only publicly accessible hospital locations and did not require human subjects or patient data, formal ethics approval was not required. However, the research adhered to principles of responsible research conduct by ensuring data accuracy, avoiding misrepresentation of hospital services, and contextualizing results for potential use in public health planning.

RESULTS

Graphical Representation of Blood Bank Network

Figure 1 shows the weighted graph representing travel distances among the eight major blood banks in Tacloban City. Each vertex corresponds to a blood bank, while edges are weighted by the distance in kilometers. The two weights correspond to the distance to and from each blood bank.

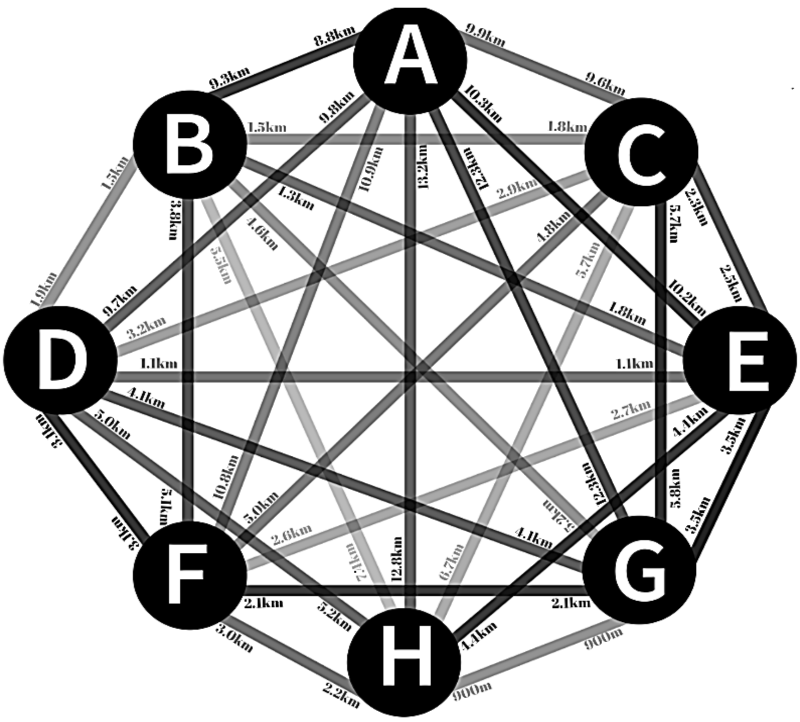

Figure 1. Weighted graph for distances (in km) between blood banks

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The graph shows that distances between blood banks range from 0.9 km (between ACE Medical Center and Tacloban City Hospital) to 13.2 km (between EVMC and Tacloban City Hospital). The data highlight two key features of Tacloban's hospital network. The graph reveals clear spatial clustering: Divine Word Hospital, Mother of Mercy Hospital, United Shalom Hospital, and the Philippine Red Cross form a dense central group, where these blood banks are within 2.5 km from each other. On the other hand, the Eastern Visayas Medical Center (EVMC) is more peripheral which suggests that routes starting within the central cluster may yield shorter overall paths than those beginning at EVMC.

Figure 2 illustrates the weighted graph representing travel time between the eight major blood banks in Tacloban City. Each vertex corresponds to a blood bank, while edges are weighted by the travel time in minutes and seconds. The two weights correspond to the travel time to and from each blood bank.

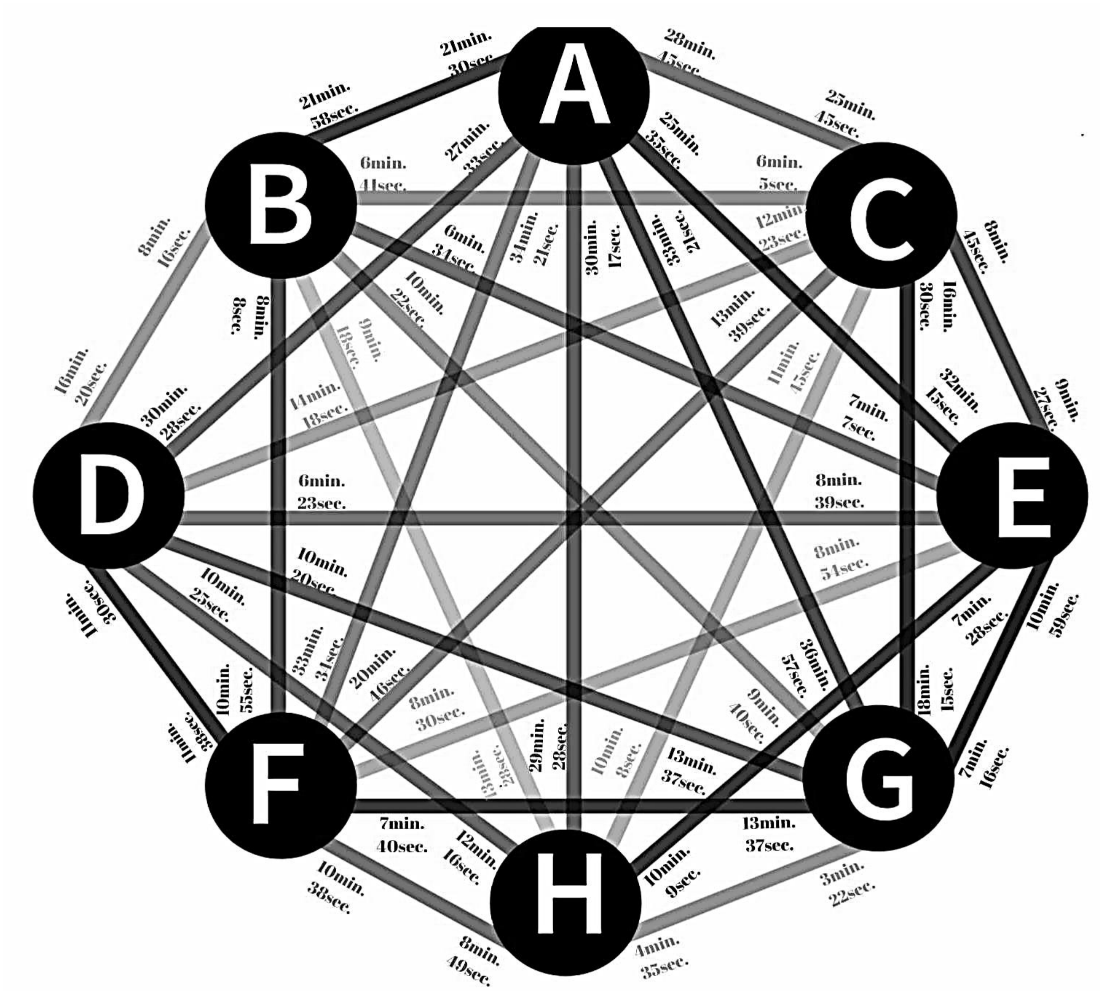

Figure 2. Weighted graph for travel time (in minutes and seconds) between blood banks

The shortest recorded time was just above 3 minutes (from ACE Medical Center to Tacloban City Hospital), while the longest little less than 38 minutes (from EVMC to Tacloban City Hospital). Notably, travel times are not strictly proportional to distance. For example, a relatively short 2.5 km route may take over 10 minutes if it passes through congested intersections.

The clustering effect observed in the distance data is reinforced here: central hospitals have travel times typically under 10 minutes between them, while EVMC requires 20–37 minutes to reach any other facility. This emphasizes the importance of accounting for time rather than distance alone when optimizing emergency-related travel.

Figure 3 shows the weighted graph representing the fare when travelling between the eight major blood banks in Tacloban City. Each vertex corresponds to a hospital, while edges are weighted by the fare paid in Philippine pesos (₱).

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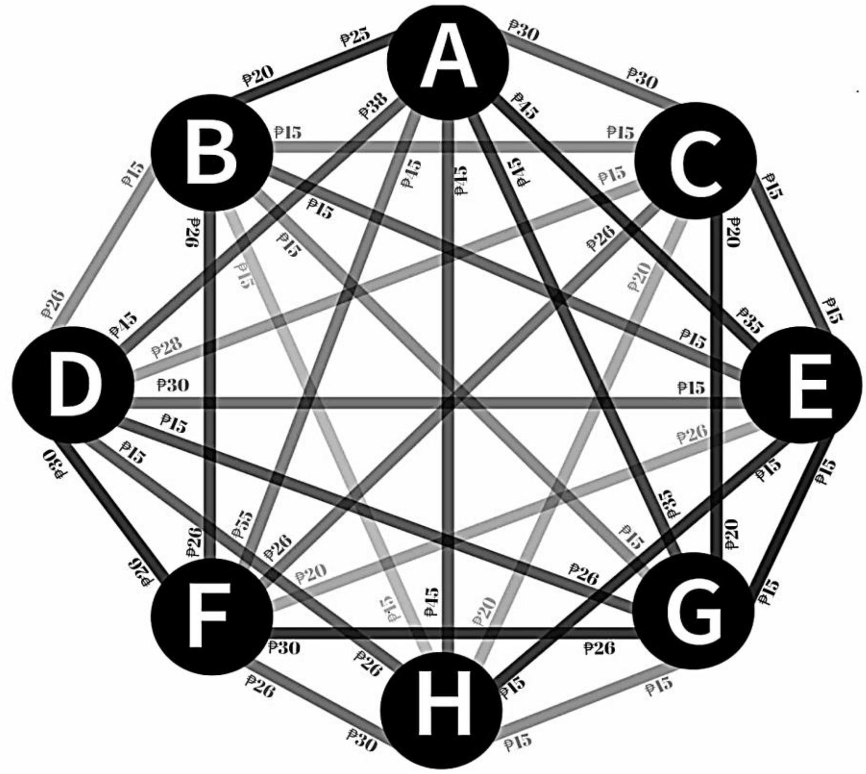

Figure 3. Weighted graph for fare between blood banks

The lowest fare recorded was ₱15, representing the minimum fare for short jeepney or tricycle rides. The highest was ₱45, for longer trips involving EVMC or peripheral hospitals. It can be observed that there is uniformity within the central cluster. Fares among Divine Word, Mother of Mercy, United Shalom, and the Philippine Red Cross are consistently ₱15–₱20, reflecting short travel distances. It also shows that there is cost escalation with EVMC. Trips involving EVMC almost always approach ₱40–₱45, reinforcing its status as the most expensive starting or ending point. Finally, there is seeming non-linearity of fare–distance relationship. Certain short routes (e.g., Mother of Mercy to United Shalom at 1.1 km) still cost ₱30, showing the influence of fare zoning rules rather than pure distance.

This suggests that minimizing fares may not always align with minimizing distances, introducing an important trade-off in route optimization.

Greedy Algorithm Application

To evaluate practical route options, the Greedy Algorithm was applied using each hospital as a starting point. The Philippine Red Cross is not considered as a starting point since they don't have patients. Succeeding blood banks to be visited are determined using the Greedy Algorithm.

Eastern Visayas Medical Center (EVMC) as Starting Point

With EVMC as the starting point, the Greedy Algorithm showed that there is a uniform route for optimal distance, travel time, and fare amount. The route is as follows EVMC to DWH to USH to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to Philippine Red Cross and finally back to EVMC. This route will yield a total of 36 km of travelled distance, total travel time of 1 hour 47 minutes and 28 seconds, and total fare of ₱175.

Divine Word Hospital (DWH) as Starting Point

Applying the Greedy Algorithm using DWH as starting point also reveals a uniform optimal route for distance, travel time, and fare amount. The route to be taken is as follows: DWH to USH to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to Philippine Red Cross to EVMC and finally back to DWH.

This route will yield a total distance of 28.8 km, travel time of 1 hour 50 minutes and 48 seconds, and a total fare of ₱180.

Mother of Mercy Hospital (MMH) as Starting Point

When MMH is employed as the starting point, the Greedy Algorithm showed that there is a uniform route for optimal distance, travel time, and fare amount. The route to be taken is as follows: MMH to USH to DWH to Philippine Red Cross to ACEMC-Tacloban to Tacloban City Hospital to RTR Hospital to EVMC and finally back to MMH. This route will yield a total of 33.8 km, travel time of 1 hour 49 minutes and 59 seconds, and a total fare of ₱218.

United Shalom Hospital (USH) as Starting Point

With USH as the starting point, applying the Greedy Algorithm also reveals a uniform optimal route for distance, travel time, and fare amount. The route to be taken is as follows: USH to DWH to Philippine Red Cross to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to EVMC then back to USH. This route will yield a total distance of 35 km, total travel time of 1 hour 47 minutes and 56 seconds, while the total fare is ₱205.

Remedios Trinidad Romualdez (RTR) Hospital as Starting Point

The Greedy Algorithm showed that, with RTR Hospital as starting point, there is a uniform route for optimal distance, travel time, and fare amount. This route is from RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to USH to DWH to Philippine Red Cross to MMH to EVMC then back to RTR Hospital. Taking this route will result to a total 36.4 km of travelled distance, 1 hour 53 minutes and 10 seconds of travel time, and ₱195 fare.

ACE Medical Center (ACEMC) - Tacloban as Starting Point

Using ACEMC-Tacloban as starting point and applying the Greedy Algorithm reveals a uniform optimal route for distance, travel time, and fare amount. The route to be taken is as follows: ACEMC-Tacloban to Tacloban City Hospital to RTR Hospital to USH to DWH to Philippine Red Cross to MMH to EVMC then back ACEMC-Tacloban. Taking this route will accumulate to a total distance of 36.1 km, total travel time of 1 hour 51 minutes and 41 seconds, and total fare of ₱215.

Tacloban City Hospital as Starting Point

Using the Greedy Algorithm and Tacloban City Hospital as starting point, the optimal route in terms of distance, travel time and fare. The route is as follows: Tacloban City Hospital to ACEMC-Tacloban to USH to DWH to Philippine Red Cross to MMH to RTR Hospital to EVMC back to Tacloban City Hospital. This gives us a total distance of 37.3 km, total travel time of 1 hour 53 minutes and 43 seconds, and total fare of ₱210.

DISCUSSION

A closer examination of the generated tours reveals patterns of similarity and divergence depending on the chosen starting point. Notably, the routes beginning from Eastern Visayas Medical Center (EVMC) and Divine Word Hospital (DWH) produce nearly identical sequences of subsequent hospitals. For instance, the path EVMC to DWH to USH to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to Philippine Red Cross to EVMC mirrors the path DWH to USH to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to Philippine Red Cross to EVMC to DWH. When treated as circular tours, these two are equivalent, differing only in their point of entry into the cycle. This outcome highlights how central locations such as EVMC and DWH naturally anchor similar traversal patterns under the Greedy Algorithm.

In contrast, the remaining five routes diverge in one or more adjacency relationships, leading to distinct traversal orders. For example, comparing the sequence MMH to USH to DWH to Philippine Red Cross to

ACEMC-Tacloban to Tacloban City Hospital to RTR Hospital to EVMC to MMH with USH to DWH to Philippine Red Cross to MMH to RTR Hospital to ACEMC-Tacloban to Tacloban City Hospital to EVMC to USH shows how small shifts in the starting point alter the subsequent order of visits. In the first case, Mother of Mercy Hospital (MMH) is immediately followed by United Shalom Hospital (USH), whereas in the second case MMH is instead followed by RTR Hospital. Similar variations are observed across routes that begin from USH, MMH, RTR Hospital, ACEMC-Tacloban, and Tacloban City Hospital, each producing unique adjacency patterns.

These findings underscore a key characteristic of the Greedy Algorithm: while it generates efficient local choices at each step, the global structure of the tour depends heavily on the starting node. Unlike exact optimization methods, which guarantee a single optimal tour regardless of the starting point, the Greedy Algorithm produces multiple plausible routes that may overlap substantially or diverge in subtle but meaningful ways. In practice, this variability suggests that families beginning their search from different hospitals may encounter different sequences of facilities, but each path will still reflect a locally optimal progression.

Although distance, travel time, and fare did not always vary in a strictly linear manner, the application of the Greedy Algorithm revealed that for any given starting point, the algorithm produced the same sequence of blood banks regardless of which metric was used. In other words, whether optimization was based on minimizing distance, minimizing travel time, or minimizing fare, the resulting route was identical so long as the starting location remained constant.

CONCLUSION

This study demonstrated the value of applying graph-based modeling and heuristic optimization to the problem of accessing blood banks in Tacloban City. By converting data on distances, travel times, and fares into weighted graph representations, the analysis provided a systematic framework for visualizing and quantifying the logistical burden faced by patients' families. The use of the Greedy Algorithm further allowed the generation of efficient routes through the network, revealing that the same sequence of facilities emerges for a given starting point regardless of whether the metric of optimization is distance, time, or fare.

Comparative analysis of the tours highlighted important patterns. Routes originating from central hospitals such as the Eastern Visayas Medical Center (EVMC) and Divine Word Hospital (DWH) produced nearly identical traversal patterns, while routes starting from other facilities introduced subtle but meaningful variations in adjacency relationships. These findings underscore a defining feature of the Greedy Algorithm: although it consistently yields locally efficient decisions, the overall tour structure is shaped by the chosen starting node. As a result, families beginning their search from different hospitals may encounter different sequences of facilities, but each sequence remains efficient relative to its point of origin.

Taken together, these results illustrate how mathematical modeling can be leveraged to ease real-world burdens in healthcare logistics. In the context of Eastern Visayas—where blood shortages are persistent and families often bear the responsibility of locating available units—such optimization approaches can help minimize wasted effort, time, and resources. More broadly, the study contributes to the growing body of work demonstrating how classical computational problems, when thoughtfully adapted, can generate actionable insights for public health planning in resource-constrained settings.

RECOMMENDATIONS

Based on the findings, the following recommendations are proposed to enhance healthcare logistics and patient support in Tacloban City:

1. Integration into hospital and community systems. Hospitals and blood banks may establish a centralized platform for real-time updates on blood availability. When combined with pre-computed Greedy Algorithm routes, such a system would help families identify the most efficient sequence of facilities to visit, minimizing wasted time, money, and effort.

2. Development of decision-support tools. Local government units, in partnership with healthcare providers, may develop mobile applications or distribute printed route guides derived from the optimized paths identified in this study. These tools would provide practical assistance to families in navigating blood bank networks during emergencies.
3. Strengthening central hubs**.** Since routes beginning at EVMC and DWH demonstrated anchoring effects within the network, policymakers may prioritize these facilities as logistical hubs. Enhancing their storage capacities and donation programs could yield system-wide benefits by reducing the need for extended searches across multiple hospitals.

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