AQUA PRO: WATER ACCESS EFFICIENCY THROUGH ANT COLONY OPTIMIZATION WITH 2-OPT LOCAL SEARCH STRATEGY

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ABSTRACT

ADRIAN JONES M. ABACHE, **MARK JEROME C. CIFRA**, AND **ANGEL MAE A. NACION**, "AQUA PRO: WATER ACCESS EFFICIENCY THROUGH ANT COLONY OPTIMIZATION WITH 2-OPT LOCAL SEARCH STRATEGY," (Unpublished Undergraduate Thesis, Bicol University College of Science, Legazpi City, May 2024)

The proliferation of water refilling stations in Legazpi City is becoming increasingly important, as they are the preferred source of water for households and other establishments. As the number of water refilling stations grows, so does the importance of efficient water delivery. The Traveling Salesman Problem (TSP) plays a significant role in logistics distribution in real-world applications such as this. This paper proposes a library-based Ant Colony Optimization (ACO) scheme with a two-optimization (2-opt) strategy to efficiently solve the TSP. To evaluate the performance of ACO with 2-opt, we have designed two challenging TSP cases with up to 51, 100, and 200 nodes and compared them with standard ACO. The experimental results show that ACO with 2-opt can effectively solve the TSPs, but it also demands significant computational resources as the number of nodes increases. The developed system aims to assist small businesses of water refilling stations in enhancing their operations and facilitating easy water access for customers. It employs ACO with a 2-opt strategy for route optimization in water delivery. From the customers' perspective, it utilizes the Haversine formula to locate nearby stores. The system also integrates real-time GPS tracking and a client-server network for seamless user interactions.

Keywords: Traveling Salesman Problem (TSP); Ant Colony Optimization (ACO); 2-optimization (2-opt) strategy

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

Chapter I

INTRODUCTION

Background of the Study

In the Philippines, access to clean and safe drinking water is a fundamental necessity. Water refilling stations serve as reliable hubs where communities can access purified water conveniently and affordably, contributing significantly to public health and environmental sustainability. Water refilling stations managed by private entrepreneurs offer a cheaper and more convenient solution to the public's drinking water needs than bottled water or the use of household filters.

Households had better access to drinking water in 2022, with more than 50% of their supply sourced from commercial refilling stations, according to the Philippine Statistics Authority's (PSA) latest Annual Poverty Indicators Survey (APIS). The 2022 Annual Poverty Indicators Survey (APIS) showed that 97.6% or 26.942 million families had an improved source of drinking water, up by 4.2% from the 97.5% or 25.848 million recorded in 2020. The article by B.B. Magtibay (2021) stated that about 3,000 water refilling stations have proliferated nationwide. They sell purified water of comparable quality to bottled water at a lower price.

With the increase of water refilling stations, water delivery is also becoming vital as it provides fresh and clean water every day. The study by Danilo Israel (2009) found that the price, quality, and accessibility of potable

water were significant factors influencing households in their choice of water source, and the most convenient option was getting it from water refilling stations through water delivery services provided by the stations themselves. Also, the water supply may only run for a few hours in some areas, and working individuals might not have the time to store it.

According to the article of Surbhi Bhatia (2023), businessmen fabricate apps that cater to consumer needs 24/7, and app users can place their orders and schedule a delivery time based on their availability. This trait of the app helps water refilling stations enhance work efficiency and stand out in the market. Water refilling stations can accelerate their business operations by using delivery apps to serve their customers. Ravi Garg (2023) stated that water delivery applications provide real-time tracking and communication capabilities, allowing businesses to monitor and manage deliveries effectively. With Global Positioning System (GPS) tracking, delivery riders can track the location of their customers, ensuring timely deliveries and improved route planning. Additionally, drivers can stay connected with the application and receive updates regarding new orders, changes in delivery schedules, or any other relevant information.

Water delivery involves picking up water bottles from the water refilling station and delivering them to customers. A vehicle with a given capacity performs both pickups and deliveries with the objective of finding the shortest possible route. We can compare this problem to the classic Traveling Salesman Problem (TSP). TSP considers a set of locations and aims to find the shortest route to visit every one of them, then return to the starting point. The problem

consists of determining a minimum cost tour such that each pickup vertex is visited before its corresponding delivery vertex. According to Feng et al. (2009), although the TSP is easily formulated, it exhibits all aspects of Combinatorial Optimization Problems (COP) as well as has served and continues to serve as the benchmark problem for new algorithmic ideas. TSP has been studied with a large number of heuristic and metaheuristic algorithms, wherein swarm and evolutionary algorithms have provided effective solutions to TSP even with a large number of vertices. Evolutionary computation algorithms have been one of the most efficient methods to solve NP-hard optimization problems. In recent decades, various types of evolutionary computation algorithms have been developed, including the Ant Colony Optimization (ACO).

ACO is a metaheuristic proposed by Marco Dorigo in 1991 based on the behavior of biological ants. Dorigo first introduced ACO in his Ph.D. thesis and applied it to the TSP. According to him, ACO is a population-based metaheuristic that can be used to find approximate solutions to complex optimization problems. In ACO, a set of software agents called artificial ants search for reasonable solutions to a given optimization problem. To apply ACO, the optimization problem is transformed into the problem of finding the best path on a weighted graph. The artificial ants (hereafter ants) incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph components (either nodes or edges) whose values are modified at runtime by the ants. Considering the effectiveness of the ACO algorithm in solving TSP, it remains a prominent choice for tackling COP due to its ability to find near-optimal solutions. Moreover, this heuristic probability search method does not easily fall into local optimization and is shown to find the optimal global solution of TSP efficiently. It has also been shown that the integration of local search operators can significantly improve the performance of ACO. Therefore, this paper embedded the 2-opt strategy into the ACO to solve TSP.

This paper focuses on proposing an efficient ACO algorithm with a two-optimization (2-opt) local search strategy to solve TSP by optimizing water delivery routes for water refilling stations. Legazpi City, situated in the Bicol Region of the Philippines, faces unique challenges related to urbanization, traffic congestion, and geographical constraints. These factors necessitate the development of efficient delivery routes to ensure timely and reliable water supply from water refilling stations across the city. By leveraging the collective intelligence of artificial ants, ACO aims to find near-optimal solutions for the TSP, taking into account factors such as road conditions, traffic patterns, and the locations of water refilling stations. The study will also use the haversine formula to calculate the minimum distance between any two points on the spherical body using latitude and longitude to determine the nearby water refilling station/s around a customer.

By combining ACO and the 2-opt strategy in the algorithm design, along with the use of the haversine formula, GPS, and a client-server network, the researchers aim to develop the Aqua Pro mobile application, which could serve as a potential catalyst for transformation. This smartphone application is targeted at enhancing the water distribution environment in Legazpi City.

Objectives of the Study

General Objectives

The general objective of the study is to develop a system capable of managing and tracking water delivery services at the least cost for both customers and delivery riders in Legazpi City. Specifically, the study aims to attain the following:

- 1. To utilize a library-based ACO scheme with a 2-opt local search strategy for solving the TSP and compare it with standard ACO,
- 2. To utilize the ACO with 2-opt for route optimization of water delivery, and
- 3. To develop a module integrating ACO with 2-opt, haversine formula, real-time GPS tracking, mapping services, and client-server network.

Scope and Delimitations of the Study

This study focuses on the development of a water delivery system integrating the ACO algorithm with a 2-opt strategy, which will enhance the water delivery services in Legazpi City. The study will include modules that will track the services through real-time tracking. The geographical scope includes areas from Legazpi City, Albay, Philippines. The specific barangays covered were Barangay 1 to Barangay 41, as well as Barangay 57 and Barangay 58, with a total of forty-three barangays. Excluded from this scope are the barangays from Northern Legazpi (Barangay 42 to Barangay 56) and Southern Legazpi

(Barangay 59 to Barangay 70). The functional modules of the project include real-time tracking mechanisms to monitor water delivery services, optimization of route planning for efficient distribution, and the application of the haversine formula to identify the nearby refilling station/s for each customer. Additionally, the researchers will design and implement a mobile application that integrates GPS tracking, mapping services, and client-server networks to enhance user interactions.

However, certain delimitations are acknowledged. Our focus will be on ACO and the 2-opt strategy, excluding other optimization algorithms. The success of the project relies on the availability and accessibility of existing refilling stations in Legazpi City. The mobile application will be tailored for the Android platform only. Legal and regulatory considerations will be addressed within this study. Factors beyond our control (e.g., weather conditions, road closures) are not within the study's scope.

Significance of the Study

The study will provide important implications for Legazpi residents and water refilling stations. The development and evaluation of the Aqua Pro app offer a practical and innovative solution, improving the effectiveness and accessibility of water delivery services. This research assures a more reliable supply of safe drinking water, significantly improving their daily lives.

The generalization of this present study would be a significant contribution to the vast knowledge in relation to other shortest-path analyses. The vital results of this study could be highly significant and beneficial specifically to the following:

Legazpi City residents - stand to benefit considerably from this study as it addresses the city's water access challenges. The implementation of the Aqua Pro app ensures a more efficient and reliable supply of safe drinking water, thereby significantly improving the daily lives of residents and addressing their water-related concerns.

Water refilling stations - The Aqua Pro app presents an opportunity to revolutionize how these businesses operate and interact with their consumer base. It offers potential benefits such as streamlined operations, cost reduction, and enhanced service quality. By optimizing delivery routes and improving overall efficiency, water refilling stations can provide better and more timely services to their customers, ultimately contributing to the growth and success of their businesses.

Bicol University College of Science - This study can contribute to the institution's expansion and development of knowledge in computer science, specifically in the field of artificial intelligence.

Researchers - This study will provide additional knowledge to researchers in the field of shortest path analysis, offering insights and methodologies that can be valuable for researchers exploring similar topics in the future. The development and evaluation of the Aqua Pro app serve as a practical case study, showcasing the application of shortest path analysis in solving real-world problems related to water delivery services.

Future Researchers – This study would serve as a comprehensive reference, providing a foundation for future research endeavors in the field of artificial intelligence and application development. The methodologies and findings presented in this study can guide future researchers in designing and conducting their own investigations, potentially leading to further innovations and improvements in water delivery systems.

Chapter II

THEORETICAL FRAMEWORK

This chapter presents the related literature and studies after the thorough and in-depth review done by the researchers. This will also show the synthesis and research gap, the conceptual framework to fully understand the research, and lastly, the definition of terms for better comprehension of the study.

Water Refilling Stations

Over the years, as the demand for cleaner water becomes higher, the price of household water purifiers and bottled water has become prohibitive. In the article of B. B. Magtibay (2023), water refilling stations managed by private entrepreneurs offer a cheaper and more convenient solution to the public's drinking water needs than bottled water or the use of household filters. The demand at the water refilling stations – water stores that sell purified water – is now increasing. The quality of purified water conforms with the national standards for drinking water and is even better than the quality of water produced by traditional water supply systems in terms of removed impurities.

The study of R. Espinosa (2023) about water refilling stations at Alaminos City Pangasinan highlighted that water refilling stations are among the most promising ventures. The demand for clean drinking water will never diminish, and water refilling stations are the preferred supplier of a growing number of people. Besides its profit potential, this business is easy to operate. Many homes and

offices rely on water refilling stations for their potable water due to fear of contaminated supply.

According to www.inettutor.com (2021), water is a basic necessity; thus, water refilling stations are everywhere, and the competition is tough and tight. People are accustomed to ordering water refills via landline or personally going to the water refilling station for refills. The deliveries are also done manually by the water refilling station, wherein the customer cannot track the location and exact delivery time of the water. The manual system is not comfortable for both the management and the clients. It is not efficient in providing customer satisfaction, and the management cannot keep track of the number of deliveries they must make.

Mobile Applications for Water Delivery

The study by Watomakin et al. (2021) sheds light on the importance of mobile applications in addressing water access concerns, although in the context of eastern Indonesia. While the physical and socio-cultural conditions in eastern Indonesia differ from those in the Philippines, the essential principle of leveraging technology to improve the efficiency and accessibility of water delivery services remains valid. In the case of the *Go-Water* app, users can quickly order clean water, locate nearby water stations, and speed up order processing. The user-centered design approach adopted in this study highlights the relevance of matching the application with user needs and preferences. Like eastern Indonesia, Legazpi faces issues linked to water access and delivery. By deploying a mobile application such as Aqua Pro, the study may aim to speed

the water delivery process, enhance accessibility for clients, and improve the overall quality of service.

The user-centered design principles utilized in the *Go-Water* study also provide a model for ensuring that the Aqua Pro app is user-friendly and responds to the specific needs of Legazpi residents. While the study by Watomakin et al. may differ in geographical scope, its emphasis on the potential of mobile applications to address water access concerns is particularly relevant to the goals of the app Aqua Pro initiative in Legazpi.

Traveling Salesman Problem (TSP)

The TSP is one of the most famous and extensively studied problems in the fields of computer science, optimization, and mathematics. It's a classic conundrum that goes something like this: imagine a salesman who needs to visit a certain number of cities, each exactly once, and return to his original city. The challenge is to find the shortest possible route that accomplishes this task**.** According to Gregory Gutin and Abraham P. Punnel (2007), the TSP is to find a routing of a salesman who starts from a home location, visits a prescribed set of cities, and returns to the original location in such a way that the total distance traveled is minimum, and each city is visited exactly once. Although a business tour of a modern-day traveling salesman may not seem to be too complex in terms of route planning, the TSP, in its generality, represents a typical 'hard' combinatorial optimization problem.

In the study of Little et al. (1963), a "branch and bound" algorithm is presented for solving the TSP. The set of all tours (feasible solutions) is broken up into increasingly small subsets by a procedure called branching. For each subset, a lower bound on the length of the tours is calculated. Eventually, a subset is found that contains a single tour whose length is less than or equal to some lower bound for every tour. The motivation for the branching and the calculation of the lower bounds are based on ideas frequently used in solving assignment problems. Computationally, the algorithm extends the size of the problem that can reasonably be solved without using methods special to the particular problem.

S. Lin and B. W. Kernighan (1973) conducted a study about an effective heuristic algorithm for the TSP. Their paper discusses a highly effective heuristic procedure for generating optimum and near-optimum solutions for the symmetric traveling salesman problem. The procedure is based on a general approach to heuristics that is believed to have wide applicability in combinatorial optimization problems. The method produces optimum solutions for all problems tested, "classical" problems appearing in the literature, as well as randomly generated test problems in up to 110 cities. Run times grow approximately as n2; in absolute terms, a typical 100-city problem requires less than 25 seconds for one case (GE635) and about three minutes to obtain the optimum with above 95 percent confidence.

In the study of Dumitrescu et al. (2008), TSP with Pickup and Delivery (TSPPD) is defined on a graph containing pickup and delivery vertices, between which a one-to-one relationship exists. The problem consists of determining a minimum cost tour such that each pickup vertex is visited before its corresponding delivery vertex. In their paper, the TSPPD is modeled as an integer linear program, and its polyhedral structure is analyzed. In particular, the dimension of the TSPPD polytope is determined, and several valid inequalities, some of which are facet-defining, are introduced. Separation procedures and a branch-and-cut algorithm are developed. Computational results show that the algorithm is capable of solving optimality instances involving up to 35 pickup and delivery requests, thus more than doubling the previous record of 15.

Ant Colony Optimization (ACO)

The ACO technique was purely inspired by the foraging behavior of ant colonies, and it was first introduced by Marco Dorigo in the 1990s. Ants are eusocial insects that prefer community survival and sustaining rather than as individual species. They communicate with each other using sound, touch, and pheromones. Pheromones are organic chemical compounds secreted by the ants that trigger a social response in members of the same species. These are chemicals capable of acting like hormones outside the body of the secreting individual to impact the behavior of the receiving individuals. Since most ants live on the ground, they use the soil surface to leave pheromone trails that may be followed (smelled) by other ants.

The study of Gue et al. (2015) proposes an ACO method for determining the optimal route between the different ports in the Philippines. Given the tropical climate and the archipelagic structure of the Philippine islands, it provides a thriving habitat for more than a thousand species of microalgae. Hence, an abundance of microalgae species is found in the country. However, the

archipelagic structure of the country may also be a disadvantage, as the transportation of biofuels may require varying shipping routes. In the life-cycle assessment of biofuels, transportation is one of the sources of environmental emissions. Thus, minimizing the distance traveled by the ship can dramatically reduce the energy usage and environmental impact of the transportation process. The results of the study showed that the choice of vehicle used has a significant impact on the total shipping distance traveled. This study can be further expanded with the inclusion of time windows.

The study of Yong Wang and Zunpu Han (2021) used ACO for TSP based on parameters optimization. The hybrid symbiotic organisms search (SOS) and ACO algorithm (SOS–ACO) are proposed for TSP. After certain parameters of ACO are assigned, the remaining parameters can be adaptively optimized by SOS. Using the optimized parameters, ACO finds the optimal or near-optimal solution, and the complexity of assigning ACO parameters is greatly reduced. In addition, one simple local optimization strategy is incorporated into SOS–ACO to improve the convergence rate and solution quality. SOS–ACO is tested with different TSP instances in TSPLIB. The best solutions are within 2.33% of the known optimal solution. Compared with some of the previous algorithms, SOS–ACO finds better solutions under the same preconditions. Finally, the performance of SOS–ACO is analyzed according to the changes in some ACO parameters.

Yan et al. (2011) introduced a heuristic way to reduce energy consumption in Wireless Sensor Networks (WSN) routing process using ACO. They introduced three ACO algorithms, the Ant System and Ant Colony System, and improved AS and their application in the WSN routing process. The simulation results show that ACO is an effective way to reduce energy consumption and maximize WSN lifetime.

In the study of Bin et al. (2009), the vehicle routing problem (VRP), a well-known combinatorial optimization problem, holds a central place in logistics management. Their paper proposes an improved ant colony optimization (IACO), which possesses a new strategy to update the increased pheromone, called the ant-weight strategy, and a mutation operation to solve VRP. The computational results for fourteen benchmark problems are reported and compared to those of other metaheuristic approaches.

Huang et al. (2022) studied solving the VRP with drones for delivery services using ACO. In their study, unmanned aerial vehicles such as drones are an emerging technology that is very useful to cope with rising customer expectations of fast, flexible, and reliable delivery services. Their research proposes a mixed integer programming formulation to address the Vehicle Routing Problem with Drones (VRPD) by assigning customers to drone-truck pairs, determining the number of dispatching drone-truck units, and obtaining optimal service routes while the fixed and travel costs of both vehicles are minimized. Given the NP-hard nature of the VRPD, an ACO algorithm is elaborated to solve this problem.

The study of J. E. Bell and P. R. McMullen (2004) used ACO techniques for the vehicle routing problem. Their research applies the meta-heuristic method of ACO to an established set of vehicle routing problems (VRP). The procedure simulates the decision-making processes of ant colonies as they forage for food and is similar to other adaptive learning and artificial intelligence techniques such as Tabu Search, Simulated Annealing, and Genetic Algorithms. Experimentation shows that the algorithm is successful in finding solutions within 1% of known optimal solutions, and the use of multiple ant colonies is found to provide a comparatively competitive solution technique, especially for more significant problems.

The study of A. E. Rizzoli et al. (2007) have successfully applied ACO to the vehicle routing problem (VRP). They introduce the basic principles of ACO, and they briefly present its application to the solution of the VRP and its variants. Also, they discuss the applications of ACO to a number of real-world problems: a VRP with time windows for a major supermarket chain in Switzerland, a VRP with pickup and delivery for a leading distribution company in Italy, a time-dependent VRP for freight distribution in the city of Padua, Italy, where the travel times depend on the time of the day; and an on-line VRP in the city of Lugano, Switzerland, where customers' orders arrive during the delivery process.

In the study of Huang et al. (2019), the ACO algorithm is employed to solve the problem with the objective of determining the number of sub-fleets dispatched and the optimal routes to minimize the total cost (fixed route and travel costs). Three benchmark datasets are generated to examine the performance of the FVPR. For comparison purposes, all instances are executed by dispatching only trucks as in the traditional VRP and a four-stage hierarchical heuristic. Additionally, ACO is compared to optimal solutions for small instances. The results indicate that the proposed ACO algorithm yields promising solutions, particularly for large instances within a reasonable time frame in an efficient manner.

In January 2019, Chaudhari, K. and Thakkar, A. conducted a study where they applied various algorithms such as ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC), firefly algorithm (FA), and genetic algorithm (GA) to solve benchmark Travelling Salesman Problems (TSPs). The empirical analysis of the results demonstrated that for the given TSPs, ACO and GA had better performance compared to ABC, PSO, and FA.

Table 1

Comparison of ACO from PSO, ABC, FA, and GA

 \blacksquare

Falcon et al. (2010) introduced a novel combinatorial optimization problem: the one-commodity TSP with selective pickup and delivery (1-TSP-SELPD), characterized by the fact that the demand of any delivery customer can be met by a relatively large number of pickup customers. While all delivery spots are to be visited, only profitable pickup locations will be included in the tour so as to minimize its cost. The motivation for 1-TSP-SELPD stems from the carrier-based coverage repair problem in wireless sensor and robot networks, wherein a mobile robot replaces damaged sensors with spare ones. The ACO meta-heuristic elegantly solves this problem within reasonable time and space constraints. Six ACO heuristic functions are put forward, and a recently proposed exploration strategy is exploited to accelerate convergence in dense networks. Results gathered from extensive simulations confirm that our ACO-based model outperforms existing competitive approaches.

The use of ACO for solving stochastic optimization problems has received a significant amount of attention in recent years. Birattari et al. (2009) presented a study of enhanced ACO algorithms for tackling a stochastic optimization problem, the probabilistic TSP. In particular, they proposed an empirical estimation approach to evaluate the cost of the solutions constructed by the ants.

Moreover, they used a recent estimation-based iterative improvement algorithm as a local search. Experimental results on a large number of problem instances show that the proposed ACO algorithms outperform the current best algorithm tailored to solve the given problem, which also happened to be an ACO algorithm. As a consequence, they have obtained a new state-of-the-art ACO algorithm for the probabilistic TSP.

A multilevel approach of ACO to solve the TSP was introduced by Martínez et al. (2007). The basic idea is to split the heuristic search performed by ants into two stages; in this case, they use both the Ant System and Ant Colony System algorithms. Also, the effect of using local search was analyzed. They have studied the performance of this new algorithm for several TSP instances. Experimental results obtained conclude that the Two-Stage approach significantly improves the Ant System and Ant Colony System in terms of the computation time needed.

ACO with 2-opt Local Search

ACO provides a global search mechanism to explore the solution space and discover promising regions. Based on the study of Wang et al. (2022), incorporating the 2-opt strategy, which is a local search method, into the ACO, can refine the solutions found by the ants. The 2-opt strategy can help in improving the solutions obtained by ACO by iteratively optimizing the tour lengths through local search. This synergy between global exploration and local exploitation will enhance performance in solving the TSP.

In the path construction, each ant selects a node as its starting node and maintains a visited node sequence to store the visited nodes. In each step of path construction, the ant selects the next node to visit. Specifically, if the current node of the ant k is i , the ant chooses the next node i in its path from the remaining nodes based on the probabilistic approach, with the selection probability of each node computed as follows:

$$
p_k(i,j) = \begin{cases} \frac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{u \in J_k(i)} [\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}, & \text{if } j \in J_k(i) \\ 0, & \text{otherwise} \end{cases}
$$

Where $J_k^{}(i)$ represents the set of nodes that can be reached directly from node i . In order to avoid selecting repetitive nodes, a tabu table is set up in the algorithm to store the nodes visited by ants. Therefore, the set of nodes $\overline{J}_k(i)$ also should not be in the sequence of the visited nodes. $\eta(i, j)$ is heuristic information calculated by $\eta(i,j) = 1/d_{ij}$. $\tau(i,j)$ represents the amount of pheromone on the edge e_{ij} . α and β are two user-defined parameters. α is the parameter of pheromone importance, β is the expectation factor.

The pheromone update includes three parts. First, after each ant finishes its travel, the pheromones on all paths decay or evaporate, which prevents the pheromone from accumulating with the increase in iteration times. Second, all ants release pheromones to the edge of their paths according to the path length. Thirdly, the ACO strengthens the pheromone update on the optimal path. That is, after the pheromone update, the ant with the best path R_h adds additional pheromones to each edge of the path R_{μ} . These additional pheromones can

make the ants search faster and converge more correctly. Based on these three parts, the update of the pheromone quantity $\tau(i, j)$ on edge between nodes i and i is shown as the following formula:

$$
\tau(i,j) = (1 - \rho) * \tau(i,j) + \sum_{k+1}^{m} \Delta \tau_k(i,j) + w * \Delta t_b(i,j)
$$

$$
\Delta \tau_k(i,j) = \begin{cases} (L_k)^{-1}, & \text{if } e_{ij} \in R^k \\ 0, \text{otherwise} \end{cases}
$$

$$
\Delta t_b(i,j) = \begin{cases} (L_b)^{-1}, & \text{if } e_{ij} \in R_b \\ 0, \text{otherwise} \end{cases}
$$

Where m is the number of ants. The greater the number of ants is, the more accurate the optimal solution will be, but many repeated solutions will be generated. As the algorithm approaches the optimal value, the positive feedback of information will be reduced, and a considerable amount of repeated work will consume resources and increase the time complexity. ρ is the evaporation rate of pheromone. When $ρ$ is too small, there are too many pheromones left on each path, resulting in an invalid path continuing to be searched, affecting the algorithm's convergence speed. When ρ is too large, and although an invalid path can be excluded from the search, it cannot guarantee that the effective path will also be abandoned, affecting the search for the optimal value. $\Delta\tau_{_{|k}}(i,\:j)$ is the amount of pheromone released by the k th ant on the edge it passes, which is equal to the reciprocal path length of ant k in this round. L_k represents the path length, which is the sum of the lengths of all edges in R^k . Parameter w is the

edge weight value, and $L_{\stackrel{.}{b}}$ is the optimal path length since the algorithm's beginning.

The integration of the 2-opt strategy in each ant is applied to the edges in each solution to generate new solutions by reserving the directions of several consecutive edges. First, the 2-opt strategy randomly selects two different edges and deletes these two edges. After the deleting operation, two edge sequences are obtained. Then, the edge sequence between these two edges is reversed, and this reversed edge sequence is re-connected to the other edge sequence to obtain a new solution. Finally, the solution with a shorter path between the new solution and the original solution is reserved.

ACO with 2-opt strategy

Input: Number of iterations, number of nodes

Start

- 1: Initialize parameters:
- 2: num_iterations: Number of iterations for the ACO algorithm
- 3: num_ants: Number of ants (solutions) to be generated in each iteration
- 4: decay: Rate at which pheromone trails evaporate
- 5: alpha: Influence of pheromone trails on ant's decision
- 6: beta: Influence of distance between cities on ant's decision
- 7: distances: Matrix containing distances between cities
- 8: Initialize pheromone trails:
- 9: Initialize pheromone trails to a small constant value for all edges
- 10: Repeat for num iterations:
- 11: Decay pheromone trails:
- 12: Evaporate pheromone trails by multiplying them by (1 decay)
- 13: Generate solutions (tours) for each ant:

Output: Best Result, Average Distance, Best Known Result

Based on the above description of ACO and 2-opt strategy, the pseudocode of the proposed ACO with 2-opt algorithm is given above. The algorithm begins by initializing parameters such as the number of iterations (`num_iterations`), the number of ants (`num_ants`), the rate of pheromone evaporation (`decay`), and the influence of pheromone trails and distance on ant's decisions (`alpha` and `beta` respectively). It also initializes a matrix (`distances`) containing distances between nodes. Then, pheromone trails are initialized to a small constant value for all edges in the graph. After that, the algorithm iterates for a predefined number of iterations (`num_iterations`). For

each ant, a solution (tour) is generated. Each ant constructs a tour by probabilistically selecting the next city based on pheromone trails and distances. After constructing a tour, a 2-opt heuristic is applied to improve the tour by swapping pairs of edges to reduce the tour length. After all ants have constructed their tours, pheromone trails are updated based on the length of each ant's tour. The pheromone trails are reinforced on edges belonging to shorter tours. Pheromone trails are decayed again to simulate evaporation. The algorithm tracks the best tour found so far and its length among all ants. Finally, the best solution found, the average distance of tours, and the optimal result are returned.

An improved 2-optimization(2-opt) and ACO Hybrid Algorithm is proposed by Zhang et al. (2018) to solve the TSP. The improved scheme of ACO is to define the indirect expectation heuristic and introduce it into the calculation method of transition probability, which will reduce the effect of pheromone on ant selecting path and increase the path's diversity of ACO. In this way, the deficiency of ACO in convergence to local optimal solutions will be made up. Considering the stronger local search ability, the 2-opt algorithm is used to optimize existing solutions, and a better solution is obtained. Finally, the performance of the proposed algorithm is evaluated using the classical TSP problem.

Martinovic, G. and Bajer, D. (2012) presented an algorithm based upon the elitist ant system for solving the TSP. 2-opt local search is incorporated in the elitist ant system, and it is used for the improvement of a given number of solutions previously constructed by artificial ants. A simple mechanism for

avoiding too-early stagnation of the search is also proposed. The aforementioned is based on depositing strong pheromones on solution edges of randomly selected ants called random elitist ants. The aim is to encourage exploration in a greater area of the solution space. Experimental analysis shows how high-quality solutions can be achieved by using the considered algorithm instead of the usual elitist ant system with an incorporated 2-opt local search.

In the paper of Du et al. (2021), an improved ACO algorithm based on an adaptive heuristic factor (AHACO) is proposed to deal with the TSP. In the AHACO, three main improvements are proposed to improve the performance of the algorithm. The proposed algorithm is tested in numerical experiments using 39 TSP instances, and results showed that the solution quality of the AHACO is 83.33% higher than that of the comparison algorithms on average. For large-scale TSP instances, the algorithm is also far better than the comparison algorithms.

The slightly harder Dynamic Traveling Salesman Problem (DTSP) is more realistic in the sense that real-time changes happen in the graph belonging to a TSP instance. Lagerqvist and Svensson (2017) studied the original ACO algorithm, the Ant System, and how the amount of pheromone deposited by the ants within the algorithm affected the performance when solving both TSP and DTSP problems. Additionally, a 2-opt local search was added to the algorithm to see how it impacted the performance. They found that when the ants deposited a greater amount of pheromone, the performance for TSP increased, while the performance for DTSP decreased. They concluded that the Ant System in its

original form is unsuitable for solving the DTSP. 2-opt local search improved the performance in all instances.

Chuan Wang et al. (2022) proposed a scheme library-based ACO with a two-optimization (2-opt) strategy to solve the DTSP efficiently. The work is novel and contributes to three aspects: problem model, optimization framework, and algorithm design. To evaluate the performance of ACO with 2-opt, they designed two challenging DTSP cases with up to 200 and 1379 nodes and compared them with other ACO and genetic algorithms. The experimental results show that ACO with 2-opt can solve the DTSPs effectively.

In the paper of Mavrovouniotis et al. (2017), a memetic ACO algorithm, where a local search operator (called unstring and string) is integrated into ACO, is proposed to address DTSPs. The best solution from ACO is passed to the local search operator, which removes and inserts cities in such a way that improves the solution quality. The proposed memetic ACO algorithm is designed to address both symmetric and asymmetric DTSPs. The experimental results show the efficiency of the proposed memetic algorithm for addressing DTSPs in comparison with other state-of-the-art algorithms.

The generalized traveling salesman problem (GTSP) is a typical combinatorial optimization problem. Many practical problems involving the allocation and optimization of multiple tasks can be reduced to the GTSP. Meng et al. (2019) modified the ACO proposed for GTSP. The modified ant colony algorithm combines a 2-opt algorithm to minimize the total path length while considering the task balance of different travelers. Simulation results show that

the modified ACO has good optimization accuracy and stability in solving the GTSP.

Haversine Formula

In the article of Simon Kettle (2017), the Haversine formula is a mathematical equation used to calculate the shortest distance between two points on the surface of a sphere, given their longitudes and latitudes. It's particularly important in navigation and geographical computations. The formula is derived from the law of haversines in spherical trigonometry and is a special case that relates the sides and angles of spherical triangles. The Haversine formula is expressed as follows:

$$
a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos\left(lat_1\right) * \cos\left(lat_2\right) * \sin^2\left(\frac{\Delta B - \Delta long}{2}\right)
$$

$$
c = 2 * \alpha tan2\left(\sqrt{a}, \sqrt{(1 - a)}\right)
$$

$$
distance = R \cdot c
$$

Where lat_1 and lat_2 are the latitudes of the two points (user and water refilling station), Δlat is the difference between the latitudes, $\Delta long$ is the difference between the longitudes, R is the Earth's radius (mean radius $= 6,371$ km), and atan2 is the arctangent function. Based on the description of the haversine formula, the pseudocode is shown below:
Input: Coordinates

Start

- 1: function haversine(lat1, lon1, lat2, lon2)
- 2: R = 6371 // radius of Earth in kilometers
- 3: dLat = toRadians(lat2 lat1)
- 4: dLon = toRadians(lon2 lon1)
- 5: $a = \sin(dLat/2) * \sin(dLat/2) + \cos(t_0)$ a = sin(dLat/2) $*$
- 6: cos(toRadians(lat2)) *sin(dLon/2) * sin(dLon/2)
- 7: $c = 2 * \text{atan2}(\text{sqrt}(a), \text{sqrt}(1-a))$
- 8: distance = $R * c$
- 9: return distance

End

Output: Distance between two points

With the advent of smart cities, information and communication technology is increasingly transforming the way city municipalities and city residents organize and operate in response to urban growth. In the paper of Prof. Nitin R. Chopde and Mr. Mangesh K. Nichat (2013), they create a generic scheme for navigating a route through the city. A requested route is provided by using combination of A* Algorithm and haversine formula. Haversine formula gives minimum distance between any two points on a spherical body by using latitude and longitude. This minimum distance is then provided to A* algorithm to calculate minimum distance. The process for detecting the shortest path is mentioned in their paper.

The study of Safitri et al. (2020) proposed a Smart Parking Reservation System with Rate Display Occupancy denoted as SORAY. This system used a simulated annealing based heuristic algorithm to optimize the queue method by considering three parameters such as the driver status (member or non-member), distance, and parking duration. This system also uses the haversine formula to calculate the distance from the current position of the vehicle to the parking lot at the time of sending the reservation request. As the proof of reservation verification process, SORAY uses a Quick Response Code. This SORAY system is also equipped with a secure member registration process by implementing SHA-256 algorithm to generate random OTP. The graph of the occupancy rate is displayed to predict the density of vehicles in the parking lot.

Synthesis and Gap

The review of Related Literature and Studies highlights the promising potential of ACO algorithms in problem-solving, particularly in tackling NP-Hard problems like the TSP and VRP. A notable milestone in this area is the successful application of ACO to solve TSP, with studies demonstrating its superiority over other nature-inspired algorithms, such as simulated annealing and evolutionary computation. However, despite the advancements, there remains a discernible gap in the existing research landscape.

While current studies have proposed various implementations of ACO for TSP, focusing on refining its convergence and addressing weaknesses inherent in other algorithms, a significant gap emerges: none have explored the integration of GPS technology for node location gathering in ACO-based TSP

solutions. This omission is striking, considering the potential enhancements in accuracy and real-world applicability that GPS integration could offer. Furthermore, while VRP is commonly utilized in delivery systems, TSP remains underexplored in this context, indicating a further research gap in optimizing delivery routes using ACO-based TSP methodologies. Thus, the synthesis underscores the need for novel research endeavors that leverage GPS technology within ACO algorithms for TSP, particularly in domains like delivery systems where route optimization is critical.

Conceptual Framework

Figure 1. Conceptual Framework

This study, as illustrated in figure 1, focuses on optimizing water delivery routes in Legazpi City. The conceptual framework for this system involves the integration of various inputs, including Geographical Coordinates, Business Names, Addresses, Contact Information, Operational Hours, Pricing and Packaging, and Delivery Services. The processing phase employs ACO for TSP, ensuring an efficient and streamlined delivery process. The haversine formula is utilized to address the customer's perspective. It will be used to find the nearby water refilling station/s in their area and calculate within a given distance radius.

The system further incorporates real-time GPS tracking, mapping services, and a comprehensive client-server network to enhance operational efficiency. The evaluation phase assesses the effectiveness of the ACO with 2-opt in optimizing routing and delivery processes, providing valuable insights into system performance. The ultimate output includes the results of this evaluation, contributing to ongoing improvements in the system's functionality. Additionally, the Aqua Pro mobile application serves as a tangible output, offering users a user-friendly interface to access optimized routing, real-time tracking, and other relevant information, ensuring a seamless experience for both businesses and customers alike.

Definition of Terms

The following terms are defined operationally and conceptually as used in the study to properly guide the readers of this study.

Algorithm - is a step-by-step procedure or set of rules used to solve a specific problem or perform a task. Algorithms are fundamental to computer programming and problem-solving, enabling computers to execute specific tasks efficiently.

Aqua Pro App - is a mobile application developed for the purpose of improving and enhancing water delivery services from water refilling stations in Legazpi City. This app allows customers to place orders, track deliveries, and interact with water delivery service providers.

Artificial Intelligence - refers to the theory and development of computer systems capable of performing tasks that typically require human intelligence. These tasks include visual perception, speech recognition, decision-making, and language translation. AI systems learn from data, adapt, and improve their performance over time.

Ant Colony Optimization (ACO) - is a nature-inspired optimization algorithm based on the foraging behavior of ants. It is particularly useful for solving combinatorial optimization problems. ACO simulates the way ants deposit pheromones on paths, and over time, the paths with higher pheromone levels are more likely to be chosen.

Best Known Result - refers to the currently known best solution to the TSP, which may or may not be the result obtained by the ACO algorithm. It could be the result of another optimization algorithm, a previously published solution, or even the theoretical optimal solution if it is known.

Best Result - refers to the optimal tour found by an algorithm during its execution. This is the tour that the algorithm has identified as the best solution based on its exploration of the solution space.

Client-Server Network - is a form of internet network that consists of a single central computer functioning as a server and directing several other computers, referred to as clients. Clients can access shared files and information kept on the serving machine by connecting to the server.

Firebase - is a set of backend cloud computing services and application development platforms provided by Google. It hosts databases, services, authentication, and integration for a variety of applications, including Android.

Flask - is a micro web framework written in Python. It can be used to develop web applications, which can serve as the server. When a Flask application is run, it starts a local server that can listen to requests coming from clients.

Geographical Coordinates - are either of the two lines of latitude and longitude whose intersection determines the geographical point of a place.

Global Positioning System (GPS) - a satellite-based navigation system that allows users to determine their precise location and track their movement.

Google Direction API - calculates directions between locations using an HTTP request. It can provide directions for different modes of transportation (driving, walking, bicycling, and transit) and can optimize routes based on various factors such as traffic conditions, distance, and time.

Google Maps API - provides mapping capabilities, allowing developers to embed interactive maps into their applications. In a delivery app, the Maps API can be used to display the locations of customers, delivery drivers, and delivery destinations.

Haversine Formula - is used to calculate the distance between two points on the surface of a sphere (like the Earth) given their latitudes and longitudes. It is commonly used in navigation and geographical applications.

Mobile Application - commonly known as an app, is software designed to run on mobile devices such as smartphones or tablets. Apps provide services similar to those accessed on personal computers (PCs).

Nodes - in the context of graphs, nodes are the fundamental units that represent points or vertices. In the Traveling Salesman Problem, for example, cities are represented as nodes in the graph, and the connections between them are represented as edges.

Percentage Error - calculates the relative difference between the best result obtained by an algorithm and the best-known result, expressed as a percentage of the best-known result. It gives an indication of how close the ACO algorithm's solution is to the currently known best solution. A negative percentage error indicates that an algorithm's result is better than the best-known result, while a positive percentage error indicates that an algorithm's result is worse than the best-known result. A percentage error of zero would indicate that an algorithm's result exactly matches the best-known result.

Route Optimization - involves finding the most efficient path or sequence of waypoints to reach a destination. It is commonly used in logistics, transportation, and delivery planning.

Running Time - refers to the duration it takes for a program or algorithm to execute and produce a result.

Shortest Path - is the minimum distance or cost between two points in a graph or network. It is a fundamental concept in graph theory and is used in various applications, such as network routing.

Traveling Salesman Problem - is a classic optimization problem where the goal is to find the shortest possible route that visits a given set of cities (nodes) and returns to the starting city, with each city visited precisely once.

Two-Optimization (2-Opt) Algorithm - improves an initial solution iteratively by swapping pairs of edges in the tour to reduce the total length of the tour.

Water Refilling Stations - are commercial establishments that provide purified and potable water for customers. These stations are responsible for purifying, storing, and sending clean drinking water.

Chapter III

METHODOLOGY

This chapter presents the research methods to be employed by the researchers in conducting the study. It encompasses research design, research instruments and its development, data gathering procedures, and analysis. Additionally, ethical considerations in conducting the study will also be addressed.

Research Design

The study, entitled "Aqua Pro: Water Access Efficiency through Ant Colony Optimization with 2-Opt Local Search Strategy," is a comprehensive exploration that adopted both experimental and developmental research methodologies. The researchers utilized experimental research methods to conduct a comparative analysis between the ACO with 2-opt and the standard ACO, aiming to ascertain whether the modified algorithm outperforms the standard one. It aims to ascertain whether the modified algorithm exhibits superior performance compared to the standard one. We conducted numerous tests and trials to evaluate the relative performance of the algorithms. Additionally, The researchers applied developmental research. These were primarily used in the design and development of the modules for the water delivery system. The system was innovatively designed to integrate the ACO with 2-opt, a testament to the researchers' commitment to improving water access efficiency.

Research Methodology

The study utilized a hybrid methodology combining Rapid Application Development (RAD) and benchmarking methodology. Christine Chien (2020) proposed that the RAD method emphasizes rapid application development through frequent iterations and continuous feedback. According to ProjectManagement.com (2023), a RAD approach is appropriate when the project scope is focused, with well-defined and narrow business objectives; project data already exists (completely or in part), and the project mainly involves the analysis or reporting of this data; project decisions can be made by a small number of people who are available and preferably co-located; and a small project team, ideally consisting of six people or fewer, aligns with RAD principles.

In the study of J. Brownlee (2007), benchmarking methodology for algorithm optimization typically follows a structured approach to systematically test, measure, and refine the algorithm. Researchers and developers can systematically improve algorithm performance and gain insights into factors affecting efficiency and effectiveness. The iterative nature of the process allows for continuous refinement until a satisfactory level of optimization is achieved.

This process will follow several phases: Planning, Data Collection, Designing, Coding, Testing, and Implementation, as shown in Figure 2.

Figure 2. Hybrid Methodology of RAD and Benchmarking

These criteria are met in the implementation of the Aqua Pro app. The initial project scope is within Legazpi City, emphasizing the enhancement of water delivery services and establishing a focused project scope with clearly defined specific objectives. Regarding project data, geographic information and other pertinent details about water refilling stations are readily accessible, with the only requirement being the collection and compilation of this available data. The project team is compact, comprising three members in close proximity, facilitating convenient discussions for project decisions.

Phase 1. Planning

In the planning phase, the researchers outlined the key parameters and constraints involved in route optimization for delivery. The TSP is an optimization problem aimed at finding the shortest possible route that visits each node exactly once and returns to the original starting point. In this study, the researchers used TSP for water delivery in Legazpi City, Albay. To solve TSP, the researchers utilized ACO with a 2-opt strategy and compared it to the standard ACO. The results of experimentation are important for developing an optimal delivery application. This phase will also focus on initiating a swift and flexible development cycle by defining a preliminary and adaptable set of project requirements, with a particular emphasis on rapid prototype iterations to ensure adaptability to evolving project needs throughout the development process.

Phase 2. Data Collection

In this phase, the researchers began a comprehensive data-gathering process by manually collecting significant data from water refilling stations across Legazpi City. Geographical coordinates of each water refilling station were gathered to represent the starting points. Spatial data of the city was gathered. The shapefiles at the barangay level of Legazpi City were obtained from the barangay hall of each barangay. This shapefile served as the primary foundation for the main map of the project.

For the TSP benchmark, researchers procured sample instances and related problems from a diverse array of sources, primarily drawn from the classic TSP library (TSPLIB). These instances encompass various types and

complexities, providing a robust set of challenges to assess the efficacy of algorithms and methodologies in solving the TSP.

For the system requirements, the researcher collected the business names, addresses, contact information, operational hours, pricing and packaging, and delivery services of each water refilling station. In addition to the system requirements, research was conducted by engaging in in-depth interviews with water refilling station owners/staff, delivery riders, and customers across Legazpi City to understand the specific features and functions they desire for a water delivery service application. This comprehensive approach aimed to gather additional insights crucial for shaping the project's success.

Phase 3. Designing

In this phase, the researchers defined the main features of the future code. This involved a comprehensive analysis and specification of the system's functionalities, architectural components, and overall structure. During this crucial stage, decisions were made regarding the system's design principles, data flow, and interaction between various modules. Clear definitions of the code's main characteristics were established, laying the foundation for the subsequent development and implementation stages. This phase served as a pivotal step in ensuring a well-structured and effective system that aligns with the project's objectives. This phase involved creating the system designs and architectures, which include diagrams such as flowcharts, class diagrams, and Entity Relationship Diagram (ERD), and the mobile application interface based on the project requirements. Thereafter, a mobile application prototype was created.

40

The cycle began by iterating on the system design and the prototype based on user feedback until it aligned with user needs. Through each iteration, the development team strives to address user concerns, optimize functionality, and fine-tune the user experience, fostering a responsive and user-centric system. This cyclical approach not only enhances the adaptability of the system but also fosters a collaborative and user-driven development environment.

The design for the experimental setup was dedicated to the simulation and benchmarking of ACO with 2-opt and standard ACO algorithms to determine whether the modified algorithm is more optimal or less optimal than the standard one. In this phase, the experimental setup was implemented using Google Colab to run the algorithms and input parameters, conduct simulations, and view results.

Phase 4. Coding

The coding phase is where the software is developed and operationally constructed. Researchers will implement the architectural design of the software. The researchers adopted the ACO with a 2-opt strategy to solve TSP efficiently and to develop a water delivery application utilizing this algorithm and various technologies, with coding serving as the instrument to visualize the desired feature. The coding process comprised four distinct steps: algorithm configuration, experimental setup, execution of experiments, analysis, and construction.

Algorithm Configuration

The study adopted the ACO with a 2-opt strategy and standard ACO for solving TSP. Configuration parameters were meticulously tuned, taking into account the nuanced requirements of the TSP. The algorithm will be modified to suit the TSP.

Experimental Setup

The Experimental Setup designed a series of experiments that test on small-scale dataset eil51, medium-scale data set and kroA100, and large-scale dataset kroA200. This ensured a comprehensive evaluation of algorithm performance across a spectrum of realistic scenarios. The study specified the number of iterations or time limits for the algorithm run, maintaining a consistent and fair experimental environment. To start the experiment, the TSP benchmark instances eil51 and kroA100 were adopted as the benchmark ACO with 2-opt from other algorithms. In this benchmark, there are 51 and 100 nodes. Besides, to further verify the robustness of the ACO with 2-opt, this paper also tests it on a large-scale dataset, kroA200. In this benchmark, there are 200 nodes.

Experimental Execution

In the experimental execution phase, the ACO with 2-opt and standard ACO were systematically applied to various predefined scenarios. The algorithm encompassed multiple scenarios, providing a comprehensive assessment of its adaptability and effectiveness in diverse real-world conditions. The study recorded key metrics such as best, average, and best-known results.

Additionally, runtime performance was closely monitored to understand how quickly the algorithm reaches the best solutions and its computational efficiency in different scenarios. Overall, this detailed exploration aims to offer valuable insights into the ACO with 2-opt algorithm behavior under practical conditions, informing its potential applications and areas for improvement in real-world problems.

Analysis

In the subsequent analysis phase, the study evaluated the performance of the ACO with 2-opt and the standard ACO algorithms using predefined metrics. The researchers analyzed the best, average, and best-known results obtained. Statistical tests have been conducted to assess the algorithm. The best result refers to the solution with the highest utility or lowest objective function value that the algorithm has discovered during its execution, while the best-known result refers to the best possible solution found by the algorithm. The average result or the mean is the average total distance over the number of trials that the algorithm independently executed.

The error percentage was also computed to determine if the algorithm had found a solution that was better than the previously best-known solution. The formula for error percentage is expressed as follows:

$$
\% Error = \left(\frac{Best_Result - Best_Known_Result}{Best_Known_Result}\right) * 100
$$

Construction

The construction phase is where the mobile application is constructed using a variety of tools, APIs, and libraries. The primary tools used are Flutter for mobile app development and Firebase for implementing a user management system. This system caters to different users, such as owners, delivery riders, and customers.

Data integration is a crucial part of this phase, which involves inputting the collected data into the system database while ensuring accuracy and consistency. For mapping services, the Google Maps API and Google Direction API were used. These APIs facilitate the plotting of water refilling stations on the map using their geographical coordinates. The ACO with a 2-opt algorithm is integrated for water delivery, enhancing the efficiency of the service. Various dart packages are utilized to support the development process. Additionally, the Flask library is used to manage the client-server network.

The construction phase also includes the integration of real-time GPS tracking, providing live location updates for effective coordination and delivery. The mobile application will be deployed on Android devices. The requirements for these devices are shown in Tables 2 and 3.

Hardware Requirements

Table 3

Software Requirements

Phase 5. Testing

In RAD methodology, testing is an integral part of the process that is conducted concurrently with coding and development. This approach, often referred to as the Unit Test phase, allows for continuous debugging and testing of the system before delivery. During this phase, the software prototype undergoes rigorous testing procedures to identify and rectify bugs or errors within the system. The researchers ensure that the correction of one bug does not introduce new bugs, maintaining the integrity of the system.

Phase 6. Implementation

The implementation phase involved deploying the enhanced system to a live production environment for thorough testing and bug resolution. Updates and enhancements were guided by user feedback, ensuring continuous improvement. The system is intended for use by the Water Refillers Association of Legazpi City, and it has comprehensive documentation for future maintenance and development. Moreover, the performance of the mobile application across its various features is tested to ensure the system's efficiency. The researchers arrange specific test cases to verify that the developed system meets its requirements.

Ethical Considerations

Ensuring informed consent, data privacy, and security are crucial. Participants must understand the research's purpose, risks, and data usage. Anonymizing data protects privacy, while robust security prevents unauthorized access. Transparency about objectives, methods, and conflicts of interest is key. Clear communication on data ownership, usage rights, and GPS tracking consent is vital. Fair compensation for data sharing should be considered. Regulatory compliance is mandatory. Continuous monitoring and addressing ethical concerns are essential.

Chapter IV

RESULTS AND DISCUSSION

In this chapter, the results of the study are presented and discussed with reference to the aim of the study, which was to develop a system capable of managing and tracking the water delivery services with the least cost for both customers and delivery riders in Legazpi City. The results focused on the ACO with a 2-opt strategy for TSP, the utilization of the algorithm for route optimization, and the developed water delivery system.

Scheme Library-Based ACO with 2-Opt Strategy

This study employed a scheme library-based ACO algorithm, combined with a 2-opt local search strategy, to solve the TSP. Numerous existing studies have demonstrated the efficiency of ACO in solving the TSP. This heuristic probability search method is not prone to falling into local optimization and has been proven to efficiently find the optimal global solution for the TSP. Given these advantages, ACO was chosen as the optimization method for solving the TSP. It has also been established that the integration of local search operators can significantly enhance the performance of ACO. Therefore, this paper incorporated the 2-opt strategy into the ACO to solve the TSP.

Experimental Setting

To evaluate the performance of the ACO with 2-opt in solving the TSP, this paper compared the proposed ACO with 2-opt to the standard ACO. The instances eil51, kroA100, and kroA200 from the classic TSP library (TSPLIB) were used in this study. In this benchmark, eil51 was adopted as a small-scale dataset, kroA100 was adopted as a medium-scale dataset, and kroA200 was used as a large-scale dataset to further verify the robustness of the ACO with 2-opt. The starting node was set as the node with serial number 0. The parameters of the ACO algorithm were set to typical values, as shown in Table 2. The experimental results were obtained from ten independent executions of each algorithm, and the best results were selected to draw roadmaps. It should be noted that both algorithms were implemented in Python and executed on Google Colab with 12.7 GB memory on a 64-bit Windows 11 system.

Table 4

Parameter Settings

The number of ants and the number of iterations were both set to 100. The pheromone weight (`alpha`) and the heuristic information weight (`beta`) both have a default value of 1. The pheromone evaporation rate was calculated as 1-1/(T+1), which is approximately 0.99. The initial quantity of pheromone is set to 1. Lastly, the edge weights for these experiments were 51, 100, and 200.

Experimental Result

This paper conducts the comparison between the proposed ACO with 2-opt and ACO on the TSP model. The results with respect to the best, average, and optimal values on eil51, kroA100, and kroA200 are shown in Tables 4 and 5. In the first column, we report the problem name and the number of nodes in parentheses. In the second column, we report the best result that the algorithm has discovered during its ten independent executions. In the third column, we report the average distance on ten independent executions and their standard deviations in square brackets. In the fourth column, we report the best-known result obtained by the algorithm. In the fifth column, we give the error percentage, which is a measure of the quality of the best result found by the algorithms. In the last column, we recorded the running time of each algorithm. This was calculated empirically by timing the execution of each algorithm on different input sizes to determine how long it takes for each algorithm to produce the best result. We also used Big O notation to analyze and understand the theoretical growth rate of each algorithm's running time in relation to the size of its input.

Table 5

Summary Results of ACO on eil51, kroA100 and kroA200

Table 4 presents the summary results of 10 independent executions of the ACO algorithm on eil51, kroA100, and kroA200. In terms of percentage error, the ACO produced less efficient solutions for eil51 and kroA100 compared to their known solutions. However, for kroA200, it produced a more efficient solution. We can conclude that as the number of nodes increases, the likelihood of obtaining a more effective solution also increases. Regarding the running time, it increases as the number of nodes increases.

Table 6

Summary Results of ACO with 2-opt on eil51, kroA100 and kroA200

Table 5 presents the summary results of 10 independent executions of the ACO algorithm with a 2-opt strategy on eil51, kroA100, and kroA200. In terms of percentage error, the ACO with 2-opt produced a negative error percentage in all problem cases. This suggests that the integration of the 2-opt strategy helped the ACO to produce optimal results for any TSP problem. Regarding the running time, while it provides more efficient results than the standard ACO, it also requires significant computational resources.

Based on the results above, conclusions can be drawn: 1) Concerning the results with respect to the best, average, and optimal value in the ten independent trials, the ACO with 2-opt achieved the best performance on eil51, kroA100, and kroA200, while the standard ACO does not obtain any best result. 2) ACO with 2-opt has been observed to have a negative error percentage on eil51 and kroA100, which suggests that the algorithm has found a solution that is better than the previously best-known result, while on kroA200, both of the algorithms have a negative error percentage. 3) In terms of the running time, standard ACO has the fastest execution and produces the result on eil51, kroA100, and kroA200, while the ACO with 2-opt has the longest running time.

Table 7

Theoretical Analysis of the Big O Notation Time Complexity of ACO with

2-opt and Standard ACO

Table 5 shows the theoretical analysis highlighting the computational complexities of both standard ACO and ACO with 2-opt, taking into account the construction of tours, updating and evaporating pheromone trails, as well as the additional complexity introduced by 2-opt optimization in the latter. In standard ACO, the construction of solution tours and updating pheromone trails exhibit linear growth rates with respect to the number of nodes (n) , ants (m) , and iterations (T) . However, the time complexity of evaporating pheromone trails grows quadratically with n and linearly with T , Indicating a greater impact from the problem size and the number of iterations. Overall, the total time complexity of standard ACO increases quadratically with $n \times T$ and linearly with $m \times T$,

suggesting that the running time is more significantly influenced by the problem size and the number of iterations.

In ACO with 2-opt, the time complexities for constructing solution tours and updating pheromone trails remain the same as in standard ACO. However, the inclusion of 2-opt optimization introduces additional complexity. The time complexity of 2-opt optimization grows quadratically with n and linearly with T (the number of iterations). Consequently, the overall time complexity of ACO with 2-opt increases quadratically with $n \times T$ and linearly with $m \times T$ and $n^2 \times T$. This suggests that as the problem size, the number of iterations, and the number of ants increase, the running time of ACO with 2-opt grows accordingly, with additional influence from the quadratic growth in problem size due to 2-opt optimization.

The superiority of ACO with 2-opt over the standard ACO algorithms becomes increasingly notable. However, it takes more time to execute and produce the best results as the number of nodes increases. Therefore, while 2-opt is necessary for ACO, in real-life applications, the number of nodes should be fewer.

The node distribution position maps for ACO with 2-opt and standard ACO on eil51, kroA100, and kroA200 are shown in Figures 3, 4, and 5. The starting node of the pentagram is indicated by a round green dot and is labeled as node 0, while the end node is represented by a round red dot. The best route produced in 10 independent executions is shown by the red path, and the blue path represents the best-known route of the algorithm. By comparing the red paths (best results) with the blue paths (best-known solutions), we can evaluate the performance of the algorithms. The closer the red paths are to the blue paths, the more effective the algorithm is at approximating the best-known solution.

Figure 3. Node distribution map of ACO with 2-opt and standard ACO on eil51 respectively

Figures 3 and 4 show the node distribution position maps of the instance eil51 on ACO with 2-opt and standard ACO. The ACO with a 2-opt strategy has produced a result that is very close to the best-known result, with a difference of only 0.02. This indicates that the 2-opt strategy has significantly improved the performance of the ant colony optimization algorithm, allowing it to find a solution that nearly matches the best-known solution. While the standard ACO algorithm's best result is not as close to the best-known result, with a difference of 5.61.

Figures 5 and 6 show the node distribution position maps of the instance kroA100 on ACO with 2-opt and standard ACO. In this case, ACO with a 2-opt strategy has also produced a result that is better than the best-known result, with the algorithm finding a shorter path by 214.42. This is an impressive outcome, as it suggests that the ACO with 2-opt not only approximated but actually improved upon the best-known result for this problem instance. While the standard ACO algorithm's best result is significantly worse than the best known result, with a difference of 709.97.

kroA200 respectively

Figures 7 and 8 show the node distribution position maps of the instance kroA200 on ACO with 2-opt and standard ACO. In this case, The ACO with a 2-opt strategy has produced a result that is better than the best-known result, with the algorithm finding a shorter path by 436.94. This indicates that the ACO with 2-opt has not only approximated but also improved upon the best-known result for this problem instance, which is a significant achievement. While the standard ACO algorithm's best result is slightly worse than the best-known result, with a difference of 385.79.

Although the standard ACO did not perform as well as the ACO with 2-opt, it still managed to come close to the best-known result, which suggests that it is a reasonably effective algorithm for TSP problem instances.

ACO with 2-opt for Route Optimization of Water Delivery

The researchers used Google Direction API to provide a convenient way to get accurate and up-to-date information about routes, including distance, duration, and turn-by-turn directions. The API can also obtain real-time data about traffic conditions, road closures, and other factors that may affect delivery routes. By combining ACO with 2-opt and Google Direction API, the researchers created a robust and efficient route optimization solution for delivery applications, helping to minimize travel time, reduce fuel costs, and improve overall delivery service.

First, we implemented the ACO algorithm to generate initial solutions for the delivery routes. This involves defining the pheromone update rules, heuristic information, and exploration-exploitation trade-offs. Then, we applied the 2-opt strategy to the initial solutions generated by ACO. Iterate through the routes, swapping edges to improve the overall distance traveled. Lastly, we used the Google Directions API to obtain the actual distances and travel times between delivery locations. This information is used to validate and refine the routes generated by ACO and 2-opt.

Since we are using the free plan of the Google Direction API, only 25 waypoints (nodes) are allowed per delivery. During our interview with the delivery riders in Legazpi City, they mentioned that their maximum stops (nodes) per delivery is 20. This means that the free plan can cover the maximum number of nodes. Additionally, based on the results of our experiment, the computational

demand increased as the size of the datasets increased. Therefore, computing with only 20 nodes will not pose a problem in terms of computational demand.

Table 8

Delivery Computational Demand Result

Through simulations and analysis shown in table 6, we found that the delivery system can calculate a maximum of 22 nodes within 265 seconds. Attempting to calculate more than 22 nodes may result in longer computational times and could lead to an error, as this exceeds the limit of the API's free plan. This finding is significant for modifying the delivery application to limit the number of orders (nodes) accepted from customers to 20 per delivery.

Features of Developed Water Delivery System

The researchers have developed the Aqua Pro mobile application using ACO with 2-opt strategy to optimize delivery routes, haversine formula to find the nearby stores, GPS tracking, client-server network, and mapping services.

Optimized Delivery Routes. ACO with a 2-opt strategy, integrated with Google Maps and Google Direction APIs, was used to optimize delivery routes for delivery riders. It finds the most efficient paths to deliver water to customers while minimizing travel time and fuel consumption.

Figure 6. Optimize Route using ACO with 2-opt strategy.

The pictures above show an example of how the algorithm works in route optimization. First, the location of the store (node 0) and the location of the customers were plotted on the map. A rider icon will appear, and it will move as the rider goes from point to point using real-time GPS. Then, the first path will appear, starting from the store to the nearest customer according to the algorithm's calculation. The next path will be constructed when the rider clicks the right arrow and can be undone if the rider clicks the left arrow. The process continues until it returns to the starting point, which is the store. It was also noted, based on the previous discussion, that the limit for the number of orders (nodes) accepted from customers is 20 per delivery.

Nearby Stores Finder. The haversine formula was applied in this context to pinpoint the closest water refilling station from each customer. By utilizing geographical data, this formula enables a precise determination of distances, aiding customers in identifying the most convenient refilling station based on their location. After obtaining the latitude and longitude coordinates of the water refilling stations and acquiring the latitude and longitude of the user's current location using GPS, it will calculate the distance between the user's location and each water refilling station.

Figure 7. Nearby Water Refilling Station Finder using Haversine Formula

The images above illustrate the application of the haversine calculation on a map, pinpointing nearby water refill stations. The green marker represents the customer's location, while the red markers indicate the surrounding water refill stations. Customers have the option to adjust the radius distance if they wish to select a store located further away. Moreover, the haversine formula offers suggestions for water refilling stations on the customer's homepage. This feature enables customers to select stores and place orders more efficiently.

However, there are some limitations. The system restricts the radius distance from the customer. If the customer's current location is beyond a 3 km radius from central Legazpi, they will not be able to log into the system.

Additionally, when searching for a nearby water refilling station, customers are confined to a 3 km radius.

Real-time GPS Tracker. Real-time GPS tracker enables customers to track their orders if they are on the way to their location. The picture below shows an example of a delivery rider being tracked by a customer on their way to the customer's location. It displays the distance (in meters) between the customer and the rider. Moreover, the interface also provides an estimated time of arrival (ETA). This ETA is calculated based on various factors, such as the rider's current location, speed, and the route they are taking. However, it's important to note that this is an estimate and can vary due to a number of deliveries and external factors. These can include traffic conditions, weather, and the number of deliveries the rider has to make along the way.

Figure 8: Real-time GPS tracker of rider to customer
Client-Server Network. The client-server network for a water delivery application involves the interactions between different components, including clients (owners, delivery riders, and customers) and a server (flask). For the water delivery application, the server manages user accounts, processes orders, and generates routes for drivers. The Internet serves as the medium for communication between the client and the server, enabling the exchange of requests and responses. The database (firebase) stores all the data related to the application, including user account information, order details, and driver routes. The server interacts with the database to retrieve, update, and store data. When a user places an order, the client sends a request to the server via the Internet. The server processes the request, which might involve interacting with the database, and sends a response back to the client.

Chapter V

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the summary of findings, conclusions, and recommendations for the study based on the results deliberated in the previous chapter.

Summary of Findings and Accomplishments

The main purpose of this study is to develop a system capable of managing and tracking water delivery services at the least cost for both customers and delivery riders in Legazpi City.

Based on the objectives of the study, the following results were accomplished:

1. The integration of the 2-opt strategy with ACO resulted in the ACO with 2-opt outperforming the standard ACO across all datasets in terms of best, average, and optimal values. However, its superior performance in finding optimal solutions suggests that the trade-off between runtime and solution quality is not acceptable. Theoretical complexity analysis revealed that while both algorithms share similar complexities in constructing solution tours and updating pheromone trails, the inclusion of 2-opt optimization in the ACO with 2-opt introduces additional quadratic growth in problem size. This suggests that as the problem size and number of iterations increase, the runtime of ACO with 2-opt also grows, albeit with notable improvements in solution quality.

- 2. Through the integration of ACO with 2-opt and the Google Directions API, this research successfully developed an efficient route optimization solution for water delivery services. The ACO algorithm generated initial solutions, subsequently refined by 2-opt to minimize travel distance. Real-time data from the Google Directions API validated and enhanced routes, ensuring accuracy and adaptability. Interviews with delivery riders confirmed compatibility with practical constraints, while experiments demonstrated computational efficiency.
- 3. The development of the Aqua Pro mobile application represents a comprehensive solution for optimizing water delivery operations through the integration of various technologies and algorithms. By leveraging ACO with a 2-opt strategy, haversine formula, real-time GPS tracking, and mapping services, and by implementing a client-server network, the Aqua Pro application offers a user-friendly and efficient platform for both delivery riders and customers, optimizing the water delivery process while enhancing customer satisfaction.

Conclusions

Based on the findings, the researchers came up with the following conclusions:

1. The study demonstrates that integrating a 2-opt local search strategy into ACO significantly enhances its performance in solving the TSP. The ACO with 2-opt consistently outperforms the standard ACO in terms of solution quality, albeit with too much-increased runtime. The theoretical analysis confirms that the additional complexity introduced by 2-opt optimization influences the algorithm's runtime, especially as the problem size grows. Despite this, the superior solution quality justifies the use of ACO with 2-opt, particularly in scenarios where finding the optimal solution is paramount.

- 2. The research successfully developed a comprehensive route optimization solution for water delivery services, leveraging ACO with 2-opt and the Google Directions API. By integrating these techniques, the study addressed practical constraints such as maximum stops per delivery and computational efficiency. The solution demonstrated effectiveness in minimizing travel time, reducing fuel costs, and enhancing overall delivery service quality.
- 3. The Aqua Pro mobile application is a useful application for enhancing the water distribution environment in Legazpi City, Albay. This innovative application serves as a catalyst for change, fostering a more efficient and sustainable water management environment in the city.

Recommendations

For future improvements of the system and research, the following work can be continued:

1. While the ACO with 2-opt exhibits longer runtime, its superior solution quality makes it suitable for real-life TSP applications where finding the optimal solution is crucial.

- 2. Given the quadratic growth in runtime with problem size, practitioners should consider the trade-off between solution quality and runtime when applying ACO with 2-opt to larger TSP instances.
- 3. Future research could explore hybrid approaches combining ACO with other local search strategies or metaheuristics to further improve solution quality and runtime efficiency.
- 4. Enhance the integration of real-time data sources beyond the Google Directions API, such as weather forecasts or dynamic traffic information, to adapt routes in response to changing conditions.
- 5. The delivery system can be replicated for future research and development.

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APPENDICES

Appendix A

Letter and Appointments

BICOL UNIVERSITY COLLEGE OF SCIENCE Computer Science and Information Technology Department Legazpi City

APPOINTMENT OF SPECIAL PROBLEM 2 EVALUATORS

May 2, 2024

Chairman: PROF. ARLENE A. SATUITO Member: FRANKLIN M. MIRANDA JR., MIT Member: LEA D. AUSTERO, DIT

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at 1:30-2:30 pm at CSB2 - 104.

As member of the panel you are asked to:

- 1) Appraise the validity and acceptability of the thesis work in terms of its scholarly quality, correctness of the facts and claims contained therein; and completeness as to its basic components.
- 2) Make sure that all the suggestions are judiciously incorporated.
- 3) Evaluate the research report based on adopted.
- 4) Provide ample time to his advisee in relation to the thesis work.
- 5) Orient the advisee on what might/will transpire in the defense session and
- 6) Be physically present during the oral defense.

You shall be entitled to an honorarium as chairman and as member of the panel, as per Board Resolution No.93, s 2006.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

PROF. ARLENE A. SATUITO Chairman

FRANKLIN M. MIRANDA JR., MIT Member

LEA D. AUSTERO, DIT Member

APPOINTMENT OF SPECIAL PROBLEM 2 EVALUATORS

May 2, 2024

PROF. ARLENE A. SATUITO Professor College of Science Legazpi City

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access" Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at 1:30-2:30 pm at CSB2 - 104.

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- 2) Make sure that all the suggestions are judiciously incorporated.
- 3) Evaluate the research report based on adopted.
- 4) Provide ample time to her advisee in relation to the thesis work.
- 5) Orient the advisee on what might/will transpire in the defense session and
- 6) Be physically present during the oral defense.

You shall be entitled to an honorarium as chairman of the panel, as per Board Resolution No.93, s 2006.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

PROF. ARLENE A. SATUITO Chairman of the Panel

APPOINTMENT OF SPECIAL PROBLEM 2 EVALUATORS

May 2, 2024

LEA D. AUSTERO, DIT Professor College of Science Legazpi City

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access" Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at 1:30-2:30 pm at CSB2 - 104.

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- 2) Make sure that all the suggestions are judiciously incorporated.
- 3) Evaluate the research report based on adopted.
- 4) Provide ample time to her advisee in relation to the thesis work.
- 5) Orient the advisee on what might/will transpire in the defense session and
- 6) Be physically present during the oral defense.

You shall be entitled to an honorarium as member of the panel, as per Board Resolution No.93, s 2006.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

LEA D. AUSTERO, DIT Member of the Panel

APPOINTMENT OF SPECIAL PROBLEM 2 EVALUATORS

May 2, 2024

FRANKLIN M. MIRANDA JR., MIT Professor College of Science Legazpi City

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access" Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at 1:30-2:30 pm at CSB2 - 104.

As member of the panel you are asked to:

- 1) Appraise the validity and acceptability of the thesis work in terms of its scholarly quality, correctness of the facts and claims contained therein; and completeness as to its basic components.
- 2) Make sure that all the suggestions are judiciously incorporated.
- 3) Evaluate the research report based on adopted.
- 4) Provide ample time to her advisee in relation to the thesis work.
- 5) Orient the advisee on what might/will transpire in the defense session and
- 6) Be physically present during the oral defense.

You shall be entitled to an honorarium as member of the panel, as per Board Resolution No.93, s 2006.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

FRANKLIN M. MIRANDA JR., MIT Member of the Panel

APPOINTMENT OF SPECIAL PROBLEM 2 CONTENT ADVISER

May 2, 2024

ENGR. JOHN RAYMOND B. BARAJAS Professor

College of Science Legazpi City

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access" Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at 1:30-2:30 pm at CSB2 - 104.

As an adviser, you shall perform the following task:

- 1) Check the format of the manuscript.
- 2) Provide general editing of thesis work.
- 3) Attend the defense session of the advisees and record suggestions and recommendations at the panel.
- 4) Orient the advisee on what might/will transpire in the defense session
- 5) Be physically present during the oral defense.

This designation shall be entitled to a professional fee as authorized under Board Resolution No.065, s 2004.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

ENGR. JOHN RAYMOND B. BARAJAS Content Adviser

APPOINTMENT OF SPECIAL PROBLEM 2 PROGRAMMING ADVISER

May 2, 2024

RYAN A. RODRIGUEZ, MSCS, MIT Professor College of Science Legazpi City

You are hereby appointed to constitute the Special Problem Panel as indicated above to evaluate the research work of Abache, Adrian Jones A., Cifra, Mark Jerome C., and Nacion, Angel Mae A. who will work on the topic, "Aqua Pro: Water Access Efficiency Through Ant Colony Optimization With 2-Opt Local Search Strategy", which is scheduled for its Final Defense on May 2, 2024 at $1:30-2:30$ pm at CSB2 - 104.

As an adviser, you shall perform the following task:

- 1) Provide technical guidance and expertise to the student in their programming tasks, algorithms, and code development.
- 2) Ensure that the coding and technical aspects of the thesis meet the highest standards of quality, efficiency, and security.
- 3) Review and provide feedback on the code, debugging, and optimization to help the student achieve their technical objectives.
- 4) Assist the student in selecting appropriate tools, technologies, and methodologies for the project.
- 5) Attend the defense session of the advisees and record suggestions and recommendations at the panel.
- 6) Assist in troubleshooting technical issues and roadblocks that the student may encounter during the research and implementation phases.
- 7) Be physically present during the oral defense.

This designation shall be entitled to a professional fee as authorized under Board Resolution No.093, s 2006.

Very truly yours,

JOCELYN E. SERRANO, M.Sc. DEAN, College of Science

Conforme:

RYAN A. RODRIGUEZ, MIT, M.Sc. Programming Adviser

Request letter to the City Mayor for conducting data collection of water

refilling stations in Legazpi City

HON. CARMEN GERALDINE B. ROSAL **City Mayor** Legazpi City Hall, Old Albay District Legazpi City, Albay 4500

Dear Hon. Rosal:

The undersigned college students of Bicol University College of Science, currently pursuing a Bachelor of Science in Computer Science, are formally requesting to conduct data gathering on water refilling stations within the vicinity of Legazpi City. This is for the thesis study entitled: "Aqua Pro: Optimizing Water Access Efficiency through Bio-Inspired Routing Solutions," in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science.

In this connection, we would like to ask permission from your good office to conduct our data gathering on December 27, 2023 - January 27, 2024. One of us is your constituent.

Thank you very much and may God bless you.

Respectfully yours,

Adrian Johes M. Abache **BSCS Student/Researcher**

Mark Jerome C. Cifra **BSCS Student/Researcher**

OFFICE OF THE MAYS: December 27, 2023

LEGAZPI CITY

TIE Nn

Noted by: Prof. Lea D. Austero **Thesis Professor**

Approved:

CARMEN GERALDINE B. ROSAL City Mayor

Appendix B

Certificate of Authorization

Authorization from Office of the Environment Sanitation Section to conduct

data collection of water refilling stations in Legazpi City

Republic of the Philippines Province of Albay City of Legazpi **CITY HEALTH DEPARTMENT**

OFFICE OF THE ENVIRONMENT SANITATION SECTION

AUTHORIZATION

To whom it may concern:

This certificate hereby authorizes the researchers, Adrian Jones M. Abache, Mark Jerome C. Cifra, and Angel Mae A. Nacion, conducting the thesis titled "Aqua Pro: Enhancing Water Access Efficiency through Ant Colony Optimization" to conduct data/information collection activities pertaining to water refilling stations across forty-three barangays, spanning from Barangay 1 to Barangay 41, as well as Barangay 57 and Barangay 58, situated within Legazpi City, Albay.

This authorization is granted solely for the purpose of facilitating the aforementioned research project. The data/information gathered must be kept highly confidential and used exclusively for academic purposes.

Given in signed this 8th day of January, 2024 at Legazpi City Health Office, Sanitation Section, Legazpi City, Albay.

> JOSE ANTONIO G. PRIETO Officer in Charge Sanitation Inspector III

Appendix C

Appendix D

Data Gathered

Water Refilling Stations of Barangay 1 to Barangay 41, Barangay 57 and

Barangay 58, Legazpi City

ANNEX A

Pricing and Packaging of each store

Annex B

Appendix E

Diagrams

Client-Server Architecture of the water delivery system

Use Case Diagram for experimental setup

ERD of the water delivery system

Appendix F

Data Gathering Documentation

Appendix G

Experiment Documentation

Experimentation using Google Colab

Appendix H

System Testing Documentation

System Testing for Customers

Delivery Simulation

Appendix I

User's Manual

Customers' User Interface

Owners' User Interface

Delivery Riders' User Interface

Appendix J

Source Code

Ant Colony Optimization with 2-opt

from flask import Flask, jsonify, request import googlemaps from datetime import datetime import pandas as pd import numpy as np import time

class Ant: def __init (self, num_cities): self.tour = np.concatenate(([0], np.random.permutation(np.delete(np $. \text{orange}(\text{num} \text{ cities}), 0))))$ self.distance = np.inf

```
def calculate total distance(tour,
distances):
                 total distance =np.sum(distances[tour[:-1], tour[1:]])
+ distances[tour[-1], 0]
  return total distance
```

```
def two_opt(tour, distances):
  num cities = len(tour)for i in range(num cities - 1):
     for j in range(i + 2, num cities +
int(i == 0):
       if j - i == 1: continue
       new tour = tour.copy()
       new tour[i+1:j] = tour[i-1:i-1]if
calculate_total_distance(new_tour,
distances) <
calculate_total_distance(tour,
distances):
         tour = new_tour
  return tour
```
def ant colony optimization(distances, num_iterations=100, num_ants=100, decay=1, alpha=1, beta=1): num_cities = len(distances) pheromones = np.ones((num_cities, num_cities)) best $tour = None$ best distance $=$ np.inf best iteration = None for iteration in range(num_iterations): decay = $1 - \frac{1}{i\pi}$ + 1) ants = $[Ant(num cities) for in]$ range(num_ants)] for ant in ants: for i in range(1, num_cities): p = pheromones[ant.tour[i], :] $**$ alpha $*$ ((1.0) $(distance[ant.tour[i], :] + 1e-10)$ ^{**} beta) $p[ant.tour[:i+1]] = 0$ if i < num_cities - 1: ant.tour[$i+1$] = np.random.choice(range(num_cities) , 1, p=p/np.sum(p)) ant.tour = two $opt(ant.tour,$ distances) ant.distance $=$ calculate_total_distance(ant.tour, distances) if ant.distance < best distance: best distance $=$ ant.distance best tour = ant.tour.copy() best iteration = iteration pheromones[ant.tour[:-1], ant.tour[1:]] $+= 1.0 / \text{ant.distance}$ pheromones $*=(1.0 - \text{decay})$

return np.concatenate((best_tour, [0])), best_distance, best_iteration, num iterations, num ants $app = Flash($ name $)$ results = $\{\}$ # Store the results here @app.route("/", methods=['GET', 'POST']) def index(): if request.method == 'POST': nodes = request.get $json()$ # Get the coordinates from the POST request gmaps client $=$ googlemaps.Client(key='placeholder') now = datetime.now() source = "13.14312265082151, 123.72490529804402" destination = "13.143697278881184, 123.72756604934412" direction $result =$ gmaps_client.directions(source, destination, mode="driving", avoid="ferries", departure time=now, transit $mode = 'bus'$) print(direction_result[0]['legs'][0]['dist ance']) print(direction_result[0]['legs'][0]['dur ation']) $df =$ pd.DataFrame(columns=['from_node' 'to node', lifrom lat long',

'to_lat_long', 'distance',

'distance_text', The lat', 'from_long']) rows $=$ [] for from node, from coords in nodes.items(): for to node, to coords in nodes.items(): row $=$ $\{$ 'from_node': from_node, 'to_node': to_node, 'from_lat_long': from_coords, 'to_lat_long': to_coords, 'distance': 0 if from node == to node else None, 'distance_text': np.nan, 'from_lat': from_coords[0], 'from_long': from_coords[1], } rows.append(row)

 $df =$ pd.concat([pd.DataFrame([row], columns=df.columns) for row in rows], ignore index=True)

start_time='now' for index, row in df.iterrows(): if row['from_node'] != row['to_node']: direction result $=$ gmaps_client.directions(row['from_lat long'], row['to lat long'], mode="driving", avoid="ferries", departure time=start time) df.loc[index, 'distance'] = direction_result[0]['legs'][0]['distance'] ['value'] df['distance $text$] = df['distance_text'].astype(str) df.loc[index, 'distance_text']

direction_result[0]['legs'][0]['distance'] ['text'] distance dict $=$ df.set_index(['from_node', 'to_node'])['distance'].to_dict() distance $=$ \Box for from_node in df.from_node.unique().tolist(): distance $1d = []$ for to node in df.to_node.unique().tolist(): distance 1d.append(distance dict[fr om_node,to_node]/1000) distance.append(distance_1d) distances = np.array(distance) distances = distances.copy() # Run ACO a large number of times to estimate the best known result best known result = $np.inf$ for $\overline{\text{in range}}(10)$: best route, total distance, _, $\overline{}$, $\overline{}$ ant colony optimization(distances, num_iterations=100, num_ants=10) if total distance \leq best known result: best known result = total distance # Initialize lists to store results best routes $=$ \Box total distances $= []$ running times $=$ \Box best iterations = $[]$ # Run ACO 15 times for trial in range(15): start $time = time.time()$ best route, total distance, best iteration, example iterations,

num ants $=$ ant colony optimization(distances, num iterations=100, num ants=10) end $time = time.time()$ # Store results best routes.append(best route) total distances.append(total distanc e) running times.append(end time start_time) best iterations.append(best iteration λ # Calculate statistics average distance $=$ np.mean(total_distances) std dev distance = np.std(total_distances) # Calculate percent error using the best result from all trials best result $=$ min(total distances) percent $error = (best result$ best known result) best known result * 100 result = $\{$ "Best Route": best_route.tolist(), "Distances": [], "Total Distance": calculate_total_distance(best_route, distances), "Running Time": end time start time, }

Calculate distances between nodes in the best route

for i in range(len(best_route) -

1):

from $node = best$ route[i] to node = best route[i + 1] distance between_nodes = distances[from_node][to_node]

result["Distances"].append(distance_ between_nodes)

return jsonify(result)

else:

return "Send a POST request with your coordinates."

@app.route("/results", methods=['GET']) def get results(): return jsonify(results) if $name = '$ main $'$: app.run(debug=True)

Haversine Formula

double calculateDistance(double lat1, double lon1, double lat2, double $lon2)$ { $const$ $p =$ 0.017453292519943295; // Convert degrees to radians final dLat = (lat2 - lat1) * p; final dLon = (lon2 - lon1) * p; final $a = sin(dLat / 2) * sin(dLat / 2)$ + cos(lat1 $*$ p) $*$ cos(lat2 $*$ p) $*$ $sin(d\text{Lon}/2) * sin(d\text{Lon}/2);$ final $c = 2 * \text{atan2}(\text{sqrt}(a), \text{sqrt}(1 - a))$ a)); final distanceInKm = $6371 * c$; // Radius of the Earth in kilometers return distanceInKm; }

PERSONAL INFORMATION

- **Name:** Adrian Jones M. Abache
- **Address:** Cagbacong, Legazpi City, Albay
- **Date of Birth:** March 23, 2002
- **Civil Status:** Single
- **Citizenship:** Filipino
- **Religion:** Roman Catholic
- **Email:** adrianjonesmanalo.abache@bicol-u.edu.ph

EDUCATIONAL BACKGROUND

- **- Tertiary Education**
	- **School:** Bicol University College of Science
	- **Address:** Rizal St. Legazpi City, Albay
	- **Academic Program:** Bachelor of Science in Computer Science
	- **Duration:** 2020-2024
- **- Secondary Education**
	- **School:** Banquerohan National High School
	- **Address:** Banquerohan, Legazpi City, Albay
	- **Duration:** 2018-2020
	- **School:** Cagbacong High School
	- **Address:** Cagbacong, Legazpi City, Albay
	- **Duration:** 2016-2018
	- **School:** Christian Ecclesiastical School
	- **Address:** Gaya-Gaya, San Jose Del Monte, Bulacan
	- **Duration:** 2014-2016
- **- Elementary Education**
	- **School:** Cagbacong Elementary School
	- **Address:** Cagbacong, Legazpi City, Albay
	- **Duration:** 2008-2014

PERSONAL INFORMATION

- **Name:** Mark Jerome C. Cifra
- **Address:** Pacol, Naga, Camarines Sur
- **Date of Birth:** February 25, 2001
- **Civil Status:** Single
- **Citizenship:** Filipino
- **Religion:** Roman Catholic
- **Email:** markjeromecleofe.cifra@bicol-u.edu.ph

EDUCATIONAL BACKGROUND

- **- Tertiary Education**
	- **School:** Bicol University College of Science
	- **Address:** Rizal St. Legazpi City, Albay
	- **Academic Program:** Bachelor of Science in Computer Science
	- **Duration:** 2020-2024
- **- Secondary Education**
	- **School:** Ateneo de Naga University
	- **Address:** Ateneo Ave, Naga City, Camarines Sur
	- **Duration:** 2014-2020
- **- Elementary Education**
	- **School:** Naga Parochial School
	- **Address:** Ateneo Ave, Naga City, Camarines Sur
	- **Duration:** 2008-2014

PERSONAL INFORMATION

- **Name:** Angel Mae A. Nacion
- **Address:** Maninila, Camalig, Albay
- **Date of Birth:** May 6, 2001
- **Civil Status:** Single
- **Citizenship:** Filipino
- **Religion:** Roman Catholic
- **Email:** angelmaealbelo.nacion@bicol-u.edu.ph

EDUCATIONAL BACKGROUND

- **- Tertiary Education**
	- **School:** Bicol University College of Science
	- **Address:** Rizal St. Legazpi City, Albay
	- **Academic Program:** Bachelor of Science in Computer Science
	- **Duration:** 2020-2024
- **- Secondary Education**
	- **School:** St. Augustine School of Nursing QC
	- **Address:** 115 DHC Building, EDSA, Veterans Village, Quezon City
	- **Duration:** 2018 2020
	- **School:** Cotmon National High School
	- **Address:** Cotmon, Camalig, Albay
	- **Duration:** 2014 2018
- **- Elementary Education**
	- **School:** Maninila Elementary School
	- **Address:** Maninila, Camalig, Albay
	- **Duration:** 2008 2014

