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Research Article

An Integration of Real-Time Vehicle Routing and Mobile Technology in Poultry Distribution

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Abstract: Handling the distribution of broilers has special attention. The distribution of poultry should be done in the shortest possible time to decrease the broiler mortality rate. Real-time monitoring and generating the shortest possible travel distance in poultry distribution is expected to control the stress level of poultry by limiting the delivery time window. The paper aims to develop a mobile Android and web dashboard that can accommodate possible solutions to optimize poultry distribution time and distance. We adopted mathematical modeling from the vehicle routing problem (VRP), which has features to optimize travel distance considering vehicle travel time, vehicle delivery distance, vehicle capacity, and pickup-delivery activity, and charge a penalty cost when the vehicle violates the delivery time windows. VRP can provide optimal tours to visit a set of customers. In this case, we used the Google API and Google OR-Tools to implement the vehicle routing problem with pickup-delivery time window (CVRPTWPD). Guided local search is used to solve the vehicle routing problem. A digital twin-enabled service framework is adopted to show how the system works. There is a significant change in travel distance in one delivery cycle after implementing the developed technology. The total travel distance of 493 km decreased to 436 km, which decreased by 11.5% from the initial total travel distance. Meanwhile, the total penalty time (delay) decreased by 16.6%. The development of this mobile technology can indirectly increase vehicle utilization by not overloading the vehicle capacity and reducing vehicle travel distance.

Keywords: cvrptwpd, poultry distribution, real-time tracking, routing technology, vrp mobile framework.

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1 Introduction

The poultry distribution is a complex and dynamic system [1]. Complexity is based on unique and perishable product properties, while dynamic is based on stochastic demand that fluctuates over time. Distribution is essential in marketing, storage, delivery, and transportation of a product [2]. The customers location in various places made the distribution system more complex. Determining the optimal distribution route is a critical decision for a company in order to be able to streamline distribution costs, delivery times, and vehicle capacity. Land transportation expenses constitute the largest share of distribution costs, making up 66.8% of the total operational costs for the company [3]. The remaining costs encompass administrative expenses, inventory handling charges, loading, and unloading expenditures, parking fees, and unauthorized levies.

Handling the distribution of broilers has special attention. According to Kettlewell *et al.* [4], heat stress during the delivery had to be considered when handling broiler distribution. In addition, road conditions, distance travelled, and the broilers' conditions affected the mortality rate during the distribution process [5]. Moreover, as highlighted by Rabbani *et al.* [6], the potential hazards associated with the distribution of perishable food are impacted by environmental shifts, distribution distances, product handling, transportation methods, and the specific type of vehicle used. To minimize broilers' mortality rate, conducting poultry distribution within the shortest feasible timeframe is advisable.

Delivery of broiler chicken during transportation to each consumer under various conditions is proven to increase dead on arrival (DoA) by 0.18% of the total daily transportation [7]. Recent research has focused on several evaluations of vehicle fleet configuration and technology integration [8]. Heilig *et al.* [8] first suggested the importance of an information system that gathers real-time information to coordinate vehicle movements on inter-terminal transport. Cavecchia *et al.* [9] suggested that vehicle synthesis routing techniques and GIS in spatial decision support systems can significantly improve the modeling of routing problems. Gayialis *et al.* [10] formulated a vehicle routing problem with real-time time windows and travel times using a mixed integer linear programming model. They assumed that deploying information through mobile technology provides better vehicle localization and an online overview of the actual traffic situation.

The combination of supply chain management (SCM), enterprise resource planning (ERP), and geographical information systems (GIS) provides a convenient method to manage and optimize a company's distribution system, compared to traditional management [11]. Instead of using ERP and GIS, Zambrano-Vega *et al.* [12] and Kasanah *et al.* [13] use Google OR-Tools to manage routing problem and scheduling.

Real-time distribution planning is a complex activity when applied to large problems. This research will develop a decision-making system for route optimization and scheduling that considers the limitations of delivery time, vehicle capacity, and limitation of time window.

The objectives of this paper are optimum use of the distribution network and transportation cost reduction. This paper aims to develop an android mobile application and web-based dashboard that can provide optimal tours (shortest distance) when a travel to a set of clients, considering the efficiency of time and fuel consumption. Integrated vehicle routing and technology are expected to solve routing problems using the server-based Google API.

The contribution of this paper is deployment of modern information system based indispensable source of real-time data on vehicle location and travel condition. Furthermore, our study considers of developed framework to integrate capacitated vehicle routing problem with time windows and pickup & delivery (CVRPTWPD) through google map navigation system and Google console API into mobile and web application that accommodate real-time milky-run delivery system, while Heilig *et al.* [8] only discussed about configuration mobile apps and real-time inter-terminal truck routing without considering time window and pickup delivery constrains. Li [14] and Taniguchi [15] created the basic model for online and real-time vehicle routing, they build framework for mobile technology without GIS or maps tools. Whereas we provide framework and implementation of vehicle routing that accommodates real-time vehicle routing with travel window and pickup-delivery problem integrated with mapping system from Google OR-tools, using particular case in poultry distribution.

In the future, the software has the potential to help companies minimize their operational costs by determining the most efficient shipping routes for products such as poultry. In the long term, reducing the shipping distance could indirectly lower the mortality rate of live birds during transportation.

2 Research Method

This section discusses routing optimization problem, definitions used in this paper, and integration of vehicle routing through mobile technology.

2.1 Routing Optimization Problem

Many problems in goods transport with a fleet of vehicles can be modeled. Routes for vehicles are usually designed to minimize total distance costs [16]. The focus of VRP is designing routes for delivery vehicles that operate from a single depot and supply a set of customers at a specific location, with time windows and involve static or dynamic demand [17]. Based on the characteristics of the poultry distribution with a time limit for delivery and travel time during delivery, this research uses a capacitated vehicle routing problem with travel time windows (CVRPTWPD) approach.

The problems faced are derivatives of the CVRPTW, which is part of a multi-objective problem [18]. The solution to this problem is to generate a route, starting from the depot, then sending the goods to a set of customers, within a predetermined time limit, without violating the vehicle capacity limit. The main goal expected from this model is to minimize the total distance travel considering the number of vehicles and their capacity and the minimization of the total travel distance by considering the overall distribution costs.

But in reality, some limitations arise, for example, in the distribution process of poultry, which requires a limited time when delivering live poultry because of the weight loss rate issue of live poultry [5, 19, 20]. Furthermore, in this case, the minimizing method needs to be considered not only fixed costs but also general transportation costs, handling costs, and penalties for violating time-windows may also arise. The optimization goal of the problem is to minimize the total cost on the basis of customers' group and their optimal route.

The assumption used in this problem are [21]:

(a) Vehicles need to reach each customer i within the designated time windows and perform loading and unloading tasks while also stopping at customer i during the service time.

(b) In a scheduling period, vehicles are limited to completing a maximum of one trip.

(c) This formulation for CVRPTWPD involving only single depot and homogenous fleet.

(d) The vehicles depart empty from the depot.

(e) Every route connecting the delivery points is assigned a defined travel time, ensuring the total travel time does not exceed the established limit.

(f) Time windows are incorporated.

(g) Consideration is given to specific logical constraints that have been chosen.

Mathematically, CVRPTWPD can be described as follows (adopted from ([22,23]), the CVRPTWPD is defined on the directed graph $G = (V, A)$, Let $N = V\{0, n+1\}$ be the set of customer vertices. There is n customer indexed by i. Assign a node i to the pickup location of customer i and a node $n+i$ to their delivery location. Additionally, designate nodes 0 and 2_{n+1} to represent the depot. This distinction ensures clarity between customers, their associated locations, and the nodes within the network. Each customer i has demand di that shipped from node i to node $n+1$, and every customer i has denoted the pickup time windows $[a_i, b_i]$ and $[a_{n+1}, b_{n+1}]$ denote the delivery time window.

Each routed and scheduled vehicle k has capacity D, and set of vehicles denoted as $K = \{1, 2, \ldots, |K|\}$. The time window for vehicle departure from the depot can be donated as $[a_o, b_o]$, and $[a_{2n+1}, b_{2n+1}]$ to be the time window when returning to the depot after completing the trip. For every distinct i, j in set of customer N, let t_{ij} represent the travel time between i to j, and c_{ij} represent the travel cost between node i and j. and service time in every customer i denoted as s_i. Keep only the arcs (i, j) that adhere to predetermined capacity and time limitations.

2.2 Definition

Let $g(Y) > 0$ represent a function that increases as the total load carried by the vehicle after it departs from node i, where $i \in N$, increases. This function will serve as a penalty factor influencing the travel cost. Model formulation for CVRPTWPD with additional constraint such as pickup and delivery with time windows for each customer is shown in (1) [24–26].

$$\text{Min} \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} \cdot x_{ij}^k \cdot g(Y_i) \tag{1}$$

Our objective is to minimize the total sum of travel costs. The first constraint (2) ensure that each customer is allocated to precisely one route.

$$\sum_{(j) \in N} \sum_{k \in K} x_{ij}^k = 1, \quad \forall i \in N \tag{2}$$

Table 1: Set, parameter, and constant definition

Symbol	Description
Indices	
N	The set of customer vertices.
K	Set of vehicles.
Parameters	
d_i	Demand in node i.
D	Vehicle capacity.
$[a_0, b_0]$	Time window for vehicle departure from the depot.
$[a_{2n+1}, b_{2n+1}]$	The window when returning to the depot.
a_i	Starting pickup time window at node i.
b_i	Ending pickup time window a node i.
a_{n+1}	Starting delivery time window at node n+1.
b_{n+1}	Ending delivery time window at node n+1.
s_i	Service time at node i.
c_{ij}	Travel cost from node i to j.
t_{ij}	Travel time from node i to j.
Decision Variables	
x_{ij}^k	Equals to one if vehicle k departures from node i to node j at time t, otherwise equals to zero.
T_i	Be the time at which service at node i begins, $i \in N$.
T_0^k	The time when vehicle to leaves the depot, $k \in K$.
T_{2n+1}^k	The time when vehicle returns to the depot, $k \in K$.
Y_i	The total load on the vehihcle just ater it leaves node i, $i \in N$.
Y_0	The vehicles depart empty from the depot.
$g(Y_i)$	A function that increases as the total load carried by the vehicle after it departs. from node i, where $i \in N$.

Next, (3), (4), and (5) establish a source-to-sink path in graph G for every vehicle k.

$$\sum_{(j)\in N} x_{ij}^k = \sum_{(j)\in N} x_{ji}^k, \quad i \in N, k \in K \tag{3}$$

$$\sum_{j\in P} x_{0j}^k = 1, \quad \forall k \in K \tag{4}$$

$$\sum_{i\in P} x_{i,2n+1}^k = 1, \quad \forall k \in K \tag{5}$$

Constraint (6) ensure that the same vehicle v visits both i and $n+i$ locations.

$$\sum_{j\in N} x_{ij}^k = \sum_{j\in N} x_{j,n+1}^k, \quad i \in N, k \in K \tag{6}$$

Constraints (7) represent precedence constraints that enforce the requirement for node i to be visited before node $n+i$.

$$T_i + s_i + t_i, n+1 \leq T_{n+1}, \quad i \in N \tag{7}$$

Constraint (8), (9), and (10) explain the conditions for compatibility between routes and schedules.

$$x_{ij}^k = 1; T_i + s_i + t_{ij} \leq T_i, \quad \forall j \in N, k \in K \tag{8}$$

$$x_{0j}^k = 1; T_0^k + t_{0,j} \leq T_j, \quad \forall j \in N, k \in K \tag{9}$$

$$x_{i,2n+1}^k = 1; T_i + s_i + T_{i,2n+1} \leq T_{2n+1}^k, \quad \forall j \in N, k \in K \tag{10}$$

Constraint (11), (12), and (13) guarantee schedule feasibility with respect to time windows.

$$a_i + T_i \leq b_i, \quad \forall i \in N \tag{11}$$

$$a_0 + T_0^k \leq b_0, \quad \forall k \in K \tag{12}$$

$$a_{2n+1} \leq T_{2n+1}^k \leq b_{2n+1}, \quad \forall k \in K \tag{13}$$

Constraint (14), (15), (16), and (17) describe the criteria for compatibility between routes and the loads carried by vehicles.

$$x_{ij}^k = 1; Y_i + d_j = Y_j, \quad \forall i \in N, j \in N, k \in K \tag{14}$$

$$x_{ij}^k = 1; Y_i + d_{j-n} = Y_j, \quad \forall i, j \in N, k \in K \tag{15}$$

$$x_{ij}^k = 1; Y_0 + d_j = Y_j, \quad \forall j \in N, k \in K \tag{16}$$

$$Y_0 = 0; d_i \leq Y_i \leq D, \quad \forall i \in N \tag{17}$$

$$x_{ij}^k \text{binary}, \quad \forall i, j \in N, k \in K \tag{18}$$

These are decision variables with non-negativity constraints.

2.3 Integration of Vehicle Routing through Mobile Technology

The novelty of mobile technology is its ability to provide accurate and real-time information. The latest developments in communication technology prove the exchange of information between the information center (admin) and on-road vehicles. This technology makes it possible to get real-time per-minute traffic data, transform it into data related to current traffic conditions, and estimate travel times.

Information related to the current conditions is transmitted through vehicle route guidance devices to assist drivers in deciding the optimal route for delivering goods. Furthermore, the use of application-based vehicle routing problems such as google OR-Tools combined with mobile technology can display the position of the driver and proposed delivery route. This method increases vehicle utilization and helps minimize travel distances.

The dynamics in the vehicle routing simulation model are described in a block density model [15], which is a simple microscopic model. According to the estimated average travel time, the vehicle is assumed to choose the shortest path when it arrives at a node. Figure 1 consists of two components, flow simulation, which describes the overall flow of driver movement from one node to another, and route choice simulation, which is a simulation of vehicle routing.

The block density model clarifies the flow in the vehicle routing simulation for adoption in mobile technology. As input, there are customer coordinates in the form of latitude and longitude, along with demand data. The algorithm to solve the vehicle routing problem will be determined when getting the API data from google OR-Tools.

In order to solve the VRP problem and find an optimal solution, in this paper, we used guided local search (GLS), which has been proven to provide optimal solutions in vehicle

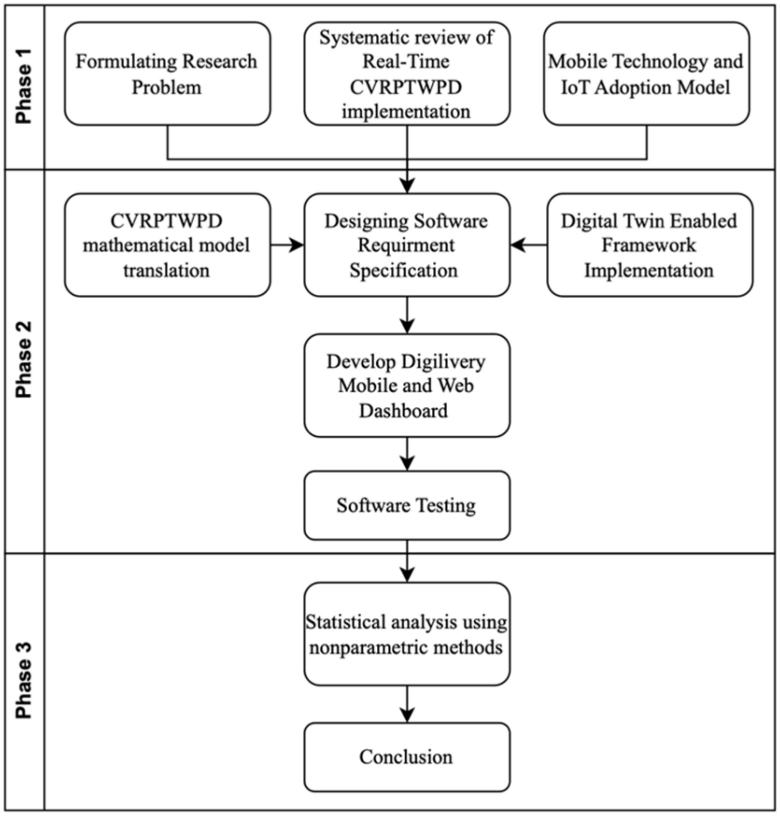

Figure 1: Research study flow diagram.

routing cases [27]. GLS can perform an intelligent search strategy utilizing problems and related search directions to guide the local search algorithm. Penalties rely on solution characteristics that are established and dynamically guided to distribute exploration in different regions of the search area [28]. Adopted from Florian [27] and Marti *et al.* [29] we proposed pseudocode framework for GLS, as follows.

There are three main stages in running the GLS algorithm. First, we conduct generated construction method as the initial (starting point) in the problem solution. In this first step, all features will be given a penalty value of zero. Secondly, the program will enter the Stopping Criterion stage, which is the stage to determine the length of the running time. Since GLS is not trapped in the local optimum, it is unclear when to stop the algorithm. Stopping criteria can be defined by setting running time limits, utilizing the number of moves performed, or tracing the gap between the best-known and lower-bound solutions. Finally, the last stage is conducted improvement method [29]. In this stage, the optimal solution search process is similar to neighborhood search or local search algorithm. However, GLS is already available in the Google OR-tools library, so users can easily call it on local search metaheurustics parameters.

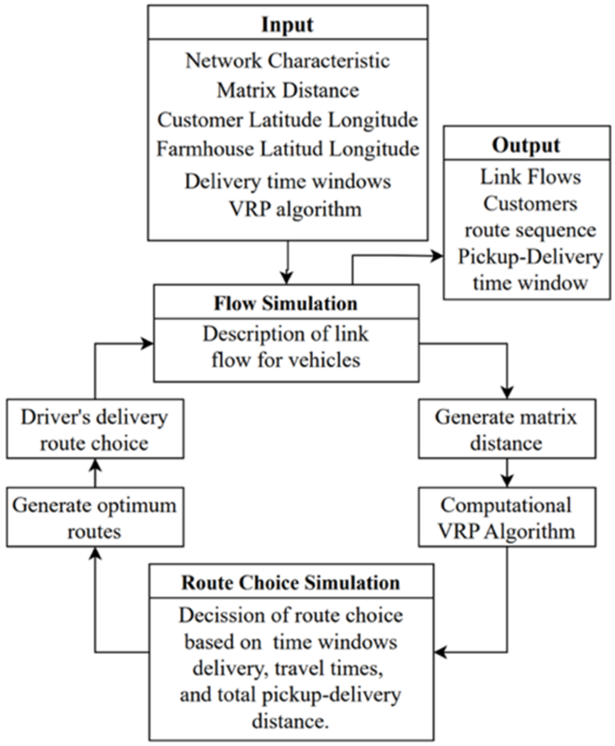

Figure 2: Block density model of vehicle routing simulation.

3 Result

This section discusses the problem definition, mobile application framework, system implementation, parameter initialization, and test results for real-time travel times.

3.1 Problem Definition

The poultry distribution process starts with each vehicle's departure from the depot. The vehicle picks up goods at the farmhouse and begins to deliver the goods to sets of consumers at different locations, then come back to the depots, this case known as closed vehicle routing problems [30]. This case is similar to the courier services case, and the difference is this case considers the limitation on the carrying capacity of each vehicle. In general, adapted from [31], supply chain poultry in level downstream shows bellow.

Figure 2 show the information, financial, and goods flow in poultry (live bird) supply chain. The mobile application submitted in this paper aims to regulate orders for live birds from the collectors/ distributors to each agent who is a reseller. In actual conditions, the slaughterhouse and farm are in different locations, and the slaughterhouse is located in the broker and each agent. We assume that poultry slaughterhouse and farm is in different places.

Algorithm 1 Guided Local Search Framework

```
procedure GUIDEDLOCALSEARCH
    ConstructionMethod. Generate an initial (starting) problem solution.
    for problem in initial features do
        penalty (p_i) ← 0
    end for
    Define the augmented objective function.
    while StoppingCriterion do
        ImprovementMethod. Improving solution as neighborhood search.
        for initial features do
            calculate feature utility
        end for
        for all features that have been utilized, with indicator function maximum do
            penalize features with maximum utility
            p_i ← p_i + 1
        end for
        Optimization. Apply local search on all routes that were changed during ImprovementMethod.
    end while
end procedure
```

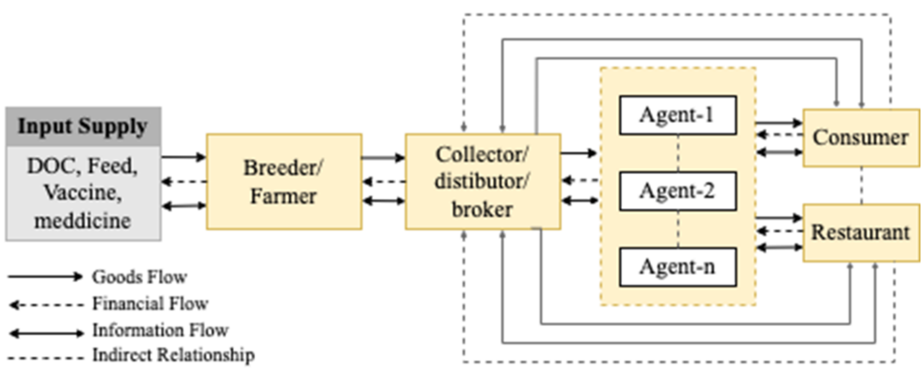

Figure 3: Poultry supply chain information flow.

Distributors have several vehicles with a set of customers, and every agent has been clustered by the distributors. This mobile application is expected to accommodate the dynamics of information flow, goods flow, and financial flow between distributors and agents. Furthermore, the development of this application used the Vehicle Routing feature to provide solutions to drivers with a proposed shortest route on their trip. In addition, restrictions on delivery time and capacity are also applied under the characteristics of handling poultry distribution.

3.2 Mobile Applications Framework

The poultry distribution management system will be supported by the internet network and a database server to send information from the database to the client computer for each user. Distributors will monitor all distribution activities through a dashboard on the main computer as a web-based and mobile application will facilitate users (drivers) to do the distribution.

This mobile technology proved the vehicle routing in more realistic things. We assume there is a real-time changing data from vehicle to database server. Therefore, there is a possibility to updated travel time between a pair of nodes. Based on design logistic system proved by [32] and systematic design for smart product services using digital twin-enabled service innovation [33], we adopted similar framework design fit with routing problems as follows.

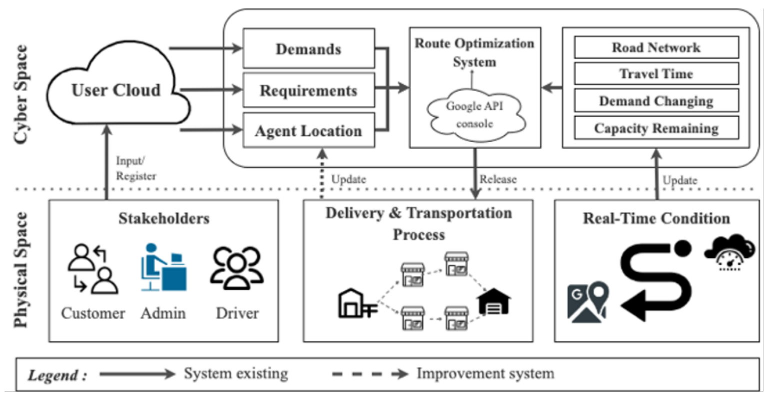

Figure 4: Digital twin-enabled service innovation framework.

A new aspect was added in our model framework, for example [33] used IoT based in every vehicle to detect traffic congestion, then generate the alternative routes. in our paper we get the driver position from the mobile cellular to generate fastest route for each vehicle, respect to CVRPTWPD constraint. While [33] used smart truck to get the actual position. Another difference is we used implementation of google API console to generate the optimum route beside [33] used IoT tracker and motion status to predict the vehicle location and traffic condition.

The system will generate the optimal route by getting API from the Google API Console [34]. The system will verify the customer's location, the number of orders, and the validated farmhouse location by the admin. A route will be generated and returned to the system to be read by the driver. Real-time conditions will affect the system's state, such as demand changes when the vehicle is already operating, changes in the remaining vehicle capacity left, total travel time, and route network [25].

The physical space consists of logistics elements, including stakeholders as users who will interact directly with the system, such as customers, admins, and drivers, including delivery and transportation processes and real-time conditions that will change over time. The mobile application will provide decision suggestions based on demand, requirements, and the real-time location of consumers and drivers through the user cloud. Meanwhile, static road network, travel time, demand change, and capacity remaining information will be generated from grounds' circumstances that change over time.

Overall, this proposed framework considers two closed loops built on the adoption of mobile technology to improve the application design [32]. The first loop updates the current state based on the data collected during the delivery process. for example, each driver has a set of customers (in this case, as an agent), which are clustered by location.

Admin/manager will assign the farmhouse location for each driver to pick up live birds/broilers according to product availability. Each customer will place an order daily, and the system will save the order and read the customer's location data from the user database. After all customers input orders, the system will cluster customers based on their location and assign the drivers to each set of customers. The system automatically generates proposed delivery routes after each driver submits order data and farmhouse location. After the product is pickup at the farmhouse, the product will be delivered to all consumers according to the clustered customer.

While the second loop updates the transportation network, travel time, total distance, changing demand, and remaining capacity data, every changed data will be stored in the user database and documented as travel history. Transportation network, total distance traveled, and travel times will be generated with the help of google maps.

3.3 System Implementation

The implementation of the application system is developed based on mobile and web-based aspects. From the web-based aspect, the application is built on a user cloud based [8], which can only be operated by the super admin. The web-based application will assign drivers to pick up certain products on the node. Furthermore, the admin can monitor the vehicle position, driver trip history, and overall delivery process. In addition, the admin can print out daily, and monthly delivery reports from the dashboard. Figure 5 shows the user interface dashboard of the daily delivery and its route network.

Figure 6 shows the user interface for the mobile application designed for drivers. Each driver will have a list of customers. The driver will input the customer's order and the farm location every time the delivery starts.

After submitting, the driver will be given a trip route recommendation validated and accepted by the driver. While Figure 7 shows the driver's travel history for each customer. The delivery status panel will provide updated information regarding the driver's position, customer order, order information, the remaining products that have not been delivered, the total distance travelled, and the estimated purchase cost.

3.4 Parameters Initialization

Every time moment t is generated, and we construct vehicle routes for the first time, the system will respond to dynamic events, so initialization/update parameters will be deployed in the system. For example, the initialized N set is a set of unserved consumers, so when generating the route for the first time, $T_0^k = N = \oslash$. Furthermore, as an important parameter, the total travel times t_{ij} are provided by the navigation system of the Google API console.

Each dataset generated using the database (csv file), and it was possible to generate a set of tests with different instances. The basic goal of real-time VRP is to fulfill all constraints.

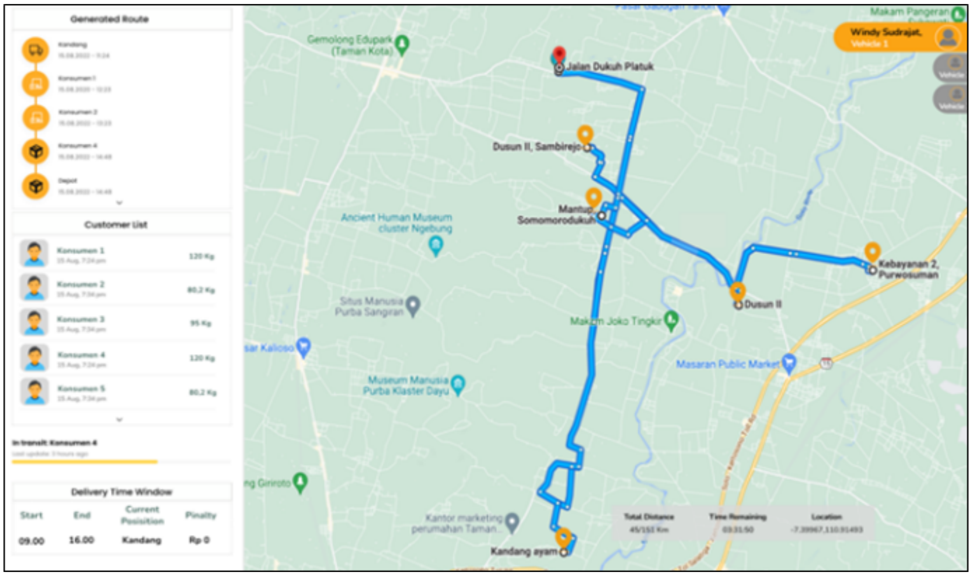

Figure 5: Proposed user interface web-based dashboard.

Table 2: Parameter initialization in Google OR-tools

Parameter	Value	Description
Time_Limit	Between 100 to 100	The search limit terminates the time for the solver to find the optimal solution.
Time_matrix	Time_windows	Contains the travel time between two nodes.
First_Solution_Strategy	Path_Cheapest_Arc	The method used by the solver to find the initial solution. Starting from the "start" route node, connect to the node that produces the cheapest route segment, then extend the route by iterating on the last node that is added to the route.
Local_Search_Metaheuristics	Guided_Local_Search	The method uses GLS to get out of the optimal local solution.
Read_Assignment_From_Routes	Initial_route	Initial point for start running.

With modern technology's development, the parameters used have been determined according to the parameters available at the GPS or GIS system provider. This study uses parameters in Google OR-Tools as parameter definitions in CVRPTWPD.

GLS is considered the most efficient method to solve metaheuristic problems, especially for traveling salesman problems and vehicle routing problems [27,35,36].

Adopted from Kruk [37] some parameter changes occur during running time is Load of vehicle k at node i T_0^k as initial assignment and will change following the vehicle capacity limits. Time windows will be generated from time_dimension in OR Tools with two forms,

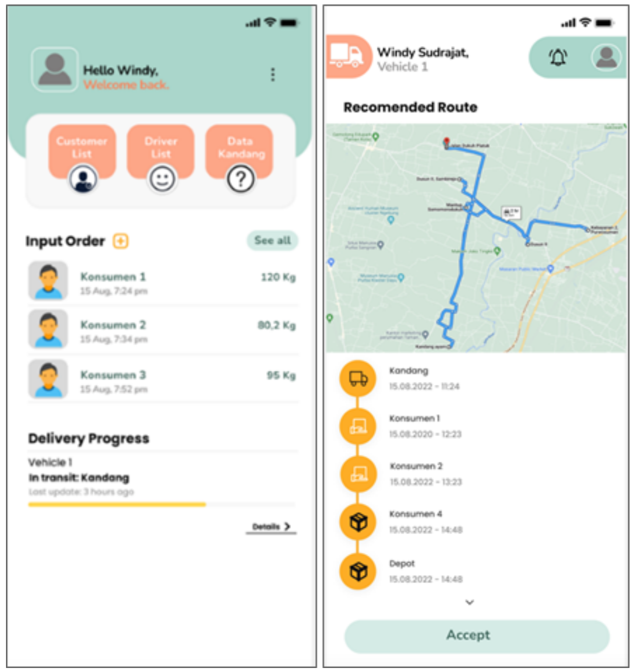

Figure 6: Proposed mobile application user interface.

Table 3: Input data

Customer ID	Latitude N	Longitude N	Average order d_i (Kg/day)	Vehicle Category K (Existing)	Pickup/Delivery P/D category	Pickup/Delivery Time Windows (Existing)	Time Window Penalty (min)
Depot	-7.39967	110.91493	0	0	-	09.00-16.00	0
Farm1	-7.39981	110.9147	2600	V1, V3	Pickup	09.00-13.00	0
Farm2	-7.39178	110.93283	1900	V2, V4	Pickup	09.00-13.00	0
1	-7.38978	110.8927012	168	V1	Delivery	13.00-13.50	0
2	-7.39175	110.932082	225	V3	Delivery	14.35-15.48	0
3	-7.40874	110.9065285	900	V1	Delivery	16.50-17.42	102
4	-7.43814	110.896925	360	V2	Delivery	13.00-14.20	0
5	-7.40544	110.8788043	129	V1	Delivery	14.55-16.50	50
6	-7.38359	110.9101745	360	V4	Delivery	13.00-13.29	0
7	-7.42994	110.9163654	270	V2	Delivery	15.23-15.59	0
8	-7.44434	110.9034564	360	V2	Delivery	14.20-16.23	23
9	-7.3689	110.8956935	90	V4	Delivery	13.29-14.30	0
10	-7.35662	110.86625	168	V4	Delivery	15.15-16.20	20
11	-7.34998	110.861841	129	V4	Delivery	14.30-15.15	0
12	-7.35515	110.9314045	264	V3	Delivery	15.48-16.15	15
13	-7.39774	110.8688865	270	V1	Delivery	13.50-14.55	0
14	-7.39893	110.969242	132	V3	Delivery	13.45-14.35	0
15	-7.40799	110.920115	219	V2	Delivery	16.23-17.35	95
16	-7.40794	110.9416416	65	V4	Delivery	13.00-13.45	0

first as time window constraints for each location except depot $[a_0, b_0]$ and second as time window constraints for each vehicle start node T_0^k. For pickup and delivery parameters we used list of pairs of pickup and delivery, contained with location and customer demand as $[a_i, b_i]$ and translated as data[pickup_deliveries].

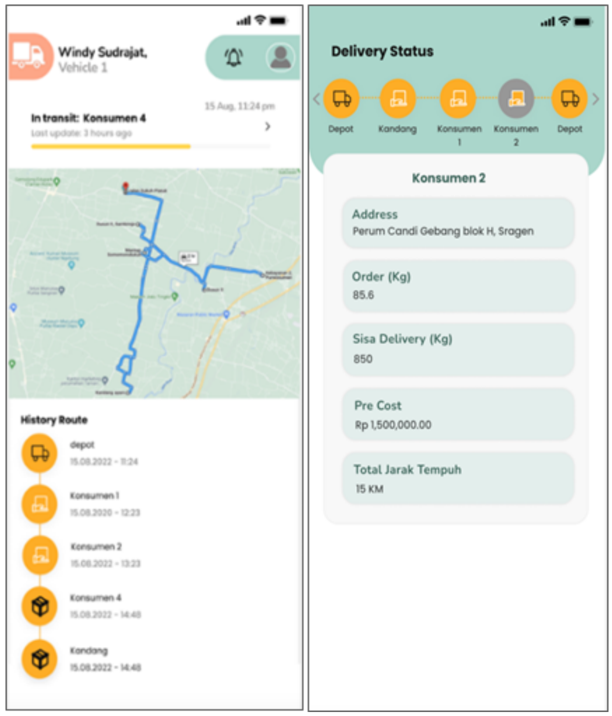

Figure 7: Proposed user interface mobile application.

There are two ways to reduce travel distance. First, travel distance is obtained by optimizing the model in the vehicle routing problem by considering all existing constraints. Second, optimization of travel distance can be done by developing CVRPTWPD using Google maps matrix distance API (from Google API Console), which can provide the shortest distance optimization. In this study, we used integration of vehicle routing problems model and Google OR-Tools to solve routing problems.

3.5 Test Results for Real-time Travel Times

Therefore, Vehicle routing problems in this case considering the optimization algorithm to monitoring the movement of every vehicle according to traffic condition [38]. In practice, actual travel time are provided by an advanced traveler information system, its similar to Yerpes et al [20] and Keenan [39] that use simulation to decide actual travel times. In order to illustrate the implementation of the mobile application and to validate the effectiveness of the application, we compared the existing system distribution (traditional) with digitals one. Table 3 shows the initial delivery data, such as customer location and the number of orders.

The clustering of the set of customers has been determined based on the coordinate points. Each vehicle has two pickup points: pickup at farmhouse 1 and pickup at farmhouse 2. The delivery flow starts from the depot and then picks up at farmhouse 1 or farmhouse 2. Each vehicle will deliver poultry according to the specified set of customers

Table 4: Model generated solution

Customer ID	Vehicle Category (Improvement) K	Pickup/Delivery P/D Time Windows (existing)	Time Window Penalty (min)	Total Distance Cumulative/Vehicle (KM)	Excess Delivery Load (Kg)	Excess Load (Kg)
Depot	0	09.00-16.00	0	0	0	679
Farm1	V1,V3	09.00-13.00	0	24	924,1450	0
Farm2	V2,V4	09.00-13.00	0	32	962,1415	0
1	V3	14.45-15.30	0	144	168	16
2	V4	13.30-14.10	0	73	225	0
3	V3	14.10-14.45	0	90	900	0
4	V3	13.00-14.10	0	68	366	0
5	V2	16.00-16.55	55	112	176	0
6	V4	14.45-15.10	0	85	460	0
7	V4	15.10-15.46	0	90	270	0
8	V4	15.46-16.30	30	100	360	360
9	V4	13.00-13.30	0	60	90	0
10	V1	13.00-13.50	0	57	168	0
11	V1	09.00-13.00	0	46	189	0
12	V1	14.55-16.00	0	80	264	303
13	V2	15.15-16.07	7	90	270	0
14	V2	13.00-13.45	0	63	132	0
15	V2	14.55-15.15	0	82	319	0
16	V2	13.45-14.55	0	77	65	0

has been determined. Delivery starts at 9:00 am and must be completed by 4:00 pm. The limitation of delivery time is done to keep the poultry from stress and can reduce the mortality rate [5]. The existing situation shows that in one delivery cycle, four vehicles were late in returning to the depot, with delays of 102 minutes, 95 minutes, 15 minutes, and 20 minutes respectively. Delays in deliveries allow for increased stress and poultry mortality.

After the implementation, improvements are obtained, as in Table 3. There are several changes in the sequence of delivery routes for each set of customers. Furthermore, there was a significant change in the total time penalty, and the total distance traveled for all vehicles. It can be seen in Table 4. There is a change in the set of customers for each vehicle compared to the existing model. It happens because the system tries to find the fastest route without considering customers grouping and only considering the vehicle capacity and time windows limitations. This paper only accommodates customer grouping by distributor and does not prove clustering by the system.

There is a significant change in travel distance in one day of the delivery cycle. The total travel distance was 493 KM decreased to 436 KM, which means a decrease of 11.5% from the initial total travel distance. In addition, there was a change in the total penalty time (delay) from 102 minutes to 85 minutes, decreasing delay time by 16.6%. This application's development can indirectly increase vehicle utilization by not overloading the vehicle capacity and reducing vehicle travel distance. In addition, this application can reduce stress levels in poultry by shortening the travel time during delivery [5].

Table 5: Summary of application testing implementation result

Vehicle	Vehicle Route Existing	Vehicle Route Improvement	Current Travel Distance (KM)	Travel Distance Improvement (KM)	Current Time Window Penalty (Min)	Time Window Penalty Improve (Min)
V1	Do-F1-C3-C1-C5-C13-Do	D0-F1-C11-C10-C12-D0	143	80	102	0
V2	Do-F2-C6-C4-C7-C8-C15-Do	D0-F2-C14-C16-C15-C13-C5-D0	138	112	95	55
V3	Do-F1-C14-C2-C12–Do	D0-F1-C4-C3-C1-D0	94	144	0	0
V4	Do-F2-C6-C16-C4-Do	D0-F2-C9-C2-C6-C7-C8-D0	118	100	20	30
Total			493	436	217	85

The Directions API is called to generate the road pathways to overlay on the map. From the CVRPTWPD calculation we generate VRP routes for existing and the improvement routes, as follows.

Figure 8 and Figure 9 show significant difference between existing and improvement routes that must be passed by the driver. There is a change in the consumer group that will be supplied by each vehicle.

With the same demand delivery, integrated real-time vehicle routing solutions are better than traditional vehicle routing. We suggest that a combination of mobile application and VRP can be extended to a range of problems with complex path restrictions and multiple vehicles that have not been successfully addressed by routing techniques in the past [39].

4 Conclusion

In this study, the integration between vehicle routing and mobile technology is demonstrated by accommodating the characteristics of poultry as a perishable product, combining customer demand information and clustering the customer based on territory. The use of Google OR tools proves the navigation sequences and vehicle scheduling. Moreover, the application was developed based on real-time traffic information obtained from the Google distance matrix and combined with Google OR-Tools, was expecting the optimum vehicle routing solution.

Compared with existing routing, real-time vehicle routing with Google API proves a better solution and increases vehicle utility. With the same demand delivery, the vehicle routing solution provides a better solution than traditional vehicle routing, with a decrease in travel distance of 11.5% and a reduction in penalty costs of 16.6%.

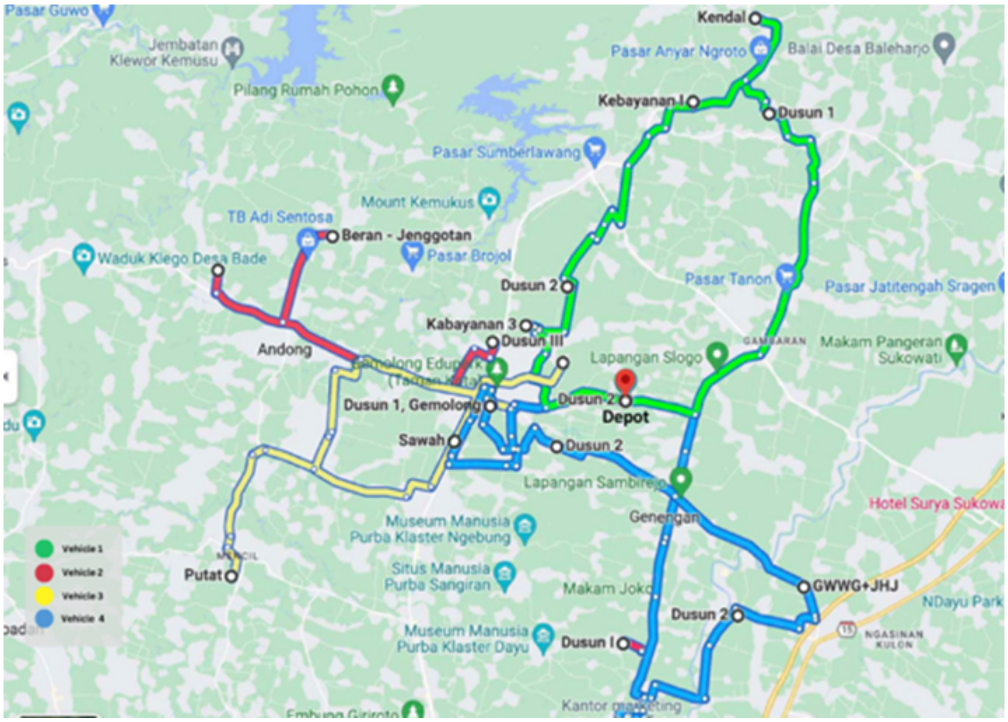

Figure 8: The poultry distribution existing routes.

However, this research is limited to poultry products which only consider the characteristics of the broiler itself. In addition, customer grouping is still inputted manually. For future research, application development can be done by considering the clustering of customers and then generating routes uses advanced dynamic vehicle routing problems.

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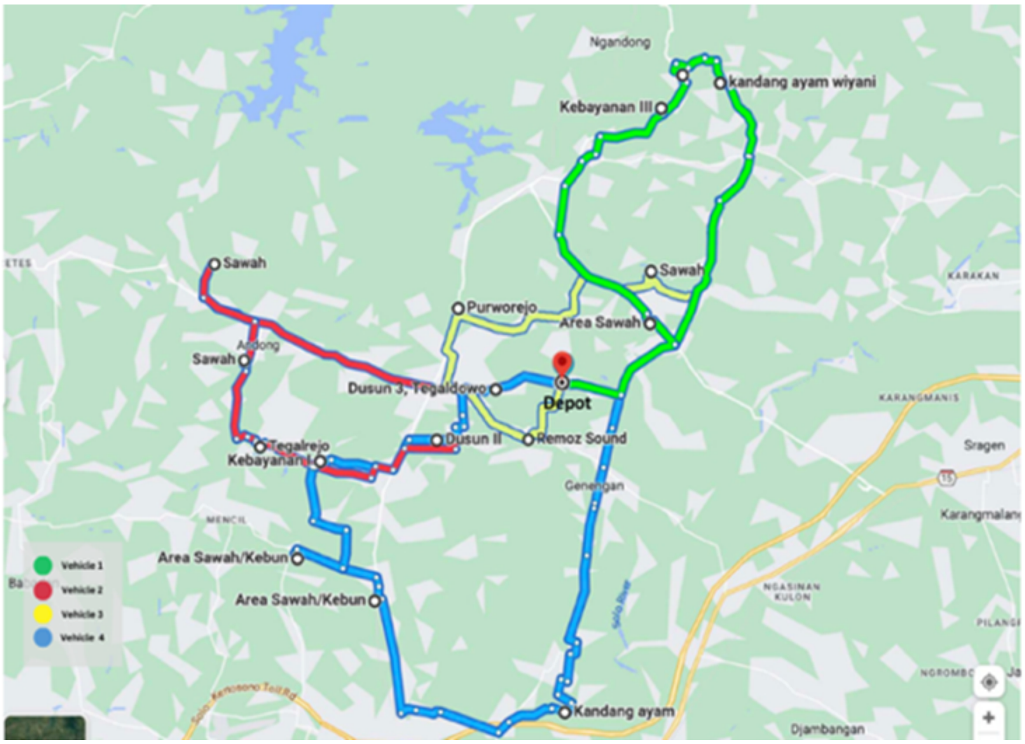

Figure 9: The improvement routes.

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