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Navigation Mobile Apps Utilization and K–MACS Algorithm for VRPTW Model of Fruits Distribution

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Abstract. This study proposed an extended multiple ant-colony system for vehicle routing problem with time windows (K-MACS VRPTW) in delivery cases considering by the temperature sensitive and perishable products (TSPPs) of strawberries. K-MACS VRPTW is organize with K-Means to partitioning, and MACS, a hierarchy of two artificial ant colonies with objective function to minimizes vehicles used and the transportation times. The designed model is concerning to obtain optimal shipment of box reefer vehicle both Colt-L300 and colt diesel-double (CDD) delivery routes and the unviolated trips time of distribution-center about 8 and 12 working hours. The parameters was the calculation shortest distances of clustering in *Euclidean* and optimal routing in *Haversine*. Experimental results was better than the single MACS-VRPTW solution, that is savings costs as diminish the vehicles used by 5 instead 4 vehicles with shorter total distance and quicker travel time. The trials of the assigned feasible routes is using Voyager, the free navigation mobile apps with API Google direction service for optimization, was found a better nodes sequences of routes mapping.

Keywords*: ant colony system, K–MACS, K–Means, perishable products, VRPTW*

1. Introduction

The challenging strategy in the logistics and distribution field is optimizing the costs and time delivery from suppliers to customers thus satisfying constraints. In the distribution of temperature sensitive and perishable products (TSPPs), the strawberries fruits particularly, customers's satisfaction are defined from the two aspects of freshness and time window (Wang *et al*, 2017).One of the most critical issues that challenge many fresh fruits logistics is the transportation. Any delay on transportation would negatively impact the price of fresh fruits and lead to a huge financial consequences (Bahebshi, 2017).Hence, the determination of delivery schedule and the routes from sources to destinations is an important thing in distribution management. Such problems known as vehicle routing problems (VRPs), the task of designing delivery or pickup routes, that originates and terminates at a central depot, for a not violated capacitated vehicles that serve a given set of geographically dispersed customers with known demand in the field of transportation and supply chain (Marinakis and Migdalas, 2002; Oyana and Scott, 2008).

The distributions main problem in Indonesia lies on infrastructure and geographical separated locations complexity. The muddy or bumpy dessert roads of village and the obvious circumstances of crowded cities roads deal with congestion and the traffic-conditions change minutes by minute are leading on that the shortest route does not necessarily mean it will be the quickest and then spend most of the cost on the fuel.The vehicle routing problems with time windows (VRPTW) is an extension of the VRPs could be a preferred solution to find a set of shortest vehicle routes or quickest travel time (Baran and Scaerer, 2003).

Most previous studies on the VRPs have focused on seeking for the shortest path to service a number of customers with a fleet of capacitated vehicles without consideration of the direction of next visits destination or the pattern of resulted routes. VRPs have contribution to find the shortest path, but not have many affect on the time constraints. VRPTW is one of its extensions of time constraints to visiting all of customer without violating the stipulation that (i) every route starts and ends at the central depot (ii) all customers must be visited only once by one vehicle, and (iii) ensure that the vehicle capacity and total trip time constraint is not violated.

This study constructed a *stochastic* VRPTW model with the *K-MACS metaheuristic* approach, to obtain optimal delivery routes and capacitated vehicle loads for a perishable horticulture produce distribution, as well as fleet dispatching and departure times. While, the *MACS* is extension of *ant colony system* (ACS) with two objectives of artificial ant colonies which one the most efficient of *ant colony optimization* (ACO) based implementations. Unfortunately, in VRPTW, an insertion of customers violates the system of the ACS and cause of its time constraints, it's rather difficult and not effective to solve the unfeasible situation that some customers with their time windows and demands are not visited. The novelty of the presented approach consists in combination of *K-Means* clustering to identifying and grouping each customers location of fleet services, and the *multiple ant colony system* (MACS) for customer sequences priority routing and optimization processes. Furthermore, the model execution was applied of *navigation mobile apps,* which has equipment of *API Google direction* service to compare and analyze the result.

2. The VRPTW Algorithm

Most solution techniques for VRPTW fall in three categories: *exact methods, heuristics and metaheuristics* (Castro and Gutierrez, 2012). This study is *heuristic* VRPs with hard time windows, which is the time constraint is known through perishable produce self-life and the depot distance diversified conditions of traffic at different timesand greatly affect to the travel time.

Constructive heuristics build feasible routes steps by step. Two-phase methods are based on the decomposition of the VRPTW solution process into the two separate sub-problems (Cordeau *et al.*, 2001):

(1). Clustering: determine a partition of the customers into subsets, each corresponding to a route, and
(2). Routing: determine the sequence of customers on each route.

2.1 K-Means Clustering

The K-Means clustering is one of the simplest and flexible heuristics clustering technique, which provides efficient analysis of large geospatial data that can minimize sum of squares of the distance from all ***n*** samples emerging in clustering domain to clustering centers to seek for the minimum k clustering on the basis of objective function (kumar and Ramaswami, 2007).

The *k* data objects as original clustering centers (initial centroid) randomly selected from clustering domain by K-Means algorithm, the centers of the clusters are iteratively recalculated as the means of the coordinates (x_j, y_j) of the customer points assigned to the cluster. The algorithm clusters observations into k groups, where k is provided as an input parameter. It then assigns each observation to clusters based upon the observation's proximity to the mean of the cluster. The cluster's mean is then recomputed and the process begins again (Shafeeq and Hareesha, 2012).

2.2 Ant Colony Optimization (ACO)

Ant colony optimization (ACO) is metaheuristic approach that imitates ants' behavior to construct and optimize feasible routes, where ants cooperate in their search for food by depositing chemical traces (pheromones). In analogy to the biological example, ACO base on indirect communication within a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. The pheromone trails in ACO serve as distributed, numerical information, which the ants used as probabilistically construct solutions to the problem solved and which the ants adapt during the algorithm's execution to reflect their search experience (Dorigo and Stutzle, 2009). Artificial ants "walk" on the solution space, adding a new decision to the solution at each step. When an ant completes its walk, its solution evaluated. After the evaluation, artificial pheromones are lefts on the path that chosen by the ant. The amount of these artificial pheromones depends on the result of the evaluation: more pheromones are puts for the better solutions (Toklu *et al.*, 2013).

2.3 Multiple Ant Colony System (MACS)

Ant colony system (ACS) is an elitist ACO algorithm, the most important component of ACS for constructing new solutions is the management of pheromone trails, it`s the constructive procedure of *new_active_ant* for ant *m*. The MACS-VRPTW algorithm initializes and coordinates the two ACS based colonies objective functions. The first goal colony, denoted as ACS-VEI, diminish the number of vehicles used, while the second colony, as ACS-TIME, optimizes the travel time distribution ($\mathbf{t}_{ij}$) as feasible solutions found by ACS-VEI. The two colonies collaborate sharing a global best solution and exchanging information through pheromone updating (Gambardella, 1999).

The pheromone informationis given by the visibility, denoted as below equation (1), where L_Ψ^h representing an initial estimation of the total delivery time, while and J_Ψ^h is represent an initial estimation of the total traveling time, and n is the initial number of nodes (depots + customers). The formula is (Barán and Schaerer, 2003):

$$\boldsymbol{\tau_0} = \frac{\mathbf{1}}{n\,x\,(L_\Psi^h J_\Psi^h)} \tag{1}$$

The visibility of the ACS-TIME objective which consisting of the travelling time $\boldsymbol{\eta_J}$***(ij)*** and the delivery time $\boldsymbol{\eta_L}$ ***(ij)*** calculation as adopted from (Donati *et al.*, 2008). To choose the next node C_j to be visited by an ant m of cluster k is chosen inN_i^m by the following procedure (Barán and Schaerer, 2003):

Algorithm 1. Chooses nextnode
Procedure ChooseNext_Node
Chooseto do exploitation with probability r
or exploration otherwise;
if(exploitation)
Choose $C_j$with the highest attractiveness value
else exploration
Choose the C_j with larger probabilityr_0

The set of available nodes, in this case the ant is not located in other cluster, not located in a duplicated depot, includes not yet visited duplicated depots. λ = *m/k,* and β weights the relative importance of the objectives with respect to the pheromone trail, given by $\boldsymbol{\tau_0}$.The two ways probability, determined by a fixed cut-off parameter $r_0 \epsilon$ (0, 1), and a random number r for each step,r ϵ (0, 1):

(a) Exploitation: pick the $\mathbf{C_j}$ which maximizes p(**j**), if $\mathbf{r}_0 \leq \mathbf{r}$;
(b) Exploration: pick the $\mathbf{C_j}$ distributed as p(**j**), if $\mathbf{r} \geq \mathbf{r}_0$.

The visibility of the ACS-TIME objective which consisting of the travelling time and the delivery time calculated in following equation (2) and equation (3) as:

$$\eta_J(i,j) = \frac{1}{\sum \tilde{t}_{ij}} \tag{2}$$

The visibility of delivery time related to the service time and the width of the time windows. It is calculated as adapted from [9]:

$$Dt_j = \max (At_i + t_{ij}, a_j)$$
$$\Delta t_{ij} = Dt_j - At_i$$
$$d_{ij} = \max(1, (\Delta t_{ij} . (bj - At_i))$$
$$\eta_L(i,j) = \frac{1}{d_{ij}} \tag{3}$$

During the execution of the ACS, the pheromones be updated in two ways: local update using equation (4) and global update using equation (5). Local updating is performed during solutions construction, while global updating is performed at the end of the constructive phase. This update done according to the formulation:

$$\tau_{ij} = (1 - \rho).\tau_{ij}(t) + \rho.\tau_0 \tag{4}$$
$$\tau_{ij} = (1 - \rho).\tau_{ij}(t) + \rho/(L_\psi^h . J_\psi^h) \tag{5}$$

Where parameter $\boldsymbol{\rho}$ configures the amount of pheromone decrease imposed by the local update, and $\boldsymbol{\tau_0}$ is calculated initially. The effect of local updating is to change dynamically the desirability of edges: every time an ant uses an edge the quantity of pheromone associated to this edge is decreased and the edge becomes less attractive. On the other side, global updating is used to intensify the search in the neighborhood of the best solution computed

3. The Design Model and Algorithm

This K – MACS VRPTW composed of vary different problem types(customer C_n clustered in vehicle used V_n, customer demand, vehicle load, route distance $\boldsymbol{d_{ij}}$, travel time $\boldsymbol{t_{ij}}$, starts time, service time, ends time, and also depot time window/time agent).

This research was using quantitative data which has been taken in CV. Yan's fruits and vegetables of Lembang, Bandung. The major types of transportation used was the road systems with vary *caroseries*-reeferbox of vehicle as main modes such as 4 units *ColtL300* measuring 237cm x 155cm x 129cm which in a single transport can load the crates to 85 approximately, and 2 units *Colt Diesel Double* (CDD) measuring 560cmx200cmx220cm which can load more than 240 crates approximately. Each data set contains 4 to 35 customers use 6 unit vehicles to serve all the customers in JABODETABEK (Jakarta, Bogor, Depok, Tangerang, Bekasi) area, including 4 is *L300 Colt* and 2 is *CDD* was the 5 units for operational vehicles and one between for backup.

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Figure 1. Customer distribution map.

The time widows of this study is that company's agreement with all of customers is enforce the rules asthe arrival goods hours should not than be later10:00 am, and also the company has time windows that the travel time such 480 minutes (8 working hours per-day) for vehicle type of *L300 Colt* and about 720 minutes *(*12working hours per-day) for *CDD*.Hence, the departing times of dispatching vehicles from Bandung to JABODETABEK area should be adjusted as the length of travel times from depot to the first customer and then to another, also the total service time of all customer destination.

In this study, the constructive procedureof *new_active_ant*was *using pseudorandom rule* (the probabilistic rule processing where select node *j* uses probability smallerq_0 node with the highest attractiveness value and *exploitation* mechanism) and global pheromone trail is updated during solutions construction.

3.1 Distances

The most important variable in VRP problems is the distance (*d*) of delivery points and the region as input basic data in order to determine and estimating time travel and the total distance covered. In this study, we used *Haversine* distance and *x, y Cartesian* coordinate of geographic latitude and longitude as following equation:

$$\boldsymbol{d = 2r\, arcsin\left(\sqrt{sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos\varphi_1 \cos\varphi_2\, sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right)} \quad (6)$$

$$\mathbf{x = r'\cos\boldsymbol{\lambda} = r\cos\boldsymbol{\varphi}\cos\boldsymbol{\lambda}} \quad (6a)$$

$$\mathbf{y = r'\sin\ \boldsymbol{\lambda} = r\cos\boldsymbol{\varphi}\cos\boldsymbol{\lambda}} \quad (6b)$$

Where $\boldsymbol{r' = r\,cos\,\varphi}$ and $\boldsymbol{r = \sqrt{x^2+y^2}}$

3.2 Distances Stochastic Hard Time VRPTW

In the classic VRP with hard time windows (VRPTW), vary capacitated vehicles (Q) isscheduled to visit the given set of N customers C_i,each characterized by ademand (q_i), a time window ($tw_j = [a_j, b_j]$) and a service time (s_i), with routes starting and ending at a depot with time constraint[t_i, e_j] is specified. One arc existing oriented arc a϶A, information about the travel time must be given to deduce the time necessary to traverse the arc when starting the trip at a time ***t***. The location of each customer address have been known also the distance from the depot to each customer or the customer distance between, then the estimated travel time (t) to each customer address can be calculated by dividing the distance (S) with the average speed of the vehicle (V) as following equation:

$$\mathbf{t} = \frac{\mathbf{S}}{\mathbf{V}} \tag{7}$$

***t** = time (hours)*
***S** = space or distance (km)*
***V**= velocity or speed (km/hours)*

The time constraint is denoted by a predefined local markets time. The travel time is stochastic, vehicle travel speed may be affected by factors such as traffic volume, the weather and accidents, which are characterized as random in nature. Let $\tilde{t}\,_{ij}^{1}$denote the new travel time on the arc (**C**$_i$, **C**$_j$) for vehicle V, A denote the sets of arc with travelling barriers and the weight respectively, can be expressed as $\tilde{t}\,_{ij}^{1} = w.t_{ij}$, where $\boldsymbol{w}$ is weight of travelling barriers (traffic congestion and damaged roads). Assume some arc of A have the weight $\boldsymbol{w}$ of being travelled barriers. Then, expected travel time on arc (**C**$_i$, **C**$_j$) for vehicle V, $\tilde{t}\,_{ij}^{1}$, is given by:

$$\tilde{t}_{ij} = \begin{cases} w.t_{ij}, & if\ (V_i, V_j) \in A \\ 0, & Otherwise \end{cases}$$

$$i=1, \ldots n;\ j=1, \ldots n;\ V=1, \ldots m \tag{8}$$

Where t_{ij} represent travel time on arc (**C**$_i$, **C**$_j$), because of the randomness of travel time on arc, arrival time at each customer location is characterized as a random variable. Since the real-time traffic conditions for every arc is unknown before departure from the distribution center, arrival time at each customer is difficult to predict. Hence, in this study, the visibility of travel time is consisting of travelling barriers weight includes of traffic congestion and damage roads rated as $\boldsymbol{w}$ (0.5 and 0.25).

3.3 Distances K-MACS VRPTW Approach

Stage 1: *K–Means* Clustering

The *K–Means* for the VRPs consist of the following steps:

Step1. Determine the K clusters, which is the clusters number are equal to $r$vehicles (K= r) or less (max $K = r - 1$). This step, applied for finding solutions of vehicles number required with the constraint of capacitated vehicle and the customer time window.

Step2. Randomly choose each centroids of K *cluster* such as x, y coordinates of customers location points as initial cluster center

Step3. Denote the cluster center as the beginning of a route to determine the customer closest in order to assigning customer location of the cluster construction.

Step4. Calculates the mean value of customers distance to depots and the customers distance to their neighbors are calculated by *Euclidean-distance*.

$$d_{\mathrm{ij}}\left(\mathrm{x}_{\mathrm{ik}}, \mathrm{c}_{\mathrm{jk}}\right) = \left[\sum_{k=1}^{n} |\ x_{ik} - c_{jk}\ |^2\right]^{1/2} \tag{9}$$

Then, constructs cluster for the minimum customer distance to the centroid and set of each depot.

Step5. Repeat Step 4 until no change.

Stage 2: Routing and Optimization

The second stage is the routing and optimization using MACS-VRPTW algorithm. The best feasible Insertion is forth process to improve routing as following algorithm works:

1. Initial value of MACS, Ψ^{gb} is a feasible VRPTW solution found with *K-Means* clustering and others heuristic routing method to identify customer (pheromone) service priority.
2. The next step, Ψ^{gb} is simultaneously looked for an improved and feasible solution, that is: (i) a solution that has a smaller number vehicle using; (ii) it has the same number of tours and has a faster travel time.
3. Denote the duplicated depot as the beginning ofa route, and ACS parameters to choose next visit nodes contains (probability ρ, attractiveness α, visibility β, vehicle capacity Q, ants number ***m*** (in this case equal to number cluster ***k***), weightparameter $\boldsymbol{w_j}$ of travel time which is contain of traffic congestion and damage roads rated as ***w*** (0.5 and 0.25) as given in equation (8), iterations number, and vehicle network, G = (v, A)
4. Set the queue order route of locations that satisfies all of constraint with nearest neighbor heuristic
5. When a new best solution is found, it is then used to perform a global pheromone update, so that both colonies can make use of the updated information about the performance of the new solution.
6. Activate ACS-VEI and ACS-TIME.
7. Decision processes.

Once each ant has built a complete solution, and then tentatively improved using a *local search* procedure. Next, the best solution found from the beginning of the trial is used to update the pheromone trails. Then, the process iterated by starting again *m* ants until a termination condition is met.

4. Results and Analysis

Refers to figure1 i.e the mapof nodes data which is containing thenumber of customers, real time data usagecorresponding longitude & latitude oflocations and then converted into a corresponding(X,Y) coordinates, and also the'Great Circle Distance' between customer's location which is calculated use the equation (6a) and equation (6b), customers demand and the time constraint. The best K-Means result of customer distances clustering to **k** number clusteras much as available vehicle transportation can made for 5 cluster (K= V1,V2, V3, V4, V5) as the following table shows the clustered customers of K-Means clustering result:

Table 1.K-Means clustering result

Cluster Name	Customer Members			Route Distance (km)	Vehicles		Time Windows (minutes)		
	Points	Total Cust	Total Demand (crates)		Max Load (crates)	Vehicle Type	Depot Time	Travel Time	Service Time
Cluster1 (V1)	C1, C2, C4, C8, C9, C14, C24, C25, C34	9	214	239.65	240	CDD	720	361	235
Cluster2 (V2)	C10, C20, C22, C29, C31	5	75	283.37	85	Colt L300	480	425	85
Cluster3 (V3)	C5, C19, C21, C35	4	70	201.98	85	Colt L300	480	303	80
Cluster4 (V4)	C7, C13, C26, C27	4	64	245.15	85	Colt L300	480	368	70
Cluster5 (V5)	C3, C6, C11, C12, C15, C16, C17, C18, C23, C28, C30, C32, C33	13	221	285.41	240	CDD	720	420	260

The K-Means result as above table1 show, the routes then rearranges inter-route or intra-route using local search optimizations and LINGO 17.0 solver to decrease the total travel distance (or total travel time) by the vehicles. The processes is resulting initials routes solution of ψ^{gb}as:**D** - C25 - C14 - C9 - C8 - C24 - C4 - C1 - C2 - C34 - **D -** C20 - C10 - C29 - C22 - C31 - **D -** C5 - C35 - C19 - C21 - **D -** C27 - C7 - C26 - C13 - **D -** C30 - C12 - C32 - C16 - C18 - C17 - C15 - C23 - C3 - C11 - C6 - C28 - C33 – **D.** Where, the agent needs 5 units of vehicle transportation with total distances 1255.54 km, and the total transportation time 2616,34 minutes including travel time and delivery time.

Considering to the constructive procedure of *new_active_ant*isaiming to find a feasiblesolution with one vehicle less than the number of vehicles used in time windows by maximizing number of visited customers. Hence, we drowned out the initials solution clusters and operated vehicle to being 4 units for serves 30 customers with total distances 972,17km; total travel time 1461 minutes; average of delivery time 70 minutes; and the ACS_VEI initials pheromone τ_0 : 3,54 x 10^{-8}.

In *exploitation* mechanism of ACS_VEI, an agent of ant *m*select node $C_j$depend on the attractiveness value of pheromone information, the information indicates how well seems to visit customer $C_j$after $C_i$considering the solutions already found. The highest attractiveness and the visibility node then its will be selected to visit destination by the agent. Thesolution computed since the beginning of the trial with the highest number of visited customers is stored in the variableψ^{ACS_VEI}. Asolution is better than ψ^{ACS_VEI} only when the number of visited customers is increased, then the *pheromone intensity* updated in *global-update*. Experimentshave been done with the following parameter settings: m=4 ants; q_0=0.9; β=1 and ρ=0.1.

The next step is ACS_TIME activation to finding the ψ^{gb} with implement a local search procedure to improve the quality of the ACS_VEI feasible solutions. In this procedure, customer is searched for the best feasible insertion (shortest travel time) until no further feasible insertion is possible.Theψ^{gb} feasible routes solution of ACS_TIME as [**D** - C19 - C14 - C25 - C17 - C15 - C23 - C6 - C11 - C13 - C9 - C24 - C4 - C26 - C34 - **D** - C16 - C32 - C20 - C2 - C7 - C8 - C10 - C28 - C3 - C33 - C35 - C5 - **D** - C27 - C29 - C1 - C18 - **D** - C21 - C35 - C12 - C31 - C30 – **D**]. With the total distances 1019.68 kmand total transportation times 2261 minutes.

The following table is the result of last processes of K-MACS algorithm routing and the optimization using *inter-route* and *intra-route* of *local search* method:

Table 2. Feasible route solution of K-MACS and the Local search optimization

Cluster Name	Customer Members			Route Distance (km)	Vehicles		Time Windows (minutes)		
	Points	Tot Cust	Total Demand (crates)		Max Load (crates)	Type	Travel Time	Service Time	Depot Time
C1 (Vehicle 1)	D-C19-C14-C25-C17-C15-C23-C6-C11-C13-C9-C24-C4-C26-C34-D	14	238	256,686	240	CDD	385,03	260	645
C2 (Vehicle 2)	D-C16-C32-C20-C2-C7-C8-C10-C28-C3-C33-C35-C5-D	12	237	271,054	240	CDD	406,58	280	686,6
C3 (Vehicle 3)	D-C27-C29-C1-C18-D	4	84	263,175	85	Colt L300	394,76	85	479,8
C4 (Vehicle 4)	D-C27-C29 - C1-C18-D	5	82	243,135	85	Colt L300	364,7	85	449,7

To analyze the methods was used in this research, we compares the method result steps by step on the along processing as well as merging both K-Means and MACS algorithms between with the *local search* optimization result for each algorithms. In the following table is presented the performance metrics calculation for every feasible solution run of each algorithm result concerned of total distances and total travel time, where it is easy to note that theunification of MAC-VRPTW is improve the optimal K-Means result with or without *local search* optimization.

Table 3. Comparison results of algorithms used

M[a]	K-MEANS			K-MEANS & LOCAL SEARCH			K-MEANS & MACS (K-MACS)			K-MACS & LOCAL SEARCH		
	V[b]	RD[c]	TT[d]	V[b]	RD[c]	TT[d]	V[b]	RD[c]	TT[d]	V[b]	RD[c]	TT[d]
V1	9	250,6	376	9	239,6	361	14	283,8	426	14	256,69	385
V2	13	420,7	631	13	285,4	429	11	359,5	539	12	271,05	407
V3	4	226,3	339	4	202	303	4	283,4	425	4	263,17	395
V4	4	247,2	371	4	245,2	368	6	340,6	511	5	243,13	365
V5	5	297,6	446	5	283,4	425	-	-	-	-	-	-
Tot	35	1442,4	2164	35	1255,6	1886	35	1267,3	1901	35	1034,05	1551

Notes :
[a]Methods
[b]Visits
[c]Route Distance (km)
[d]Travel time (minutes)

When the feasible routes result was tried to applying into *Google Maps* to navigate, the figure of map result are out-of sync neither by *Google Maps* calculation (shortest distance and the travel time estimation) nor the continuity of directions travel lines. Then, its' tried into routes optimizations mobile Appwith *API Google direction service* commonly available applications (we used *Voyager* mobile App) in *play store* of *Android* smart phone to gets the optimize routes comparison as the following example presented of cluster-4 (Vehicle 4) feasible result.

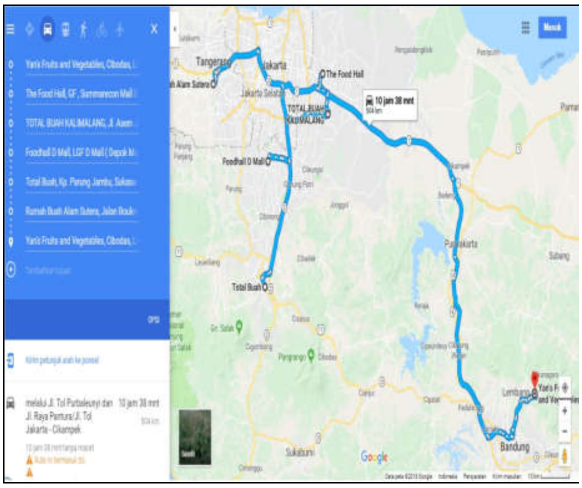

Figure 2. V4-routes solutions using *Google Maps*.

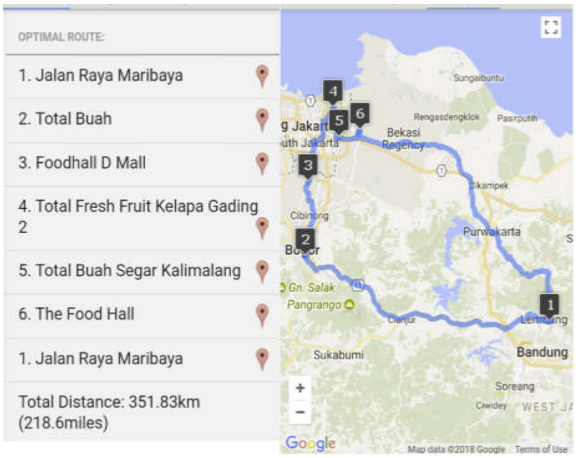

Figure 3. V4-routes optimize solution using *API Google direction service* of *Voyager* mobile Apps.

5. Conclusions

The present research modifies the MACS-VRPTW algorithmwith merge of *heuristics* K-Means clustering and *metaheuristics ACS* supported byenhanced local search proceduresto propose. The model is developed to solvethevehicle routing problem with time windows (VRPTW)ofthe temperature sensitive and perishable products (TSPPs) logistics transportation,which is provides a combined approach for both minimizing the number of vehicles used and the total transport time. From the results and analysis it is concluded that, the model built can be help savings distribution costs by diminish the vehicles used from 5 to 4 units as 2 *Colt*-L300 and 2 *CDD Box*-reefer with total trip time less than 8*working hours* and 12 *working hours* approximately constraint. According to optimizations assigning trials of each feasible routes in *Voyagernavigationmobile App*s with *API Google direction* service of *Android* smart-phone, it's found the better result of visit nodes sequences of routes due to direction of traffic network consideration. Therefore, in additions ofthe shortest mileage parameter, the *API direction service* is important to optimization routes of geographical visiting point and the obtained result substantiates the effectiveness of the application of the proposed method. This work can also be refined further for different applications.

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