ABSTRACT Indoor waste collection that utilizes mobile robots can solve the labor cost and manpower shortage but has the problem of limited energy resources, making it difficult to operate for long periods of time. Therefore, it is important to reduce the energy consumption for efficient waste collection. The waste collection robot can be modeled as a Capacitated Vehicle Routing Problem (CVRP), where heuristics algorithms can be deployed to search for the most energy-efficient path. This paper proposes the Ant Colony Optimization (ACO) algorithm for finding the optimal path of the waste collection robot. Energy consumption of the robot depends not only on the travel path but also on the weight of the waste it carries. Therefore, the proposed ACO algorithm utilizes the path distance and waste weight as the visibility. The travel distance and energy consumption are also used to determine the updated pheromone. Whereas the conventional and adapted ACO algorithms use only either the path distance or the waste weight as the visibility, respectively. The simulation experiments are conducted to compare the travel distance and the energy consumption that the waste collection robot takes by using the conventional, adapted, and proposed ACO algorithms. In the simulation experiments, the number of nodes, the waste weight, and the carrying capacity are used as parameters to verify the performance under the determined environment. The simulation results express that the proposed ACO algorithm provides a better energy optimal path in terms of travel distance and energy consumption than the conventional and adapted ACO algorithms.

INDEX TERMS Ant colony optimization, energy consumption, mobile robots waste recovery.

I. INTRODUCTION Solid Waste Management (SWM) has always been an important consideration for any country. Municipal solid waste is the waste generated from urban life, and its quantity has increased significantly as a result of rapid population growth [1]. Among the operational steps of SWM, Solid Waste Collection (SWC) has become one of the most challenging. SWC consists of the collection and transportation of waste. Inefficient collection and transportation of solid waste increases the operational cost and waste money. The typical process of waste collection employs a vehicle that leaves the depot and collects all the waste in trash bins located on a fixed path [2]. This is similar to the case of indoor waste collection, where a human worker collects the waste instead of the vehicle.

Currently, labor shortages are a global issue due to an aging society, and indoor waste collection is also affected. In order to solve such problems, there are various kinds of mobile robots being developed to supplement the workforce, some examples are shown in [3], [4], and [5]. The idea is similar to the indoor waste collection robot explained in this paper. However, mobile robots face the problem of limited energy resources. The most important operation of a mobile robot is to be able to move to its destination. The robot is mostly equipped with the motors used to drive it along a predetermined path. If the robot’s movement to the destination is
inefficient, the motors will consume more energy and will be unable to complete the path. It is therefore necessary to search for an energy optimal path that can be taken to reach the destination, which is the same as the waste collection robot. Finding the optimal path for the waste collection robot can be considered a region-specific Vehicle Routing Problem (VRP), as shown in [2], [6], [7], [8], and [9]. However, in this paper, the VRP is used as a capacitated vehicle routing problem (CVRP) where the capacity capability of the vehicles is more similar to the carrying capacity of the waste collection robot.

Some studies apply the Ant Colony Optimization (ACO) algorithm to plan the path of the vehicle for the CVRP [7], [8], [9]. They can be deployed to the waste collection robot for finding the path that optimizes the distance traveled by the robot. The research work in [10] and [11] applies the ACO algorithms to determine the shortest path of mobile robots, which is closely related to the work in this paper. This is because the shortest path that the robot takes implies less energy consumed by the robot. However, the energy consumption of the waste collection robot does not rely only on the travel path but also on the weight being carried by the robot. Therefore, the ACO algorithms used in [7], [8], [9], [10], and [11] may not work for all waste collection robots. Although in [12], [11], and [13], the ACO algorithms are applied on the mobile sink path to maximize the network lifetime, sensor energy consumption, and mobile sink tour length, they are used in path determination for wireless sensor networks, which is different from the research work in this paper.

Our preliminary work in [14] and [15] considers the energy-efficient path of the waste collection robot by using the adapted ACO algorithm, where either the path distance or the waste weight is used as the visibility, or path heuristic information, only. The aim of research work in this paper focuses on optimal energy consumption of the waste collection robot by proposing the ACO algorithm that employs a combination of the path distance and the waste weight as the path visibility. The travel distance and the energy consumption are also deployed to update the pheromone used in the path selection probability for searching for the energy optimal path. In addition, the simulation experiments are conducted to compare the travel distance and the energy consumption that the robot takes between the conventional ACO, the adapted ACO, and the proposed ACO algorithms. The number of nodes, the waste weights, and the carrying capacities will be used as parameters to verify the performance under the determined environment in the simulation experiments.

The rest of this paper is organized as follows: In Section II, the CVRP and related literature are described. In Section III, the conventional and adapted ACO algorithms will be presented, including the proposed ACO algorithm. Section IV explains simulation experiments and results discussion. Finally, the conclusion will be provided in Section V.

II. RELATED WORK

A. CAPACITATED VEHICLE ROUTING PROBLEM

To find the most energy-efficient path, the waste collection robot is modeled as a CVRP at first. The CVRP requires the determination of many geographically dispersed customers and one or more depots. The CVRP can be treated as an equivalent problem to the VRP if the demands of all customers do not exceed the capacity of the vehicle. The VRP and CVRP aim to reduce the total travel cost of serving customers with known demand [2], [7], [8], [9]. In the CVRP, the capacity capability of the vehicles makes it similar to the carrying capacity of the waste collection robot. Therefore, as shown in CVRP [2], [9], the following variables can be applied to the waste collection robot model.

- The complete graph is given by \( G = (Z, E) \), where \( Z = \{0, 1, \ldots, n\} \) denotes the position of the node and \( E \) denotes the arc, or the path. If \( Z = 0 \), it means that the node is a depot, or the start or the dumping point. If \( Z \geq 1 \), the node represents the trash bin’s position. A depot is represented by \( c_{Z} = 0 \) because there is no waste to collect. Each trash bin has a waste of \( c_{Z} \) inside it.
- A vehicle traveling in the graph can be represented as the waste collection robot \( k = \{1, 2, \ldots, K\} \) and is placed in a depot. Each robot is given a carrying capacity of \( C \).
- Arc \((i, j) \in E\) has a non-negative cost \( d_{ij} \) associated with it. The cost corresponds to the distance parameter from node \( i \) to node \( j \) when \( i \neq j \). The distance between each node and depot, as well as the distance between each two nodes \((i, j)\), is defined in Euclidean space as shown in (1), where \( x \) and \( y \) are the coordinates of each node, respectively. Therefore, the two-dimensional coordinates of the node, or the position of the trash bin, \( i \) are shown as \((x_{i}, y_{i})\).

\[
d_{ij} = \sqrt{(x_{i} - x_{j})^2 + (y_{i} - y_{j})^2} \quad (1)
\]

Using the modeled parameters defined above, the mathematical model of the waste collection robot can be shown in the following equations: The objective of the waste collection robot is to minimize the cost function \( w_{ij} \) traveled on all paths without infringing on the individual capabilities of each robot, as shown in [9]. Therefore, the general objective of the waste collection robot is defined as \( w_{ij} = d_{ij} \).

\[
\min \sum_{k=1}^{m} \sum_{j=0}^{n} \sum_{i=0}^{n} w_{ij} x_{ij}^{k}
\]

\[
x_{ij}^{k} = \begin{cases} 
1, & \text{if the robot } k \text{ goes from } i \text{ to } j \\
0, & \text{otherwise}
\end{cases} \quad (2)
\]

Subject to:
\[
\sum_{k=1}^{m} \sum_{i=0}^{n} x_{ij}^{k} = 1, \quad j \in Z \quad (3)
\]

\[
\sum_{k=1}^{m} \sum_{j=0}^{n} x_{ij}^{k} = 1, \quad i \in Z \quad (4)
\]
The use of the conventional ACO is a meta-heuristic inspired by the behavior of ants when moving from their nests to their feeding sites. To solve the waste collection robot by using the conventional ACO used in this work.

Therefore, ACO is considered an appropriate algorithm to be reviewed, it shows that ACO can produce better results than responds to the nature of the problem. Based on the literature swarm intelligence is found to be the most suitable, as it corresponds to the scale of the problem is not fixed, the category of swarm intelligence is found to be the most suitable, as it corresponds to the nature of the problem. Based on the literature review, it shows that ACO can produce better results than other methods, although it requires more computational time. Therefore, ACO is considered an appropriate algorithm to be used in this work.

III. PROPOSED METHOD

A. ACO ALGORITHM DEPLOYMENT

ACO is a meta-heuristic inspired by the behavior of ants when moving from their nests to their feeding sites. To solve the waste collection robot by using the conventional ACO algorithm as shown in the CVRP [7], [8], [9], [14], a total of \( k \) artificial ants, representing the robot, is placed in the graph of the optimization problem. Let \( N_i^k \) be the set of trash bins that have not been collected by artificial ant \( k \) when it is located at node \( i \). Each time each artificial ant chooses a node \( j \) as its destination, it is removed from \( N_i^k \), the set of unvisited trash bin nodes. Each artificial ant constructs a path for the robot by repeatedly moving until \( N_i^k = 0 \). If the next trash bin cannot be selected due to a constraint, each artificial ant selects a depot and starts a new tour. Artificial ants that select the nodes to be visited can sense the visibility and pheromones.

The perceived visibility \( \eta_{ij} \) of an artificial ant indicates a priori desirability of choosing node \( j \) to visit from node \( i \). This visibility is the path heuristic information for the ACO algorithms. In most cases, the visibility is calculated based on the path distance between the nodes as shown in (7).

As shown in (7), the shorter the distance between the nodes, the higher the visibility, and the farther the distance, the lower the visibility.

\[
\eta_{ij} = \frac{1}{d_{ij}} \quad (7)
\]

The pheromone updated by the artificial ants indicates how beneficial it was in the past to choose node \( j \) to visit from node \( i \). In other words, it indicates the posterior desirability of choosing node \( j \). In many cases, the conventional ACO algorithm searches for new paths by using the pheromones applied to the paths in combination with an objective function. The information contained in the pheromones applied to the pathways and the use of that information is an important factor in finding better solutions.

Artificial ants probabilistically select the nodes to be visited, or the trash bin to collect waste from. The probability \( p_{ij}^k \) that an artificial ant \( k \) located at node \( i \) will choose nodes \( j \) as its destination is calculated by the probability in (8) using two parameters: visibility and pheromone. \( p_{ij}^k(t) \) indicates the transition probability used for the \( t \)th iteration [14].

\[
p_{ij}^k(t) = \begin{cases} 
\frac{[\tau_{ij}]^\alpha[\eta_{ij}]^\beta}{\sum_{j \in N_i^k} [\tau_{ij}]^\alpha[\eta_{ij}]^\beta}, & \text{if } j \in N_i^k \\
0, & \text{otherwise}
\end{cases} \quad (8)
\]

The parameters \( \alpha \) and \( \beta \) are user-defined values to control the relative importance of pheromone and heuristic information. As can be seen from (8), the transition probability increases in proportion to the value of \([\tau_{ij}]^\alpha[\eta_{ij}]^\beta\). After the artificial ant \( k \) constructs the path, the pheromone applied to each edge is updated based on the objective value \( L_i^k \). The pheromone increase \( \Delta \tau_{ij}^k(t) \) for each iteration is given by (9).

\[
\Delta \tau_{ij}^k(t) = \frac{Q}{L_i^k} \quad (9)
\]

\( Q \) indicates the system parameter that converts the objective value into pheromone increment. \( Q \) is defined by the user. To prevent local optimization, the existing pheromone \( \tau_{ij} \) evaporates according to the evaporation rate \( \rho \). The pheromone \( \tau_{ij}^k \) to be applied between nodes \( i \) and \( j \) at the next
iteration is updated as shown in (10) [14].

\[
\tau_{ij}^k(t) = (1 - \rho)\tau_{ij} + \sum_{k=1}^{K} \Delta \tau_{ij}^k(t), \quad 0 \leq \rho \leq 1
\]  

(10)

**B. WASTE COLLECTION ROBOT CONSIDERATION**

The waste collection robot accomplishes the task by departing from the depot, start, or dumping point, and visiting all the unvisited trash bins that have been installed. However, the robot has a limited carrying capacity. If continuous waste collection is not possible due to capacity constraints, it will move to the depot and unload the waste. The robot will then start collecting waste again in the unvisited trash bin. The waste collection considered in this study consists of one depot and several trash bins with the waste weight as the demand. Therefore, the waste collection robot modeled complies with the CVRP and can follow the complete CVRP graph.

The waste collection robot adds the visited trash bins to the preconstructed sub-path \( SP \). \( SP \) is denoted as \( SP = \{0, 1, \ldots, n\} \), since \( SP \) is from the robot’s departure from the depot to its return to the depot. \( n \) denotes the number of trash bins visited in once \( SP \), defined as \( I < n \leq N \), where \( N \) is the number of unvisited trash bins in the optimization problem. Since the robot continues to collect waste while building the \( SP \), the waste weight \( M_j \) carried by the robot moving to bin \( j \) is denoted as shown in (11).

\[
M_j = \sum_{h=0}^{j-1} c_h, \quad j \in SP
\]  

(11)

**C. ENERGY CONSUMPTION MODEL**

Since the waste collection robot uses motors to drive between the nodes, or trash bin positions, the energy consumption of the motors must be defined. In [19], the energy consumption of the motor was presented as the sum of the mechanical output power and the transformer losses. Therefore, the energy consumption can be modeled as a function of speed, acceleration, and mass, as defined in (12) [19].

\[
P_m(m, v, a) = p_l + m(a + g\mu) v
\]  

(12)

\( P_m \) is the motion capability (W) and \( p_l \) is the conversion loss. The parameter \( m \) is the weight of the robot (kg), and \( \mu \) is the installation friction constant. \( v \) is the speed of the mobile robot (m/s), \( a \) is the acceleration (m/s²), and \( g \) is the gravity constant (m/s²). The weight of the robot \( m \) indicates the weight supported by the motor. The weight supported by the motor becomes heavier each time the robot collects waste. Therefore, the waste collection robot will consume additional energy, which depends on the path. The additional energy consumption increases in proportion to the waste weight carried by the robot. In \( SP \), the additional energy consumption \( e_j \) of the robot moving to trash bin \( j \) is indicated by (13).

\[
e_j = p_l + M_j(a + g\mu) v
\]  

(13)

When \( SP \) is constructed with \( n \) trash bins, the total additional energy consumption \( E_{sp} \) consumed by the robot up to that point can be shown by (14).

\[
E_{sp} = \sum_{h=0}^{n+1} e_h
\]  

(14)

where \( n + 1 \) indicates that the robot returns to the depot at the end of \( SP \). The waste collection robot returns to the depot either by capacity constraints or by achieving waste collection.

The path \( P \) that accomplishes waste collection is constructed from several sub-paths, denoted by \( P = \{SP_1, SP_2, \ldots, SP_O\} \). More sub-paths are created when the number of trash bins to be collected is large or the allowable capacity is low. When the robot \( k \) that achieves waste collection creates path \( P \) by \( O \) sub-paths, the total additional energy consumption \( E_{mk} \) can be defined by (15).

\[
E_{mk} = \sum_{h=1}^{O} E_h
\]  

(15)

**D. ADAPTED ACO AND PROPOSED ACO ALGORITHMS**

In our previous work [15], the conventional ACO algorithm is adapted to minimize the energy consumption of the waste collection robot by setting the amount of pheromone update for each iteration by (16).

\[
\Delta \tau_{ij}^k(t) = \begin{cases} \frac{Q}{E_{mk}}, & (i, j) \in T^k \\ 0, & (i, j) \notin T^k \end{cases}
\]  

(16)

\( T^k \) indicates the pathway constructed by the artificial ant \( k \). The part of the pathway that is not constructed by the artificial ant does not update the pheromone. The order in which waste is collected is important to optimize energy consumption. Energy consumption can be reduced if heavy waste is transported over short distances and light waste over long distances. Thus, when constructing a path, the lighter waste weight should be selected first. Therefore, the adapted ACO algorithm sets visibility \( \eta_{ij} \) based on the waste weight \( c_j \) of the next trash bin to collect, as shown in (17).

\[
\eta_{ij} = \frac{1}{c_j}
\]  

(17)

By using the visibility, or the path heuristic information, (17), it is possible to preferentially select the lighter waste weight and plan a path to collect more waste in a sub-path.

The adapted ACO algorithm presented in [15] can achieve energy-efficient path findings. However, since the amount of pheromone update is set by (16) and the visibility in (17), the total distance traveled by the robot is not optimized. If waste collection is performed on a path defined using this equation, the distance traveled will be longer and waste collection will take more times to accomplish. Therefore, in this paper, the proposed ACO algorithm uses the combination of the path distance and the waste weight between the trash bins as the visibility instead. The proposed ACO algorithm aims to optimize the travel distance and energy consumption of
the waste collection robot. Therefore, in the proposed ACO algorithm, the amount of pheromone updates per iteration is defined by (18).

\[
\Delta t_{ij}^k(t) = \begin{cases} 
Q/j^k, & (i,j) \in T^k \\
0, & (i,j) \notin T^k
\end{cases} \tag{18}
\]

\( J^k \) refers to the multi-objective function that normalizes the travel distance \( D^k \) and the energy consumption \( Em^k \) that achieves waste collection. The multi-objective function \( J^k \) is computed by (19).

\[
J^k = \gamma_1 \times D^k + \gamma_2 \times Em^k \tag{19}
\]

where \( \gamma_1 \) and \( \gamma_2 \) represent the parameters that adjust the travel distance and the energy consumption, respectively. The adjustment parameters can be defined by (20) and (21).

\[
\gamma_1 = \frac{Em^k}{D^k + Em^k} \tag{20}
\]

\[
\gamma_2 = \frac{D^k}{D^k + Em^k} \tag{21}
\]

In the multi-objective function proposed, the order in which the waste weight is collected and the distance information between the trash bins are important. Therefore, in the proposed ACO algorithm, the visibility is set by (22) to optimize the multi-objective function.

\[
\eta_{ij} = \frac{1}{\varepsilon_1 \times d_{ij} + \varepsilon_2 \times c_j} \tag{22}
\]

\( \varepsilon_1 \) and \( \varepsilon_2 \) indicate the adjustment parameters for normalizing the path distance between the trash bins and the waste weight in the next trash bin, respectively. This is because, in each optimization problem, the difference between the waste weight in each trash bin and the path distance between the trash bins is different. Thus, the \( \varepsilon_1 \) and \( \varepsilon_2 \) can be calculated by (23) and (24), respectively.

\[
\varepsilon_1 = \frac{c_{avg}}{d_{avg} + c_{avg}} \tag{23}
\]

\[
\varepsilon_2 = \frac{d_{avg}}{d_{avg} + c_{avg}} \tag{24}
\]

where \( d_{avg} \) indicates the average distance between the trash bins of each optimization problem. \( c_{avg} \) is the average waste weight of each optimization problem. \( d_{avg} \) and \( c_{avg} \) are defined by (25) and (26), where \( n \) indicates the number of trash bin nodes in each optimization problem.

\[
d_{avg} = \sum_{i,j=1}^{n} \sum_{j=1}^{n} d_{ij} / \sum_{k=1}^{n} (k-1), \quad i \neq j, i < j \tag{25}
\]

\[
c_{avg} = \frac{\sum_{j=1}^{n} c_j}{n} \tag{26}
\]

IV. SIMULATION EXPERIMENT AND DISCUSSION

A. EXPERIMENTAL SET

The performance of the proposed ACO algorithm is evaluated by simulation experiments and will be compared with the conventional ACO algorithm and the adapted ACO algorithms. In the simulation experiments, the waste weight in each trash bin is divided into two scenarios, i.e., heavy-load environment and light-load environment. These reflect the carried load of the robot along the paths. The waste weight ranges from 10 kg to 40 kg in a heavy-load environment. For the light-load environment, the waste weight ranges from 1 kg to 10 kg. In addition, the area used in the simulation scenario has the size of 1000 m \( \times \) 1000 m, representing a huge factory or warehouse. There are four groups of nodes where the trash bins are located, i.e., 50, 100, 150, and 200, respectively. These nodes reflect the denseness of the trash bins placed in the working space and will be used to observe the overall performance accordingly. The carrying capacities of the robot are 50 kg, 100 kg, 150 kg, and unlimited (\( \infty \)). These values reflect the number of rounds that the robot will take to accomplish the task. For instance, the unlimited capacity means the robot runs to collect all the waste in only one round. Based on the parameters defined above, the average distance and the average waste weight between the trash bin nodes used in (23) and (24) will be calculated by (25) and (26), and the results are shown in Table 1. In addition, it is assumed that the distance information between nodes and the weight information of waste are data that have been obtained in advance before path planning. Each ACO algorithm uses that information to plan paths for the waste collection robots. Therefore, the time complexity is not our major concern for the simulation experiments in this study.

For simulation parameters, the total number of artificial ants performing pathfinding is set to be equal to the number of nodes specified. Simulation experiments are conducted 20 times each. Also, for simplicity, the waste collection robot performs the task based on the following assumptions;

- The travel speed of the robot is set to \( v = 1 \) m/s and acceleration \( a = 0 \) for all paths.
- The weight of the robot is assumed to be \( m = 1 \) kg for all paths. Therefore, only the additional energy consumption is used for comparison.
- In this study, the transformation losses are not important, so \( p_l \) is set to be equal to 0.
- The gravitational acceleration is set to \( g = 9.8 \) m/s\(^2\) and the installed friction coefficient of the rubber wheel is equal to \( \mu = 0.8 \).

| Node | Heavy-load environment | Light-load environment |
|------|------------------------|------------------------|
|      | \( d_{avg}[m] \) | \( c_{avg}[kg] \) | \( d_{avg}[m] \) | \( c_{avg}[kg] \) |
| 50   | 486.33                 | 22.42                  | 486.33                 | 4.68                  |
| 100  | 509.92                 | 22.18                  | 509.92                 | 5.14                  |
| 150  | 507.52                 | 23.78                  | 507.52                 | 5.29                  |
| 200  | 508.2                  | 24.12                  | 508.2                  | 5.24                  |
In addition, the simulation experiments are set up with reference to the system parameters used in [14] and [15], where the system parameters are \( \alpha = 1, \beta = 2, Q = 1, \rho = 0.1, \) and iteration = 100, respectively.

**B. SIMULATION RESULTS**

We evaluate the performance of the proposed ACO algorithm using the visibility in (22) and the updated pheromone in (18). The results will be compared with the conventional ACO algorithm and the adapted ACO algorithm. The conventional ACO algorithm determines the pheromone updated with \( L^k = D^k \) and uses the visibility in (7). The adapted ACO method uses the visibility in (17) and the pheromone updated in (16). The performance metrics for comparisons comprise the travel distance and the energy consumption of the waste collection robot under the heavy-load and light-load environments within the area, the number of nodes, and the carrying capacity as specified in Section IV-A. We also observe the carrying capacities of the robot affecting the performance as well. In addition, we analyze the system parameters, i.e., \( \alpha, \beta, \rho, \) and \( Q \) to observe their impact on the energy consumption of the robot as well. The simulation was implemented using Python programming language.

Figure 1 shows the energy consumption of the waste collection robot under the heavy-load environment by using the conventional ACO algorithm, the adapted ACO algorithm, and the proposed ACO algorithm for comparison. The results also express the energy consumption under different numbers of nodes, i.e., 50, 100, 150, and 200, with a different carrying capacity of the robot that can collect the waste, i.e., 50 kg, 100 kg, 150 kg, and \( \infty \) (unlimited), respectively. As can be observed in Fig. 1(a), it can be found that the energy consumption of the robot with a 50 kg carrying capacity under the adapted ACO algorithm and the proposed ACO algorithm is almost the same. They are lower than the conventional ACO algorithm around \(-13.67\%\) and \(-13.52\%,\) respectively. From Fig. 1(b) to 1(d), when the carrying capacity of the robot increases from 100 kg to 150 kg and unlimited, it can be noted that the energy consumption of the robot under the adapted ACO algorithm is lower than the conventional ACO algorithm at \(-7.39\%, -8.86\%, \) and \(-16.17\%\) respectively. While the proposed ACO algorithm consumes energy lower than the conventional ACO algorithm at \(-4.14\%, -2.47\%, \) and \(-9.38\%\) respectively. Table 2 summarizes the numerical values resulting from the energy consumption under the heavy-load environment.

Figure 2 expresses the energy consumption of the waste collection robot as similar to Fig. 1, but under the light-load environment. Table 3 also summarizes the numerical values resulting from the energy consumption under the light-load environment. As can be observed from Fig. 2(a) to 2(d), the energy consumption of the adapted ACO algorithm is the...
Table 2. Energy consumption under heavy-load environment.

| C    | ACO            | Energy | Avg. | % Dec. |
|------|----------------|--------|------|--------|
| 50   | Conv. 12.922   | 26.959 | 39.884 | 53.878 | 52.986 | -13.67 |
|      | Adapt. 10.877  | 34.386 | 46.352 | 28.478 | -11.67 |
|      | Prop. 10.814   | 34.382 | 46.329 | 28.527 | -13.52 |
| 100  | Conv. 21.499   | 44.975 | 67.054 | 90.010 | 55.785 | -12.59 |
|      | Adapt. 18.788  | 59.792 | 66.607 | 81.957 | 51.661 | -7.39  |
|      | Prop. 20.726   | 62.621 | 69.223 | 53.273 | -11.44 |
| 150  | Conv. 31.380   | 63.433 | 95.758 | 127.344 | 79.531 | -14.97 |
|      | Adapt. 26.890  | 69.791 | 87.499 | 118.755 | 72.484 | -8.86  |
|      | Prop. 29.405   | 61.110 | 93.713 | 126.044 | 77.582 | -2.47  |
| Inf. | Conv. 225.398  | 497.761 | 1.706 | 1.870 | 1.746 | -0.28 |
|      | Adapt. 178.998 | 719.799 | 1.795 | 2.126 | 1.646 | -0.17 |
|      | Prop. 207.468  | 793.843 | 1.912 | 2.342 | 1.683 | -0.38 |

Table 3. Energy consumption under light-load environment.

| C    | ACO            | Energy | Avg. | % Dec. |
|------|----------------|--------|------|--------|
| 50   | Conv. 10.161   | 20.467 | 36.845 | 41.725 | 25.800 | -12.88 |
|      | Adapt. 7.848   | 17.720 | 27.367 | 36.971 | 22.477 | -12.88 |
|      | Prop. 8.511    | 18.582 | 28.794 | 38.754 | 23.647 | -8.35  |
| 100  | Conv. 18.237   | 30.066 | 58.913 | 79.710 | 48.732 | -13.78 |
|      | Adapt. 15.822  | 32.875 | 51.166 | 70.214 | 42.019 | -13.78 |
|      | Prop. 15.997   | 36.591 | 55.661 | 75.652 | 45.875 | -5.86  |
| 150  | Conv. 25.267   | 55.558 | 85.949 | 118.772 | 71.387 | -15.66 |
|      | Adapt. 18.911  | 46.498 | 73.602 | 102.014 | 66.206 | -15.66 |
|      | Prop. 22.412   | 51.766 | 80.560 | 111.685 | 66.666 | -6.70  |
| Inf. | Conv. 46.675   | 203.247 | 469.942 | 826.125 | 386.496 | -15.19 |
|      | Adapt. 32.120  | 151.915 | 335.843 | 618.061 | 289.475 | -25.19 |
|      | Prop. 38.203   | 171.493 | 393.299 | 677.799 | 326.206 | -17.15 |

The adapted ACO algorithm consumes less energy than the proposed ACO algorithm but is higher than the conventional ACO algorithm. In Fig. 2(a) under the carried load at 50 kg, the adapted ACO algorithm consumes the energy lower than the conventional ACO algorithm at -12.88%, while the proposed ACO algorithm is at -8.35%. When the carrying capacity is increased from 100 kg to 150 kg and unlimited, as shown in Fig. 2(b) to 2(d), the energy consumption of the adapted ACO algorithm is decreased from -13.78% to -15.66% and -25.10%, respectively. The decreasing direction is similar to the proposed ACO algorithm but a little higher than the adapted ACO algorithm, i.e., -5.86%, -6.70%, and -17.15%, respectively.

Figure 3 expresses the results of the travel distance that the robot takes to collect the waste in the heavy-load environment by using the conventional ACO algorithm, the adapted ACO algorithm, and the proposed ACO algorithm. The results show the travel distances under various numbers of nodes, i.e., 50, 100, 150, and 200, and the carrying capacities, i.e., 50 kg, 100 kg, 150 kg, and ∞ (unlimited), respectively. Table 4 also expresses the numerical results of the traveled distances under the heavy-load environment. It can be observed from Fig. 3 that, by using the conventional ACO algorithm, the robot takes the shortest distance in all nodes.
and every carrying capacities, while the adapted ACO algorithm takes the longest distance. Also, the travel distance of the proposed ACO algorithm is a bit higher than the conventional ACO algorithm. In Fig. 3(a), the travel distances of the adapted ACO algorithm and the proposed ACO algorithm are not much different, which are higher than the conventional ACO algorithm at 43.15% and 31.27%, respectively. But, as shown in Fig. 3(b) to 3(d), when the carrying capacity is increased, the travel distance of the adapted ACO algorithm increases dramatically from 126.31% to 188.75%, and 527.26%, while the proposed ACO algorithm increases lower at 31.22%, 51.39%, and 164.37%, respectively.

Figure 4 shows the travel distance of the waste collection robot, as similar to Fig. 3, but under the light-load environment. Table 5 summarizes the numerical result of the travel distances. As can be observed from Fig. 4(a) to 4(b), by using the adapted ACO algorithm, the robot takes the longest distance, which is quite different from the conventional and proposed ACO algorithms for all cases. The travel distances of the adapted ACO algorithm increase from 259.98% to 364.34%, 416.32%, and 531.22%, when the carried loads increase from 50 kg to 100 kg, 150 kg, and unlimited, respectively. In contrast, by using the proposed ACO algorithm, the
travel distances increase from 68.30% to 101.53%, 117.25%, and 158.60%, respectively.

The last simulation experiment is to investigate the effect of $\alpha$ and $\beta$ used in the proposed ACO algorithm only for energy consumption since it is the main method to consider in this research work. In the experiment, the system parameters are defined as follows; $\alpha$ is varied from 0.1 to 0.9, $\beta$ is varied from 0.1 to 0.9, $Q$ is equal to 1, and $\rho$ is equal to 0.1. Figure 5 expresses the simulation results of the energy consumption under the heavy-load environment only. This is because we aim to see the trend of how these varying parameters affect performance.

**C. RESULTS DISCUSSION**

From the results expressed in Fig. 1 and 2, it can be concluded that, by using the conventional ACO algorithm, the waste collection robot consumes more energy than the adapted and proposed ACO algorithms in every carrying capacity under both environments. Also, when the number of trash bins is 50 nodes, the robot consumes less energy than when the number of nodes increases to 100, 150 and 200 nodes, respectively. It can be further noted that, under the carrying capacity of 50 kg in the high-load environment as shown in Fig. 3(a), the energy consumption of the robot using the adapted and proposed ACO algorithms is increased at a similar value in every group node. It comes from the fact that, in a high-load environment, the waste weight is around 10 kg to 40 kg. Due to its limited carrying capacity, it causes the robot to have a full load in a short period, and to have fewer chances to collect more waste from the other nodes in each round. The results confirm that the adapted and proposed ACO algorithms under this research work can provide less energy consumption to the robot than the conventional ACO algorithm.

For the travel distances under the high-load and light-load environments in Fig. 3 and 4, it can be concluded that, by using the conventional ACO algorithm, the robot takes the shortest distance to collect the waste in all cases. For the adapted and proposed ACO algorithms, the robot travels a longer distance to travel. By using the adapted ACO algorithm that uses only the waste weight as its visibility, the robot travels a dramatically longer distance than the proposed ACO algorithm in all cases. Also, the distances are increased in proportion to the number of nodes increased accordingly. It can be further noted that, at 50 kg carrying capacity in the high-load environment, as shown in Fig. 3(a), distance traveled by the robot using the adapted and proposed ACO algorithms are increased in similar values when the number of nodes increases from 100 to 150, and 200 nodes, respectively. The results conform to the energy consumption as shown in Fig. 1(a), which is the same reason expressed previously.

In addition, when taking the average distance and average energy from Table 2 to V to plot the graph, we can see the...
FIGURE 5. Energy consumption for varying $\alpha$ and $\beta$ from 0.1 to 0.9 at $Q = 1$ and $\rho = 0.1$.

The trend between the energy consumption and the travel distance compared in both environments at the carrying capacity of 50 kg, 100 kg, and 150 kg, respectively (as shown in Fig. 6 and 7). As the results expressed, it can be confirmed that the conventional ACO algorithm takes the shortest distance but consumes the highest energy as the carrying capacity increases. On the other hand, the adapted ACO algorithm consumes less energy but takes the longest distance. The increased energy and the decreased distance are in correspondence with the carrying capacity of the robot, as can be observed in Fig. 6 and 7. The robot tends to consume the highest energy when the carrying capacity is unlimited. This is because the robot can move to collect the waste in the trash bins at all nodes within one round. So, it results in the highest energy consumption. It is different from the limited carrying capacity of 50 kg, 100 kg, and 150 kg, in that the robot consumes less energy. This is because the robot can pick up the waste and takes it to the dumping point in many rounds.

The reason why the energy consumption and the travel distance appeared, as shown in the results, comes from the visibility and the updated pheromone that affects the path selection probability in each round. When using only the path distance in the conventional ACO algorithm, or the waste weight in the adapted ACO algorithm, as the visibility, it results in obtaining either only the shortest distance or the lowest energy, respectively. Therefore, when considering the optimal result, it can be found that the proposed ACO algorithm can achieve both the optimal energy consumption and travel distance. This is because it consumes less energy than the conventional ACO algorithm and takes a shorter distance than the adapted ACO algorithm in all carried load capacities and every group node, as can be observed in Fig. 6 and 7. It results from using both path distance and waste weight as the visibility, including the updated pheromone using both the travel distance and the energy consumption as presented in this research work.
that the adapted ACO algorithm provided the most energy-efficient path, although the travel distance was longer than the conventional ACO algorithm. Furthermore, the proposed ACO algorithm yielded the most energy-efficient path by achieving efficiency in both energy consumption and travel distance. Therefore, by using distance and weight for visibility including the travel distance and energy consumption for updated pheromones, the proposed ACO algorithm is shown to be more effective than the conventional ACO algorithm and the adapted ACO algorithm.

The ACO algorithms proposed in this paper can be used for path planning for a waste collection robot performing in a flat, obstacle-free environment. In addition, the proposed ACO algorithms will be implemented on the actual robots to achieve energy-efficient waste collection by using the mobile robots in the future.

REFERENCES

[1] A. Pires, “Fundamental background,” in Sustainable Solid Waste Collection and Management. Cham, Switzerland: Springer, 2016, pp. 3–44, doi: 10.1007/978-3-319-93200-2.
[2] M. Akhtar, M. A. Hannan, R. A. Begum, H. Basri, and E. Scavino, “Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization,” Waste Manage., vol. 61, pp. 117–128, Mar. 2017, doi: 10.1016/j.wasman.2017.01.022.
[3] C. Wang, J. Wang, C. Li, D. Ho, J. Cheng, T. Yan, L. Meng, and M. Q.-H. Meng, “Safe and robust mobile robot navigation in uneven indoor environments,” Sensors, vol. 19, no. 13, p. 2993, Jul. 2019.
[4] C. Wang, J. Cheng, J. Wang, X. Li, and M. Q.-H. Meng, “Efficient object search with belief road map using mobile robot,” IEEE Robot. Autom. Lett., vol. 3, no. 4, pp. 3081–3088, Oct. 2018, doi: 10.1109/LRA.2018.2849610.
[5] J. Wang and M. Q. H. Meng, “Socially compliant path planning for robotic autonomous luggage trolley collection at airports,” Sensors, vol. 19, no. 12, p. 2759, 2019.
[6] A. Gupta, M. J. van der Schoor, J. Brautigam, V. B. Justo, T. F. Unland, and D. Gohlich, “Autonomous service robots for urban waste management—Multiagent route planning and cooperative operation,” IEEE Robot. Autom. Lett., vol. 7, no. 4, pp. 8972–8979, Oct. 2022, doi: 10.1109/LRA.2022.3188900.
[7] X. Wu, Y. Fu, and T. Liu, “A hybrid ACO algorithm for capacitated vehicle routing problems,” in Proc. IEEE 2nd Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC), Mar. 2017, pp. 510–514, doi: 10.1109/IAEAC.2017.8054067.
[8] R. J. Kuo and F. E. Zulvia, “Hybrid genetic ant colony optimization algorithm for capacitated vehicle routing problem with fuzzy demand—A case study on garbage collection system,” in Proc. 4th Int. Conf. Ind. Eng. Appl. (ICIEA), Apr. 2017, pp. 244–248, doi: 10.1109/ICIEA.2017.7939215.
[9] M. L. Mutar, M. A. Burhanuddin, A. S. Hameed, N. Yusof, and H. J. Mutashar, “An efficient improvement of ant colony system algorithm for handling capacity vehicle routing problem,” Int. J. Ind. Eng. Computations, vol. 11, pp. 549–564, Mar. 2020.
[10] Q. Luo, “Research on path planning of mobile robot based on improved ant colony algorithm,” Neural Comput. Appl., vol. 32, no. 6, pp. 1555–1566, Apr. 2019.
[11] C. Miao, G. Chen, C. Yan, and Y. Wu, “Path planning optimization of indoor mobile robot based on adaptive ant colony algorithm,” Comput. Ind. Eng., vol. 156, Jun. 2021, Art. no. 107230.
[12] P. K. D., T. Amgoth, and C. S. R. Annavarapu, “ACO-based mobile sink path determination for wireless sensor networks under non-uniform data constraints,” Appl. Soft Comput., vol. 69, pp. 528–540, Aug. 2018.
[13] Z. Wu and G. Wan, “An enhanced ACO-based mobile sink path determination for data gathering in wireless sensor networks,” J. Wireless Commun. Netw., vol. 2022, no. 1, pp. 8991–9006, Oct. 2022.
[14] K. Tomitagawa, S. Chotiphan, S. Kuchii, A. Anuntachai, and O. WongwiraT, “Energy optimal path finding for waste collection robot using ant colony optimization algorithm,” in Proc. 13th Int. Conf. Inf. Technol. Electr. Eng. (ICITEE), Oct. 2021, pp. 57–62, doi: 10.1109/ICITEE53064.2021.9611924.
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