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Research Article ANewHybridButterflyOptimizationAlgorithmforGreenVehicle Routing Problem Dana Marsetiya Utama ,1Dian Setiya Widodo ,2Muhammad Faisal Ibrahim ,3 and Shanty Kusuma Dewi 1 1 University of Muhammadiyah Malang, Jl. Tlogomas No. 246, 65144 Malang, East Java, Indonesia 2University of 17 Agustus 1945 Surabaya, Jl. Semolowaru, Sukolilo, Surabaya 60118, East Java, Indonesia 3Universitas Internasional Semen Indonesia, Jl. Veteran, Sidokumpul, Gresik 61122, East Java, Indonesia Correspondence should be addressed to Dana Marsetiya Utama; dana@umm.ac.id Received 25 March 2020; Revised 31 October 2020; Accepted 7 December 2020; Published 22 December 2020 Academic Editor: Kun An In the industrial sector, transportation plays an essentialrole in distribution. (is activity impacts climate change and global warming. One of the critical problems in distribution is the green vehicle routing problem (G-VRP). (is study focuses on G-VRP for a single distribution center. (e objective function is to minimize the distribution costs by considering fuel costs, carbon costs, and vehicle use costs.(isresearchaimstodevelopthehybridbutter?yoptimizationalgorithm(HBOA)tominimizethedistributioncostsonG-VRP.

Itwasinspiredbythebutter?yoptimizationalgorithm(BOA),whichwasbycombiningthetabusearch(TS)algorithmandlocalsearch swap and ?ip strategies. BOA is a new metaheuristic algorithm that has been successfully applied in various engineering ?elds. Experimentswerecarriedouttotesttheparametersoftheproposedalgorithmandvarythespeedofvehicles.(eproposedalgorithm was also compared with several procedures of prior study. (e experimental results proved that the HBOA could minimize the total distribution cost compared to other algorithms. Moreover, the computation time is also included in the analysis. 1.Introduction In distribution, transportation plays an essential role in the industrial sector. It proposes to distribute products from warehousestocustomers[1].Transportandlogisticsarealso signi?cant in the economic development of the world [2].

However, these activities impact climate change and global warming[3, 4]. InChina,30% ofthetotalcarbon emissions are caused by the goods transportation sector [5]. Fur- thermore, in the United States, 28.5% of greenhouse gas is caused by the transportation of goods [6]. Global climate change prevention was declared at the Copenhagen global climate summit in 2009 [7]. Generally, vehicles use fossil fuels as the source of engine-driving energy. (erefore, air pollutionismostlycausedbythetransportationsector[8,9]. One of the e?orts to solve this problem is determining the right route.

(e problem of minimizing carbon emissions and fuel energy on this vehicle route is classi?ed as a green vehicle routing problem (G-VRP) [10, 11]. (is issue has attracted the attention of many researchers [12, 13]. G-VRP is the development of the classic vehicle routing problem (VRP).(eVRPaimstominimizethetotalcost[14,15]and the distance of travel [16–18]. However, the G-VRP aims at reducing the environmental impacts, such as reducing fuel consumption and carbon emissions caused by the distri- bution process [19, 20]. (erefore, several e?ective proce- dures have been developed to solve G-VRP.

In recent years, there has been an increase in research interest in this problem. (e researchers classify G-VRP as NP-hard problem [21–23]. (ey argue that the search for solutions to these problems is di?cult to ?nd at the time of polynomials. Recently, one popular procedure is metaheuristics [24]. SeveralresearchersinvestigatetheissueofG-VRPtoreduce fuelconsumptionandcarbonemissionspartially.Inthefuel consumption problem, some metaheuristic algorithms have been used to solve this problem. Cooray and Rupasinghe [25] proposed genetic algorithms (GA) to reduce energy Hind Journal ofation Volume 2020, Article ID 8834502, 14 pages https://doi.org/10.1155/2020/8834502 consumption.

Particle swarm optimization (PSO) was proposed by Poonthalir and Nadarajan [26] in a fuel-e?- cient G-VRP with varying speed. PSO was also used by Norouzi et al. [27] to minimize fuel consumption with time dependency. Zhang et al. [28] o?ered the ant colony opti- mization (ACO) algorithm for minimizing fuel consump- tion in multidepot. Other studies to minimize fuel consumption such as simulated annealing (SA) have been proposed by Kuo [29] and Normasari etal. [30], the revised hybrid intelligent algorithm was developed by Wang et al. [31], and Andelmin and Bartolini [32] o?ered the heuristic multistartlocalsearchprocedure.Meanwhile,Macrinaetal.

[33] proposed a hybrid extensive neighborhood search, and Wang and Lu [10] developed the memetic algorithm with competition. Besides, some researchers have resolved G-VRP to minimize carbon emissions. Some popular algorithms for this problem are GA [34, 35], tabu search (TS) [36–38], the Clarke and Wright algorithm [39], and GA with dynamic programming[40].(edi?erentialevolutionalgorithmwas developed by Kunnapapdeelert and Klinsrisuk [41] to solve G-VRPwithpickupanddeliveryproblems.Molinaetal.[42] proposed the TS with neighborhood variables to reduce pollutant emissions.

On the other hand, several studies on G-VRP to minimize carbon emissions and energy con- sumption simultaneously have been carried out successfully by researchers. Li et al. [43] proposed a modi?ed PSO to reduce the total costs, including quality loss cost, vehicle operating cost, penalty cost, product freshness cost, emis- sionscost,andenergycost.TSwaso?eredbyPoonthalirand Nadarajan [26] to solve G-VRP by considering heteroge- neous ?xed ?eet. Zhang et al. [7] also proposed the TS al- gorithmtoreducethetotaldistributioncosts,includingfuel costs, carbon costs, and vehicle use costs. Hybrid GA was o?ered by Wang et al.

[44] to minimize total cost distri- bution, which includes carbon emission costs. Shen et al. [45]developedPSOandTStoreduceminimumdistribution costs, including penalty costs, the driver salary, fuel costs, and carbon emissions costs. Improved ACO algorithm was proposed by Li et al. [46], and Karagul et al. [47] employed the SA algorithm. Based on the trend of problem-solving methods, advanced metaheuristic algorithms have gained popularity in solving G-VRPs. Even a hybrid algorithm is used to solve this problem, and it has the advantage of solvingNP-hardproblems.Unfortunately,littleresearchhas addressed the use of a hybrid algorithm to solve G-VRP. Recently,oneoftheadvancedalgorithmsisthebutter?y optimizationalgorithm(BOA).Itisanewalgorithmthatcan solve optimization problems proposed by Arora and Singh [48]. BOA has been e?ectively used to solve problems in various?elds.WenandCao[49]appliedapredictingmodel forexploringhouseholdCO2emissionmitigationstrategies. BOAwasimplementedbySharmaetal.[50]incompression string design, welded beam design, and pressure vessel design. Yildiz et al. [51] used BOA to design automobile suspension components. Several studies have applied the BOAtosolveseveralproblems.However,therehasnotbeen anyresearchaboutsolvingG-VRPusingthehybridbutter?y optimization algorithm (HBOA). (ose reasons motivate the author to conduct this research.

Moreover, although some researchers have investigated G-VRP, minimizing carbon emissions and energy still receives little attention in the research literature. One interesting issue of G-VRP was investigated by Zhang et al. [7]. (ey solved the G-VRP to minimize the total distribution costs by considering fuel costs, carbon costs, and vehicle use costs with the TS al- gorithm. Unfortunately, the study of Zhang et al. [7] and previousstudiesdonotconsidercomputationtime,anditis an essential aspect of optimization. (erefore, we propose the HBOA to minimize distribution costs that include fuel consumption, carbon emission, and vehicle use costs.

(ere are two main objectives of this research: (1) developing the HBOA to minimize distribution costs of G-VRP and (2) comparing the performance of the proposed algorithm computation time. (e HBOA was tested with several ex- periments to ?nd out the best parameters. It is also com- pared to several algorithms. (is research provides a signi?cant contribution as the HBOA is a new algorithm in the G-VRP. (is paper structure is presented as follows: Section 2.1 describes assumptions, notations, and problem description; Section 2.2 explains the HBOA algorithm; Section 2.3

presents data and experimental procedures; Section 3 pro- vides results and discussion; and Section 4 presents con- clusions and future work. 2.Materials and Methods 2.1.Assumptions,Notations,andProblemDescription. Inthis section, assumptions, notations, and problem descriptions are based on studies from Zhang et al. [7]. We consider transportation with one distribution center and a set of nodes. Vehicles have equal capacity (homogeneous). (e distribution cost considered is fuel consumption cost, car- bon emission cost, and a used vehicle cost. Highly total distribution costs require proper distribution management.

(erefore, distribution centers need to manage the right transportation routes to minimize the total distribution costs. In this problem, vehicle fuel consumption is based on the distance traveled from node s to node s+1. We assume that the weight of the additional load M of the vehicle in- creases fuel consumption p percent. Furthermore, the fuel consumption of unloaded vehicles is also considered in the total distribution costs. Assumptions, notations, and problem descriptions are described inthe following section. 2.1.1. Assumptions and Notations.

(is study employed several assumptions in G-VRP, including the following: (1) the route begins and ends at the distribution center; (2) the costsconsistoffuelconsumptioncost,carbonemissioncost, and vehicle rental cost; (3) the vehicle has a ?xed load ca- pacity for each trip; (4) fuel, emissions, and vehicle usage costs are ?xed;(5) vehicle speedis ?xed;(6) thedemand for each node is ?xed; (7) each customer service time is ?xed; and (8) this problem considers one distribution center. (is study used notations to make it more practical to decipher the problem description.

(e notations are as follows: 2 JournalofAdvancedTransportation TDC: total distribution cost Rs r: the sth node on the rth route (for example, R3 2 ?1, the 2 path is 0-3-1-7-0, and node in the 3 is 1) d(Rsr)(Rs+1 r): distance in rth route from node s to node s+1 FC(Rs r)(Rs+1 r): total fuel consumption in rth route from node s to node s+1 KPL(Rs r)(Rs+1 r): the traveled distance per unit fuel in rth route from node s to node s+1 LPH(Rs r)(Rs+1 r): the fuel consumption per unit time of unload vehicle in rth route from node s to node s+1 v(Rs r)(Rs+1 r): the average speed of unloaded vehicles L(Rsr)(Rs+1 r): load of vehicle in rth route from sth node to s+1 node M: additional load weight p: percentage increase of fuel N: number of vehicles or number of routes Vr: number of nodes on route r, r ?1, 2, . . .,

N stRsr: service time at the sth node on the rth route qRsr: demand at the sth node on the rth route Q: vehicle capacity Cf: fuel consumption cost (fuel prices) Ce: emission carbon cost per unit of fuel consumption CV: vehicle usage cost per unit time 2.1.2.ProblemDescription. (isstudymadeamathematical model to describe the problem. (e mathematical model is used to minimize distribution costs. (e distribution costs considered are fuel cost, carbon emissions cost, and vehicle usagecost.Furthermore,theproblemdescriptionillustrated is modeled as follows: MinTDC ? ?? N r?1 ?? vr-1 s?1 Cf + Ce ?? ?? ×(LPH Rsr ( ) Rs+1 r ( ) × d Rs r ( ) Rs+1 r ( ) V Rsr ( ) Rs+1 r ( ) ×(1 + p × L Rsr ( ) Rs+1 r ( ) M)) + ?? N r?1 ?? Vr-1 s?1 CV × d Rs r ( ) Rs+1 r ( ) V Rs r ( ) Rs+1 r ( ) + stRs r ?? ? ?, (1) subject to ?? Vr-1 s?2 qRsr= Q, ?r ? 1,2, . . . , N, (2) L Rs r ( ) Rs+1 r ( ) ? ?? Vr-1 s'?s+1 qRs' r , ?r ? 1,2, . . . , N, (3) R1 r ? RVr r ? 0, ?r ? 1,2, . . . , N, (4) N=0, Vr=0, Rs r? V, ?r ? 1,2, . . . , N,?s ? 1,2, . . . , Vr.

(5) Equation (1) formulates the objective function in min- imizingthetotaldistributioncost,includingvehicleusecost, fuel consumption cost, and carbon emissions cost. (e cost offuelconsumptionandcarbonemissionscostconsidersthe increase in fuel consumption (p) for each additional load (M). (e fuel consumption per unit time of the unloading vehicle in rth route from node s to node s+1 also is con- sidered. Constraints (2) and (3) describe formulas to ensure that the total load does not exceed the vehicle capacity. On each route r, the total vehicle load must not exceed the vehiclecapacity. (etotalvehicle loadmustbe ensuredthat it does not exceed the capacity.

It becomes essential in the G-VRP. Constraint(4)showsthatthe?rstand lastnodesof each vehicle route are the distribution center. As a G-VRP with one distribution center, this constraint ensures that each route starts at the distribution center and also ends at the distribution center. Constraint (5) formulates well-de- ?ned decision variables. (is constraint de?nes the number ofnodesandroutes=0,anditdescribesthedecisionvariable at the sth node on the rth route. 2.2. 1e Proposed Hybrid Butter?y Optimization Algorithm (HBOA). (is study o?ered HBOA to solve G-VRP.

(e proposed algorithm was inspired by a BOA metaheuristic algorithm by combining the TS heuristic algorithm and the local search strategy. (e main inspiration for the proposed algorithm was from BOA. (e BOA was initially proposed by Arora and Singh [48] in 2019. (ere are two main characteristics in BOA, namely, the fragrance and move- ment of butter?ies. (ese characteristics distinguish BOA from otheralgorithms.(e basicBOAisshowninFigure1. AlthoughtheBOAhasbeenproposed,thisalgorithmhas not yet been satisfactory as it can only solve continuous problems.Meanwhile,theproposedalgorithmisexpectedto solve G-VRP that constitutes sophisticated and discrete characteristics.

G-VRP is categorized as an NP-hard com- binatorial problem that must be addressed by a discrete searchspace.(erefore,thisstudyo?eredanewapproachto solve G-VRP. (is research proposed ?ve main steps on HBOA, such as (1) convert search agent position to travel orderwithlargerankvalue(LRV),(2)changethepositionof 10% search agent based on the TS algorithm, (3) fragrance update, (4) movement of butter?ies, and (5) local search. (is study proposed an LRV procedure for converting continuous values to discrete values. To improve the BOA performance, this study combined TS and local search al- gorithms. Swap and ?ip rules were suggested in the local search strategy.

(e proposed algorithm is shown in Fig- ure2.(e?vestagesoftheproposedalgorithmaredescribed in the following section. 2.2.1. Convert Search Agent Position to Travel Order with Large Rank Value (LRV). In this section, initializing the search agent position was generated randomly according to JournalofAdvancedTransportation 3 theupperandlowerlimits.(eupperandlowerlimitvalues weresettodeterminethepositionoftheBOAagent.Atthis stage, the search agent’s position was ensured with no re- peating numbers on the same search agent (Figure 3). Furthermore, we proposed the principle of LRV to convert from the position of the search agent (continuous value)totheorderoftravel(discretevalue).LRVisapopular method to convert from continuous value to discrete value in combinatorial problems [52–55]. At this stage, each searchagentpositionvaluewassortedfromthelargestvalue to the smallest one. (e LRV representation is shown in Figure 4.

However, the illustration of Figure 4(b) could not beappliedbecause,inoneposition,thesearchagenthadthe same value (0.43). In other words, the search agent position couldnotbeappliedastheorder/routeofvehiclesvisitedthe same two places. 2.2.2. Tabu

Search Algorithm. In this section, this study proposed that 10% of the initial search agent positions were adjusted to the tabu search (TS) algorithm solution. (e TS algorithm is a popular heuristic algorithm widely used to solve G-VRP. (is study used the TS procedure developed by Poonthalir and Nadarajan [26].

To solve G-VRP, the ?ve main stages [37] of the TS algorithm comprise (1) representation of solution, (2) initial solution, (3) neighborhood solution, (4) tabu list, and (5) criteria for aspiration and dismissal.Figure5representsthestagesoftheTSalgorithm. (e TS algorithm used three neighborhood solution rules. (ese rules were swap (Figure 6), ?ip (Figure 7), and slide (Figure8).Swapisaruleinwhichitswapstwonodes.Flipis the rule of a node exchange by reversing the order of the node. Meanwhile, a slide is an exchange of nodes by shifting their sequences. For the tth iteration to t, the swap and ?ip rules were repeated n(n -1)/2 times. (e slide rule was repeated n2 times in each tth iteration.

For the solution inspection stage, the TS algorithm checked the tabu test by using the tabu list. It was to avoid repetition in ?nding a solution. In the aspiration criteria stage, the TS algorithm comparedthenewsolutionintheiteration ttotheprevious solution in the iteration t -1. (e new solution would be listedasthebestsolutionifithadabetterqualitythanthatof thepreviousone.Furthermore,thestoppingcriteriausedin theTSalgorithmreferredtothenumberofful?llediteration. As mentioned earlier, this study proposed that 10% of search agent positions were adjusted to the TS algorithm’s solution.(erefore,thepositionofthenewsearchagenthad tobeadjustedtotheTSsolution.(isstudyalsosuggesteda new position adjustment procedure. (e illustration of Figure 2: Pseudocode of hybrid butter?y optimization algorithm (HBOA). Figure 1: Pseudocode of butter?y optimization algorithm (BOA).

4 JournalofAdvancedTransportation convertingTSsolutionstothepositionofthesearchagentis exempli?ed in Figure 9. 2.2.3. Update Fragrance. In BOA, each butter?y has a unique fragrance and personality. It is one of the main characteristics that distinguish BOA from any other meta- heuristic algorithms. All BOA behaviors are based on the sensory modality(c), stimulus intensity(I), andexponential strength(a).Fragrance(f)isformulatedasafunctionofthe physicalintensityofthestimulusfromBOA.(efformulais presented as follows: f ? c.Ia, (6) where f is the value of fragrance that changes in every it- eration. (is value shows howstrong thefragranceis feltby other butter?ies. (e butter?y stimulus intensity is formulated as I.

a is the power exponent that depends on the modality.cformulatesthesensorymodality.Valuesofaand c on the used butter?y are in the range [0, 1]. (a) (b) Figure 4: LRV representation. (a) Correct travel sequence and (b) wrong travel sequence. Figure 6: Swap illustration. Figure 3: Initialization of the search agent position. Figure 5: Flowchart of the tabu search algorithm. Figure 7: Flip illustration. Figure 8: Slide illustration. JournalofAdvancedTransportation 5 2.2.4. Movement of Butter?ies. (is section explains the phase of the movement of butter?ies. (ere are two main phases in the basic BOA, namely, the initial phase and the movement of the butter?y phase. In the butter?y phase movement,thebutter?iesmovetheirpositionasmanytimes asthenumberofiterations.Inthisphase,allbutter?iesinthe solution room move to a new position. (en, the ?tness value of each butter?y is evaluated. In each iteration, the ?tness value of all butter?ies is updated. Furthermore, the butter?ies produce fragrance in their calculated position based on equation (6).

Two movements in BOA are the globalsearch phaseand thelocal search phase. In theglobal search phase, butter?ies take steps towards other butter?ies that have the best solution. (e global search phase for butter?ies is represented in equation (7). Meanwhile, the local search phase is shown in equation (8): Xt+1 i ? Xt i + r2g* - Xt i ?? ??fi, (7) where Xt i isthevectorsolution Xi fortheithbutter?yinthe iteration t.rshowsarandomnumber intherange[0, 1]. g* indicates the best solution in the current iteration. (e ith butter?y fragrance is represented by fi. Xt+1 k ? Xt i + r2Xt j - Xt k ?? ??fi. (8) Equation(8)indicatesthelocalbutter?ysearchformula.

Xt j and Xt k arethej-thandk-thbutter?iesfromthesolution room.ristherandomnumberintherange[0,1].Movement ofbutter?iesstopsuntiltheterminationcriteriaaremet.(e stopping criterion used is the maximum number of the achieved iteration. After the movement of butter?ies, the algorithm produces the best solution based on the ?tness values. 2.2.5. Local Search. To improve the BOA performance, this study proposed the local search procedure. Swap and ?ip were the two local search rules chosen to improve the BOA performance.Figure6illustratestheproposedswaprules.In this rule, two positions (nodes) were chosen randomly and exchanged. Another local search rule used was ?ip.

In this rule, two nodes were selected randomly and continued to reversetheorderoftheselectednodes.(isruleisillustrated in Figure 7. In the proposed HBOA, for each iteration t, the swap and ?ip operations were repeated as many as the number of nodes. 2.3. Data and Experimental Procedure 2.3.1. Data. In this study, the data of the number of nodes, coordinates, vehicle capacity, and demand were taken from Gaskell[56]andChristo?desandEilon[57].(eyusedcases with nodes as many as 22 nodes (Table 1) [56], 32 nodes (Table 2) [57], and 50 nodes (Table 3) [57]. Distance (d(Rsr)(Rs+1 r))inrthroutefromnode stonode s +1isbasedon formula d(Rs r)(Rs+1 r) ?

?????????????????????? (Xs - Xs+1)2 + (Ys - Ys+1)2 ?? .

Mean- while, the data of the costs and speed data were obtained fromZhangetal.[7].(efuelcostwas7.3yuan/liter[7].(e carbon emissions were 0.64 yuan/liter [7]. Furthermore, the vehicle usage fee was 80 yuan/hour [7]. (is research employed three categories of vehicle speed (high, medium, and low speed). (e high, medium, and low speeds were 107km/hr, 63km/hr, and 43km/hr, respectively. Nine variations of problems (three nodes and three-speed vari- ations) were carried out in this study. Service time for each customer is 0.1 hours. (e increase in fuel consumption (p) for each additional load M ?50 is 2%. 2.3.2. Experimental Procedure.

(e experiments were designed to determine the e?ect of HBOA (iteration and population) and speed parameters on the distribution cost and computation time. (e experiments were carried out with di?erent parameters. (e parameters included the number of populations and iterations. (e population pa- rameters used three di?erent levels (10, 50, and 100 pop- ulations). (e iteration parameters also employed three levels(10,50,and100iterations).(isstudyusedthesensory modality of 0.01 and power exponent of 0.1 from BOA parameters. Eighty-one trials were designed in this study. Each result of the trial was recorded for cost and compu- tation time. (e HBOA was compared to other algorithms such as BOA[48],TS[7],SA[29],ACO[28],PSO[27],andGA[58].

To compare with several algorithms, this study used one hundred iteration parameters at each vehicle speed in every algorithm. One hundred populations were used in the BOA experiment. Moreover, we used an initial temperature pa- rameter of 1000 and the cooldown factor based on the Kuo [29] formula. One hundred ant populations were adopted fortheACOalgorithm.Onehundredparticlesandaninertia weightof0.5areusedinthePSOalgorithm.100populations, Figure 9: Illustration of tabu search converted solution to the position of search agent. 6 JournalofAdvancedTransportation a crossover probability of 0.8, and a mutation probability of 0.25 were applied in the GA algorithm experiment.

(e performance was measured using relative error percentage (REP) as presented in equation (9). A positive REP showed that the proposed algorithm is better than the other algo- rithms. However, a negative REP showed that the proposed algorithm is not competitive as compared to other algorithms. REP ? costotheralgorithms -costproposedalgorithm costproposedalgorithm ×100%. (9) Besides, this study also compared the computation time in all cases. It was carried out to determine the time e?- ciency of solving G-VRP. (e e?ect of iteration (t) on distribution costs was also analyzed.

(is analysis was carried out in 50 nodes, 100 populations, and 100 iterations in the case

of medium-speed vehicles. Furthermore, all experiments were conducted with the means of Matlab R2014a software on Windows 8 Intel Celeron with x64-64 2GB RAM processor. 3.Results and Discussion
3.1.1eComparisonofVariedParametersandSpeedtowards Costs. Table 4 shows the results obtained from eighty-one experiments with variations of nodes, speed, iteration, and population. It shows that the minimum distribution cost solution is produced in the population parameters and high iterations.

(erefore, overall, these results suggest that population parameters and signi?cant iterations e?ectively minimize distribution costs for G-VRPs . It is interesting to note that with successive increases in both iteration and population, the distribution cost declined. It shows that the number of iterations and large population minimized the total costs. Besides, the speed of the vehicle a?ects the total distributioncost.Lowspeedrequireshighdistributioncosts. Average distribution costs are produced from medium- speed vehicles. However, high speed results in small dis- tribution costs.

(erefore, this result shows that the high speed reduced the total costs in the case of G-VRP. Overall, these ?ndings are consistent with the ?ndings reported by Zhang et al. [7]. Overall, these ?ndings are consistent with Zhang et al. [7], which indicate variation, speed, iteration, and population e?ect in the distribution cost. (e results of the iteration (t) e?ect on the distribution costs are shown in Figure 10. It illustrates the algorithm ef- fectivenessthatcanbeseenfromtheimpactofiterationonthe distribution costs. From the data in Figure 10, the cost of distribution decreased as the iteration was added.

Besides, the e?ect of iteration on the distribution costs shows that the convergence curve on HBOA is better than other algorithms. (e HBOA produces better total distribution in each iteration compared to BOA [48], TS [7], SA [29], ACO [28], PSO [27], and GA [58]. (e results of this study indicate that the pro- posed algorithm is e?ectively used to solve the G-VRP. 3.2.1eComparisonofVariedParametersandSpeedtowards Computation Time. Table 5 illustrates the experimental comparison between the varied parameters and speed to- wards the computation time. Small populations and itera- tions result in less computation time.

However, large populations and iterations require considerable Table 1: Problem of 22 nodes. Node Coordinate Demand X Y Depot 266 235 0 1 295 272 125 2 301 258 84 3 309 260 60 4 217 274 500 5 218 278 300 6 282 267 175 7 242 249 350 8 230 262 150 9 249 268 1100 10 256 267 4100 11 265 257 225 12 267 242 300 13 259 265 250 14 315 233 500 15 329 252 150 16 318 252 100 17 329 224 250 18 267 213 120 19 275 192 600 20 303 201 500 21 208 217 175 22 326 181 75 Capacity: 4500.

computationtime.(erefore,themostapparent?ndingthat emergesfromtheanalysisisthatthenumberofiterationand largepopulationincreasedthecomputationaltime.Another important ?nding is that di?erent vehicle speed did not appear to a?ect the computation time.

Low speed, medium speed, and high speed produce relatively the same com- putation time. Furthermore, the number of nodes a?ected the com- putationaltime.Caseswith22nodesneedlittlecomputation time. However, in the case of 50 nodes, the computation time required is considerable. (erefore, the experimental results show that the number of nodes increased the computing time. (e comparison between the proposed algorithm's computation time and several other algorithms inthemediumspeedispresentedinFigure11.Itcanbeseen that the proposed algorithm provided a relatively higher computation time as compared to several other algorithms, suchasBOA[48],TS[7],SA[29],ACO[28],PSO[27],and GA [58]. Besides, the addition of nodes also increased the time signi?cantly.

(erefore, it can be concluded that the number of nodes has a signi?cant e?ect on the computa- tional time. It con?rms the ?ndings of Oesterle and Bauernhansl[21]andBraekersetal.[23],statingthatVRPis an NP-hard problem. Based on these results, further re- search is expected to be carried out to reduce the compu- tationtimesothatthealgorithmmaybecomemoree?cient. Although HBOA produces considerable computation time, the resulting total distribution costs are minimal. (e small total cost of distribution is one of the most critical decisions in operations management. Decision-makers prefer to choose decisions with minimal total distribution costs because they provide bene?ts.

Conversely, decision- makerspaylessattentiontocomputationtimebecauseshort computing time does not guarantee a minimal total dis- tribution cost. 3.3. 1e Comparison of Algorithms. Table 6 shows the comparison of the REP values between the proposed al- gorithm and other algorithms. As shown in Figure 3, the REP values (basedon equation (9)) of BOA [48], TS [7], SA [29], ACO [28], PSO[27], and GA[58] were 9%,46%, 27%, 31%, 28%, and 23%, respectively.

(e positive values from REPindicatethattheproposedalgorithmismoree?ectivein Table 2: Problem of 32 nodes. Node Coordinate Demand X Y Depot 292 425 0 1 298 427 700 2 309 445 400 3 307 464 400 4 336 475 1200 5 320 439 40 6 321 437 80 7 322 437 2000 8 323 433 900 9 324 433 600 10 323 429 750 11 314 435 1500 12 311 442 150 13 304 427 250 14 293 421 1600 15 296 418 450 16 261 384 700 17 297 410 550 18 315 407 650 19 314 406 200 20 321 391 400 21 321 398 300 22 314 394 1300 23 313 378 700 24 304

382 750 25 295 402 1400 26 283 406 4000 27 279 399 600 28 271 401 1000 29 264 414 500 30 277 439 2500 31 290 434 1700 32 319 433 1100 Capacity: 8000. 8 JournalofAdvancedTransportation solvingG-VRP.Dataprocessingresultsshowthatthereisno REP average, which results in a negative REP value in the comparison algorithm.

(e order of the algorithm that has thesmallesttolargestpositiveREPisBOA[48],GA[58],SA [29], PSO [27], ACO [28], and TS [7]. (us, the ?ndings con?rm that HBOA is more competitive as compared to other algorithms. In other words, HBOA can signi?cantly improve the quality of the G-VRP solution. (e experimental results show that the HBOA can produce a minimal total distribution cost. (is result is an Table 3: Problem of 50 nodes. Node Coordinate Demand X Y Depot 30 40 0 1 37 52 7 2 49 49 30 3 52 64 16 4 20 26 9 5 40 30 21 6 21 47 15 7 17 63 19 8 31 62 23 9 52 33 11 10 51 21 5 11 42 41 19 12 31 32 29 13 5 25 23 14 12 42 21 15 36 16 10 16 52 41 15 17 27 23 3 18 17 33 41 19 13 13 9 20 57 58 28 21 62 42 8 22 42 57 8 23 16 57 16 24 8 52 10 25 7 38 28 26 27 68 7 27 30 48 15 28 43 67 14 29 58 48 6 30 58 27 19 31 37 69 11 32 38 46 12 33 46 10 23 34 61 33 26 35 62 63 17 36 63 69 6 37 32 22 9 38 45 35 15 39 59 15 14 40 5 6 7 41 10 17 27 42 21 10 13 43 5 64 11 44 30 15 16 45 39 10 10 46 32 39 5 47 25 32 25 48 25 55 17 49 48 28 18 50 56 37 10 Capacity: 80. JournalofAdvancedTransportation 9 Figure 10: E?ects of iteration (t) of each algorithm on distribution cost in the medium speed.

Table 4: Results of the comparison between varied parameter and speed towards costs (yuan). Vr Iteration High speed Medium speed Low speed Population Population Population 10 50 100 10 50 100 10 50 100 22 10 2814.4 2813.1 2385.9 2971.5 2967.7 2654 3949.6 3621.7 3442 50 2786.3 2666.9 2403.5 2909.3 2587.5 2518.5 3739.3 3577 3180.5 100 2211.8 2161.0 2020.7 2857.2 2423.6 2300.9 3511.1 3065.7 2808 32 10 3392.6 2806.5 2687.4 3955 3777 3261.5 4487.9 3889.5 3753.8 50 2955.9 2732.6 2412.9 3627.3 3295.9 3068.5 4171.3 3657.5 3049.6 100 2922.1 2647.3 2399.6 3116.6 2836.3 2614.5 3442.3 2922.2 2998.3 50 10 7629.0 7398.3 6950.1 9127 8528.5 8381.7 11391 11078 10095 50 7090.3 7002.6 6289.5 9090 8321.3 7987 10991 9806 9066 100 6876.9 6614.3 6097.2 8883 8193 7327.4

10423 9333 8836 10 JournalofAdvancedTransportation Figure 11: Comparison between the computation time of the proposed algorithm and several other algorithms in the medium speed. Table 6: Comparison of distribution cost and the relative error percentage (REP) values between the proposed algorithm and other algorithms. Speed Vr Distribution cost (yuan) REP (%) HBOA BOA TS SA ACO PSO GA BOA TS SA ACO PSO GA High 22 2020.7 2161.0 2990.8 2355.1 2572.4 2416 2347.6 7 48 17 27 20 16 32 2399.6 2647.3 3567.6 3117 3107.1 3100.4 3009.3 10 49 30 29 29 25 50 6097.2 6614.3 8694.6 7868.5 7713.7 7707 7515.9 8 43 29 27 26 23 Medium 22 2300.9 2423.6 3444.7 2870.8

3240.7 2988.1

2675 5 50 25 41 30 16 32 2614.5 2836.3 4021.5 3720.8 3775.4 3768.6 3686.2 8 54 42 44 44 41 50 7327.4 7987.0 9148.5 8472.3 8382 8375.2 8292.8 9 25 16 14 14 13 Low 22 2808 3065.7 4299.1 3650.4 3791.6 3757.3 3585.2 9 53 30 35 34 28 32 2998.3 3657.5 4875.9 4279.4 4326.3 4289.2 4193.1 22 63 43 44 43 40 50 8836 9333.0 11779 9880.6 10667.5 9972.1 9553 6 33 12 21 13 8 Average 9 46 27 31 28 23 Table 5: Results of the comparison between varied parameters and speed towards computation time (seconds). Vr Iteration High speed Medium speed Low speed Population Population Population 10 50 100 10 50 100 10 50 100 22 10 21.68 110.05 305.19 21.76 110.17 305.51 21.76 110.41 305.96 50 111.79 512.59 707.73 113.37 513.59 707.91 114.71 515.14 709.35 100 205.34 1139.50 1334.64 206.36 1140.88 1336.20 206.45 1141.16 1337.93 32 10 26.98 116.47 312.67 27.05 116.58 312.98 27.06 116.83 313.44 50 143.18 546.20 747.43 144.76 547.20 747.61 146.09 548.74 749.05 100 267.98 1212.40 1413.01 269.00 1213.78 1414.57 269.09 1214.06 1416.30 50 10 32.28 122.88 320.14 32.35 123.00 320.46 32.36 123.25 320.91 50 174.57 579.81 787.13 176.15 580.81 787.31 177.48 582.35 788.75 100 330.62 1285.30 1491.37 331.64 1286.68 1492.93 331.73 1286.96 1494.66 JournalofAdvancedTransportation 11 essential strength of the HBO algorithm. Unfortunately, there is a contradiction in the resulting computation time. (e HBOA requires a relatively high computation time compared to other algorithms.

However, in large nodes (50 nodes), the resulting computation time can compete with the TS algorithm. (e high computation time of HBOA is causedbythelargecomputationtimeTSalgorithmthatused toreplace10%ofsearchagentsBOA.Furthermore,theswap and ?ip procedure require repetition in each iteration, re- quiring a large computation time. In addition, this study usedthesensorymodalityof0.01andpowerexponentof0.1 from BOA parameters. In future investigations, it may be possible to use di?erent sensory modality parameters and power exponent to test the quality of the solution (total distribution cost and computation time). 4.Conclusion (is study discussed the green vehicle routing problem (G- VRP). (e main objective of this research was to develop HBOA to minimize the distribution costs on G-VRP. (is researchsuccessfullydevelopedHBOAtosolveG-VRP.(e HBOA is proposed based on the BOA, which is improved with TS and local search procedures such as swap and ?ip. (e experimental results show that the increase in pop- ulation parameters and the HBOA iteration can minimize the total distribution costs.

To test the algorithm perfor- mance, this algorithm was compared with several proce- dures. (e experimental results proved that the HBOA produced a minimum total distribution cost than other algorithms. (erefore, the proposed algorithm is more competitive than the comparison algorithm. In the com- putation time, the results showed that the number of nodes signi?cantly a?ects the computational time in HBOA. However, the proposed algorithm provides a relatively higher computation time compared to several other algo- rithms. (erefore, further research needs to be done to reduce the computation time so that the algorithm may become more e?cient.

Moreover, sensory modality and power exponent parameters need to be tested at various values. Future research should also aim at developing al- gorithms and problems with dynamic vehicle speeds, multidepot (distribution centers), and perishable products. Data Availability Alldatageneratedoranalyzedduringthisstudyareincluded in this article. Conflicts of Interest (e authors declare that they have no con?icts of interest. Acknowledgments (e authors would like to thank the Directorate of the Research University of Muhammadiyah Malang for sup- porting the research and would also like to extend their gratitude to the Department of Industrial Engineering Optimization Laboratory for providing facilities. References [1] G. Poonthalir and R. Nadarajan, “Green vehicle routing problem with queues,” Expert Systems with Applications, vol. 138, Article ID 112823, 2019. [2] N.Rezaei,S.Ebrahimnejad,A.Moosavi,andA.Nikfarjam,“A greenvehicleroutingproblemwithtimewindowsconsidering the heterogeneous ?eet of vehicles: two metaheuristic algo- rithms,” European Journal of Industrial Engineering, vol. 13, pp. 507–535, 2019. [3] M.Syafrizal,B.Sugiarto,S.S.Moersidik,J.Fortin,N.Hamani, and E. Bretagne, “Dynamic vehicle emissions reduction with technical and behavioral approach,” International Journal of Technology, vol. 7, no. 5, pp. 871–880, 2016. [4] M. F. Ibrahim, M. M. Putri, and D. M.

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