

A Modified Artificial Bee Colony Algorithm with a Load-Dependent Fuel Model for the Bi-Objective Green Capacitated Vehicle Routing Problem

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Abstract: The capacitated vehicle routing problem (CVRP) conventionally minimizes total travel distance, yet a distance-minimal route need not minimize fuel. As fuel rate rises with payload, so demand distribution across arcs matters even at fixed total distance. To address this gap, this study formulates a bi-objective green CVRP minimizing total distance and fuel under an arc-wise fuel rate that increases linearly with vehicle load, solved by an improved artificial bee colony algorithm (IABC). The IABC combines a scattered construction-based population, a dual-group employed-bee neighbourhood, and a forward-insertion scout, with an iteration-dependent capacity penalty in a normalized weighted-sum fitness, one tunable weight traces the distance–fuel trade-off. Across twelve Augerat instances (twelve runs each), the IABC matches the best-known distance on four, reduces mean fuel by 3.50% versus the Clarke–Wright savings baseline, and yields only capacity-feasible routes. On P-n16-k8, a two-stage lexicographic mixed-integer program certifies the distance-then-fuel optimum (450 km, 116.73 L), attained exactly by the IABC. Non-parametric tests rank the IABC above standard ABC, a genetic algorithm, and the savings heuristic on both objectives. Ablation attributes the gain to the load-aware objective, and the saving persists under $\pm 20\%$ fuel-coefficient perturbations, supporting robust green route planning.

Keywords: Artificial bee colony; Bi-objective optimization; Capacitated vehicle routing problem; Fuel consumption; Green vehicle routing.

1. INTRODUCTION

Road freight is a major source of transport-related energy use and greenhouse-gas emissions. Routing decisions determine the distance travelled and, through the evolving payload, the fuel consumed on every arc. The capacitated vehicle routing problem (CVRP), introduced by Dantzig and Ramser [1], asks for minimum-distance routes for a capacity-constrained fleet serving customers from a single depot. As an nondeterministic polynomial-time (NP)-hard combinatorial problem, it has been addressed by exact methods, classical heuristics, and metaheuristics [2, 3].

The conventional CVRP objective equates shorter routes with greener routes. Fuel consumption depends jointly on arc length and on payload that is a truck burns more fuel per kilometer when heavily laden. Pollution-routing and green-vehicle-routing studies therefore embed load-dependent fuel models into routing [4-6] and repeatedly observe that minimum distance and minimum fuel do not coincide [7]. A distance-optimal plan can thus be suboptimal for emissions.

Among metaheuristics, the artificial bee colony (ABC) of Karaboga [8] is attractive for its simplicity and few control parameters, and discrete ABC schemes for the CVRP follow Szeto *et al.* [9]. Yet ABC was designed for continuous optimization. Its application to a capacity-constrained, combinatorial, bi-objective problem requires dedicated encoding, neighbourhood operators, initialization, and feasibility handling. Three gaps remain: (1) ABC-based CVRP studies almost universally optimize distance alone, and a load-dependent fuel term has rarely entered the bee fitness; (2) The standard single-customer neighbourhood and random initialization are prone to premature convergence, while feasibility is enforced through a fixed, blunt penalty; (3) When two objectives are scalarized, the weight is rarely normalized, and the distance-fuel trade-off frontier is seldom characterized.

This study addresses these gaps by integrating a load-dependent fuel model into a modified discrete ABC for the bi-objective green CVRP. We formulate a green CVRP minimizing distance and fuel through a normalized, scale-free weighted-sum scalarization evaluated arc by arc, and validate it with a two-stage lexicographic mixed-integer linear program (MILP) certifying the distance-then-fuel optimum on a small instance. We then propose an improved ABC (IABC) with scattered construction-based initialization, a dual-group employed-bee neighbourhood that adds a simultaneous two-pair (four-customer) exchange to single-customer moves, a forward-insertion scout, and an iteration-dependent capacity penalty. Each

component is isolated in an ablation study. We close by characterizing the distance-fuel frontier through weight-sensitivity and robustness checks, reporting repeated-run statistics, non-parametric tests, effect sizes, and non-significant findings.

The distinction from the closest existing works is explicit. Unlike the bee-based CVRP methods of Szeto *et al.* [9], Karaboga and Basturk [11], and Ji and Wu [12], which optimize distance alone, the IABC drives an arc-wise load-dependent fuel objective and returns a tunable distance–fuel compromise. Unlike the adaptive bee algorithm of Guo *et al.* [13], which serves a single-objective low-carbon problem for electric industrial vehicles, it targets conventional diesel fuel under two objectives on shared benchmarks with statistical validation. Unlike the Pareto-based green algorithms [18–21], which maintain an approximation set, the weighted-sum IABC yields one solution per preference setting and attains an exactly certified point on the small instance. Relative to the exact CO₂-minimizing model of Boonmee *et al.* [26], it handles instances with up to 80 customers within a few seconds.

Section 2 reviews routing approaches, Section 3 formulates the bi-objective green CVRP, Section 4 presents the IABC, Section 5 reports experiments, Section 6 discusses implications and Section 7 concludes with limitations and future work.

2. LITERATURE REVIEW

2.1 Exact Methods for the CVRP

The CVRP [1] asks for a minimum-cost set of routes for a capacity-constrained fleet serving a single depot [10]. As an NP-hard problem, it has motivated integer linear programming, branch-and-bound, branch-and-cut, branch-and-price-and-cut, and set-partitioning formulations [2], which certify optimality by partitioning the solution space but whose cost grows combinatorially with instance size. Exact methods therefore remain practical only for small and medium instances [3], so approximate methods are needed for larger problems.

2.2 Classical Construction and Improvement Heuristics

Constructive heuristics, led by the Clarke-Wright savings algorithm and nearest-neighbour, insertion, and scanning procedures, build feasible routes incrementally [10]. Improvement heuristics then refine an incumbent through intra-route operators (2-opt, Or-opt) and inter-route operators (2-opt*, relocate, swap, cross exchange). They are fast but myopic and tend to settle in the first local optimum reached [2]. They mainly supply the route-splitting and neighbourhood moves a discrete swarm must reuse to preserve capacity feasibility.

2.3 Metaheuristics and the Artificial Bee Colony for Vehicle Routing

Metaheuristics combine global exploration with local exploitation. CVRP variants include genetic algorithm (GA), differential evolution, ant colony, particle swarm optimization (PSO), simulated annealing (SA), tabu search, variable neighbourhood search (VNS), and ABC [3]. Introduced by Karaboga [8], and Karaboga and Basturk [11], ABC is valued for its simplicity and few parameters. Szeto *et al.* [9] gave one of the first discrete ABC schemes for the CVRP. Later work extended it to time-dependent travel times [12], hybridised it with SA, and redesigned it with adaptive phases for electric industrial vehicles [13]. Yet, standard ABC was conceived for continuous optimization and is prone to premature convergence. On a discrete, capacity-constrained, bi-objective problem, it needs dedicated encoding, diversified initialization, structured operators, and explicit feasibility repair, which the literature addresses only partially.

2.4 Green Vehicle Routing and Load-Dependent Fuel and Emission Modelling

A parallel stream questions whether minimizing distance is adequate. Figliozzi [14] treats fuel and emissions as primary objectives. Bektaş and Laporte [4] formulate the pollution-routing problem (PRP) around the comprehensive modal emission model (CMEM) model. Xiao *et al.* [5] introduce a load-dependent fuel consumption rate (FCR) into the CVRP and report fuel savings near 5% even when distance barely changes. Kopfer and Schönberger [15] and Zhang *et al.* [16] show that payload-dependent fuel justifies differentiated fleets and multi-cost routing, while Pradenas *et al.* [7] observe that emissions can fall while distance slightly rises. Recent reviews [2, 3, 6, 17] conclude that fuel and CO₂ depend jointly on arc length and payload, so a distance-only objective mis-specifies environmental cost. Two recent studies also take an environmental perspective on routing. Boonmee *et al.* [26] minimize CO₂ emissions in a special capacitated vehicle routing problem (VRP) with an exact Gurobi model on a real beverage-distribution case, and Morsidi [27] proposes an intensification-enhanced adaptive hybrid memetic algorithm for the multi-depot VRP with time windows.

2.5 Bi- and Multi-Objective Green Routing: Scalarization versus Pareto

Because economic and environmental goals diverge, green routing is intrinsically multi-objective. Pareto methods, commonly non-dominated sorting genetic algorithm II (NSGA-II) [18] and multi-objective PSO, return a trade-off front. Kumar *et al.* [19] couple self-learning PSO with NSGA-II for a cost-versus-emissions PRP. Xu *et al.* [20] devise an adaptive NSGA-II for a time-varying soft-time-window green CVRP. Fatemi-Anaraki *et al.* [21] hybridise *k*-means, GA, and NSGA-II for a bi-objective green delivery-and-pick-up problem. Scalarization aggregates normalized objectives into a single compromise, easier to embed in a local-search fitness and to reproduce statistically. Both families confirm that shortest routes need not burn least fuel, but weighted-sum studies rarely normalize weights or trace the frontier, while Pareto studies are computationally expensive. The present study closes that gap with systematic weight-sensitivity analysis.

2.6 Benchmark Practice, Synthesis, and Positioning

Empirical work in this field relies on shared benchmarks. The 73 Augerat [22] A/B/P instances, together with Eilon and

Christofides, supply known best distances and support repeated-run gap, runtime, and Friedman/Wilcoxon comparisons. The Section 1 gaps are confirmed and refined by this literature. ABC-based CVRP studies almost universally optimize distance alone, load-dependent green objectives are mainly solved with GA, tabu, SA, PSO, or VNS rather than ABC on standard CVRP instances. The closest adaptive bee study [13] targeting electric industrial vehicles, a load-sensitive fuel term has rarely entered the bee fitness with capacity handling and the distance-fuel frontier remains under-characterized. The present model integrates a load-dependent fuel term into a dual-group, feasibility-aware discrete ABC and exposes the weight-dependent compromise on standard Augerat benchmarks.

3. MATHEMATICAL FORMULATION OF THE BI-OBJECTIVE GREEN CVRP

3.1 Graph, Assumptions, and Sets

The green CVRP is defined on a complete undirected graph $G = (V, E)$. The node set $V = \{0, 1, \dots, n\}$ contains one depot (node 0) and n customers, and $V' = V \setminus \{0\}$ denotes the customer set. A homogeneous fleet K of vehicles, each with capacity Q , is stationed at the depot. Customer i has a non-negative demand q_i , with $q_0 = 0$, and d_{ij} denotes the Euclidean distance between nodes i and j , with $d_{ij} = d_{ji}$ and $d_{ii} = 0$. A route is a sequence $0 \rightarrow i_1 \rightarrow \dots \rightarrow i_r \rightarrow 0$. A feasible solution satisfies the following criteria: (1) each customer is visited exactly once by exactly one vehicle; (2) every route starts and ends at the depot; (3) the cumulative demand on any route does not exceed Q ; (4) both total distance and total fuel consumption (and hence CO₂ emissions) are minimized.

Distances follow the CVRPLIB EUC_2D convention, $d_{ij} = \text{round}(\sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2})$, where X_i and Y_i are the planar coordinates of node i , so that distances are integers comparable to published best-known solutions. The decision variables, the fuel parameters, and the objective weights of the model are introduced in the sections where they are first used (Sections 3.2-3.4).

3.2 The Distance Objective and Routing Constraints

The binary decision variable x_{ij}^k equals 1 if vehicle k travels directly from node i to node j and 0 otherwise. The auxiliary payload variable f_{ij}^k records the demand remaining on board vehicle k while traversing arc (i, j) . For the exact model, a cumulative-load variable u_i additionally eliminates subtours. The first objective minimizes the total distance travelled over all routes:

$$\text{Min} Z_1 = \sum_{k \in K} \sum_{i, j \in V} d_{ij} x_{ij}^k \quad (1)$$

subject to the classical CVRP constraints. Each customer is served exactly once:

$$\sum_{k \in K} \sum_{i, j \in V} d_{ij} x_{ij}^k = 1, \quad \text{for all } j \in V' \quad (2)$$

Each vehicle that is used leaves the depot and returns to it at most once:

$$\sum_{j \in V'} x_{0j}^k = \sum_{i \in V'} x_{i0}^k \leq 1, \quad \text{for all } k \in K \quad (3)$$

The flow conservation holds at every customer node:

$$\sum_{i \in V} x_{ih}^k - \sum_{j \in V} x_{hj}^k = 0, \quad \text{for all } h \in V', k \in K \quad (4)$$

The cumulative demand carried by any vehicle cannot exceed its capacity:

$$\sum_{i, j \in V} q_i x_{ij}^k \leq Q, \quad \text{for all } k \in K \quad (5)$$

and the payload on any arc cannot exceed the capacity of the traversing vehicle, while payload balance at each customer requires the inflow minus the outflow of payload to equal that customer's demand:

$$0 \leq f_{ij}^k \leq Q x_{ij}^k, \quad \text{for all } i, j \in V, k \in K \quad (5a)$$

$$\sum_{i \in V} f_{ih}^k - \sum_{j \in V} f_{hj}^k = q_h, \quad \text{for all } h \in V', k \in K \quad (5b)$$

and the decision variables are binary:

$$x_{ij}^k \in \{0, 1\}, \quad \text{for all } i, j \in V, k \in K \quad (6)$$

Equations (2) and (4) impose single service and degree balance at every node. They do not by themselves exclude disconnected subtours. The exact model additionally imposes the single-commodity subtour-elimination constraints $u_i - u_j +$

$Qx_{ij}^k \leq Q - q_j$. Constraints (5a) and (5b) bound the payload on each arc by the capacity of the traversing vehicle and balance the payload flow at every customer. Equation (5) is the capacity restriction that the penalty mechanism of Section 4.5 enforces during the stochastic search. In the metaheuristic, single service follows from the permutation encoding and route splitting, and the same capacity and payload conditions are enforced implicitly by the penalty of Section 4.5.

3.3 Load-Dependent Fuel Consumption and Carbon Emissions

The fuel parameters are the empty (curb-weight) fuel rate ρ_0 , the fully loaded rate ρ^* , and the fuel-to-CO₂ conversion factor η , expressed in kg-CO₂ per liter. A vehicle leaves the depot carrying the total demand of its route and unloads q_i at each customer, so the payload declines along the route and equals zero on the empty return leg. Following the linearized comprehensive modal emissions/fuel consumption rate model [4, 5], the fuel rate per kilometer increases linearly with the load fraction:

$$\rho(f) = \rho_0 + (\rho^* - \rho_0) \frac{f}{Q} \quad (7)$$

and the fuel consumed on arc (i, j) is the arc length times the prevailing rate:

$$FC_{ij} = d_{ij} \rho(f_{ij}^k) \quad (8)$$

The second objective minimizes total fuel, and the associated carbon emissions are proportional to fuel through the conversion factor η :

$$\text{Min} Z_2 = \sum_{k \in K} \sum_{i,j \in V} FC_{ij}, E_{CO_2} = \eta Z_2 \quad (9)$$

Because the fuel rate rises with payload, routing the heaviest loads over the shortest arcs reduces aggregate fuel even when the total distance is unchanged. This divergence between distance and fuel optima is what the bi-objective model exploits. We adopt literature values for a light/medium diesel truck, $\rho_0 = 0.185$ L/km, $\rho^* = 1$ L/km, and $\eta = 2.63$ kg-CO₂/L, consistent with the FCR table of Xiao *et al.* [5]. CO₂ is the dominant greenhouse gas emitted by diesel combustion and is directly proportional to fuel under complete combustion, so fuel serves as the environmental measure and the associated CO₂ is reported. Other greenhouse gases such as CH₄ and N₂O are not considered, and this simplification is stated as a limitation in Section 6.4.

3.4 Normalized Weighted Bi-Objective Fitness

The objective weights w_1 and $w_2 = 1 - w_1$ express the relative importance of the distance and fuel objectives and sum to one. To combine the two objectives within a single fitness while avoiding the dominance of their different physical units, each objective is normalized by the best single-objective value Z_1^0 and Z_2^0 obtained during initialization, and a capacity penalty $R(x) = R(cv(x), t)$ defined in Section 4.5 is added:

$$\text{Min} F(x) = w_1 \frac{Z_1}{Z_1^0} + w_2 \frac{Z_2}{Z_2^0} + R(x) \quad (10)$$

The main experiments set the balanced weight $w_1 = 0.5$, whereas w_1 in $\{0, 0.25, 0.5, 0.75, 1\}$ is swept in Section 5.6 to trace the distance-fuel frontier. Weighted-sum scalarization is used for its transparency and statistical reproducibility. The swept non-dominated solutions approximate the supported (convex) portion of the Pareto front, and we do not claim a complete Pareto set (Section 6.4). Both normalized terms are dimensionless and of order one, which is the ideal-point normalization commonly applied in weighted-sum multi-objective optimization when the objectives carry different physical units, e.g., distance in kilometers and fuel in liters [25]. Without this step, w_1 would not express a true preference between the two objectives. The penalty term $R(x)$ in Equation (10) is not assigned a weight because it encodes constraint violation rather than preference. It enters the fitness as an additive term, it vanishes for feasible solutions, and its iteration-dependent coefficient (Section 4.5) steers the search toward the feasible region without biasing the economic-environmental trade-off.

4. THE IMPROVED ARTIFICIAL BEE COLONY ALGORITHM

4.1 Overview, Encoding, and Route Splitting

ABC mimics honey-bee foraging through three groups namely employed, onlooker, and scout bees, where each food source is a candidate solution and its nectar is its quality. A solution is encoded as a permutation of the n customer indices. The depot is fixed and the permutation is split into capacity-feasible routes by a greedy procedure. Customers are appended in order and a new route opens when adding the next would exceed Q . Arc distances follow EUC_2D and the green evaluation of Section 3.3 is layered on top.

4.2 Scattered Initialization

Standard ABC draws the initial population from uniformly random permutations, diverse but often far from efficient. The IABC instead builds a scattered population: one source from Clarke-Wright savings, one from nearest-neighbour, and the rest mixing randomized nearest-neighbour tours with random permutations. Every candidate is repaired, evaluated, and thenumber of population (nPop) best are retained, treating two sources as distinct unless their route sets are identical.

4.3 Dual-Group Employed Bees

Each employed bee explores the neighbourhood of its food source, generating up to three candidates and retaining the best greedily. The IABC uses a dual-group operator set. Group 1 (G1) performs single-customer moves: a relocate reinserts one customer at the best position, and a swap exchanges two customers within or between routes (overload penalized per Section 4.5). Group 2 (G2) is a coarser perturbation exchanging two disjoint pairs of customers in one step. A candidate is drawn from G2 with probability 0.35 and from G1 otherwise. After each move routes are repaired and the weighted fitness recomputed. The two-pair move reaches configurations that single swaps approach only slowly.

4.4 Onlooker Bees and Roulette-Wheel Selection

Onlooker bees do not explore every source equally. From the penalized, minimized fitness F_i , a non-negative nectar value $fit_i = 1/(1 + \max\{0, F_i\})$ is formed, and source i is selected with roulette probability $p_i = fit_i / \sum_l fit_l$. Exactly $nPop$ selections are drawn. The same G1/G2 neighbourhood and greedy acceptance used by employed bees are then applied to the selected source. The wheel concentrates exploitation on low-distance, low-food, capacity-feasible food sources while retaining a non-zero probability of exploring weaker ones.

4.5 Forward-Insertion Scouts and the Dynamic Capacity Penalty

A food source that fails to improve for limit consecutive trials is abandoned, with $limit = \text{round}(p_{val} \cdot n \cdot nPop)$ and $p_{val} = 0.065$. The standard ABC reinitializes an abandoned source from a random permutation, the IABC applies a forward-insertion perturbation: two distinct customers c_i and c_j are sampled and c_i is relocated to the position immediately following c_j , producing a structured rather than random restart that helps the search escape local optima without discarding all accumulated structure.

Capacity violations are handled inside the normalized fitness through the relative overload cv/Q , where cv is the total overload over routes. A feasible solution incurs no penalty, $R = 0$. The proposed dynamic penalty is

$$R(cv, t) = 10^{(0.5+3.5\lambda)} \cdot \left(\frac{cv}{Q}\right), \lambda = \min\left\{1, \frac{t}{T}\right\} \quad (11)$$

where t is the current iteration and T the maximum. The coefficient grows from about 3 at initialization to 10^4 on termination, so the search may cross mildly infeasible regions early but is pushed toward feasibility as it converges. The StdABC baseline instead uses a fixed prohibitive coefficient $R = 10^4 \cdot (Cv/Q)$. The two are compared in Sections 5.4 and 5.7. Only solutions with $Cv = 0$ enter the best-so-far archive, so that every reported result is feasible.

4.6 Fuel-Aware Evaluation, Local Search, and Complete Procedure

The payload on every arc is obtained by recursion. For each route, the remaining demand starts at the route total, the rate uses remaining/ Q on the arc leaving the current node, and served demand is subtracted. The empty return leg is charged at the empty rate. Summing over arcs gives Z_2 , then the normalized weighted fitness (Equation (10)) with penalty (Equation (11)) is computed. A single intra-route 2-opt pass is applied to the best feasible incumbent after each iteration and a full 2-opt polish at termination. The same terminal local search is given to all stochastic algorithms, isolating global-search mechanisms rather than local-search presence.

5. COMPUTATIONAL RESULTS

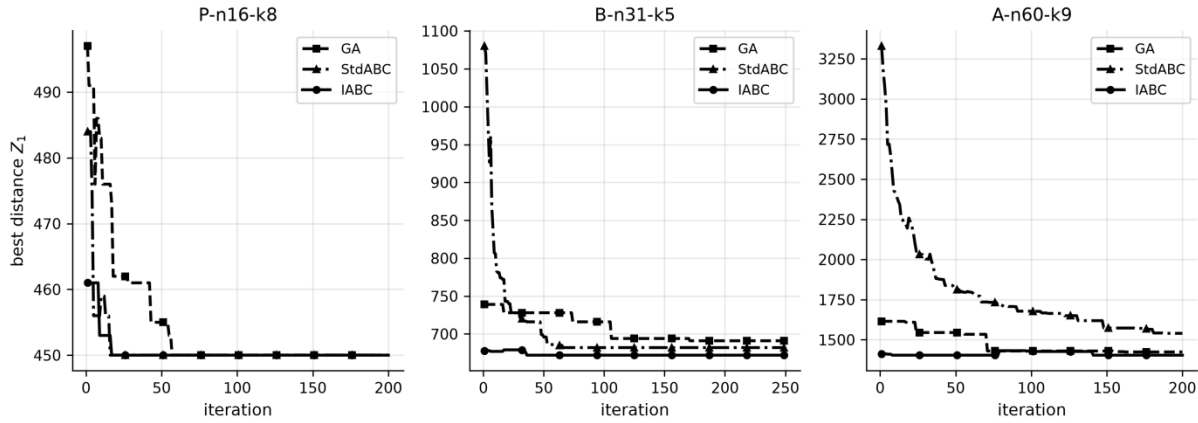
5.1 Experimental Setup and Benchmark Instances

Experiments cover twelve Augerat [22] CVRPLIB instances spanning 15 to 79 customers across the P, B, and A sets (Table 1), all with published best known solution (BKS). The three largest (A-n48-k7, A-n60-k9, A-n80-k10) probe scalability and distances follow EUC_2D. The IABC is compared against three baselines under the same budget: the deterministic Clarke-Wright savings heuristic, a permutation GA seeded with savings and nearest-neighbour (size-3 tournament, order crossover, swap and inversion mutation at 0.25, elitism), and a StdABC with random initialization, single-customer neighbourhood, random-restart scouts, and a fixed penalty.

All metaheuristics minimize the same weighted fitness: Equation (10), $w_1 = 0.5$, use the same tiered budget (population 26-30, 160-250 iterations), the same seeds, and the same terminal local search. Only IABC adds in-search 2-opt. The baselines are tuned to a strong level: the GA reaches BKS on P-n16-k8 (450) and B-n45-k5 (751), and StdABC on P-n16-k8 (450), B-n31-k5 (672), and A-n32-k5 (784). The main experiment uses 12 independent runs per algorithm per instance, as recommended by Derrac et al. [23] for non-parametric comparison. Metrics include best/mean/SD of Z_1 , mean Z_2 and CO_2 , E_{CO_2} , gap to BKS, fuel saving vs savings, feasibility rate, and central processing unit (CPU). Significance uses Friedman, Holm-corrected Wilcoxon signed-rank, and rank-biserial effect sizes [23, 24]. The Nemenyi critical difference (CD) is shown at $k = 4, N = 12$. These three baselines deliberately span the three families most used in the ABC-CVRP and green-routing literature: a classical construction heuristic (Clarke-Wright savings), an established population-based metaheuristic (GA), and the direct ancestor of the proposed method (StdABC). Extending the comparison to PSO and differential evolution is noted as future work (Section 6.4). All algorithms were implemented in Python 3 with NumPy. The exact MILPs of Section 5.7 were solved with the HiGHS high-performance optimization solver, available through SciPy's milp interface (SciPy 1.18.1 with bundled HiGHS), using the default mip_rel_gap of 0 and default feasibility tolerances with a 120 s time limit, and the P-n16-k8 instances solve in far less than that limit. Metaheuristic runs use the fixed seed set 0–11, and the G2 probability of the IABC is 0.35 (Section 4.3).

Table 1. Characteristics of the twelve Augerat benchmark instances.

Instance	Customers, n	Vehicles, k	Capacity, Q	Total demand	BKS distance
P-n16-k8	15	8	35	246	450
B-n31-k5	30	5	100	412	672
A-n32-k5	31	5	100	410	784
A-n34-k5	33	5	100	460	778
B-n35-k5	34	5	100	437	955
A-n37-k6	36	6	100	570	949
A-n39-k5	38	5	100	475	822
B-n41-k6	40	6	100	567	829
B-n45-k5	44	5	100	486	751
A-n48-k7	47	7	100	626	1073
A-n60-k9	59	9	100	829	1354
A-n80-k10	79	10	100	942	1763

Figure 1. Convergence of best distance (Z_1) over iterations for the GA, standard ABC, and IABC on P-n16-k8, B-n31-k5, and A-n60-k9 (representative seeds).

5.2 Main Comparison: Distance, Fuel, and Feasibility

Table in Appendix reports aggregate results over 12 runs. Figure 1 shows convergence on three representative instances. In its best run the IABC matched the BKS on four of twelve instances (P-n16-k8=450, B-n31-k5=672, A-n32-k5=784, B-n45-k5=751), with a mean best-run gap of 1.34% and a mean gap over runs of 2.71%. Every IABC run was feasible (100%), with per-run CPU between 0.80 and 2.01 s.

The IABC reduced mean fuel versus savings on 11 of 12 instances (0.31% to 10.04%, largest on A-n32-k5), a mean of 3.50%; on B-n41-k6 the saving was essentially null at -0.04%. The gain is largest on medium A-n32-k5, where placing heavy loads on short arcs has most room, and smallest on tightly constrained instances where capacity forces near-fixed routes. Figure 2 shows that this advantage is design-specific. Although GA and StdABC optimize the same load-aware fitness, their narrower construction diversity and single-customer neighbourhoods make them converge prematurely as n grows, their mean fuel even exceeding savings (e.g. -8.42% for StdABC on A-n80-k10). The IABC's distance advantage widens with n , with run time below 2.1 s.

5.3 Statistical Significance and Effect Sizes

Across the twelve instances, the Friedman test finds a significant effect of algorithm on distance ($\chi^2(3) = 15.31, p = 0.0016$) and fuel ($\chi^2(3) = 14.90, p = 0.0019$), with the IABC holding the best mean rank on both (1.33 and 1.29; Table 2). Holm-corrected pairwise Wilcoxon tests favour the IABC over every baseline on both objectives (adjusted $p \leq 0.014$ on distance, ≤ 0.003 on fuel): on distance, adjusted $p = 0.003$ vs StdABC and 0.014 vs GA and savings, with rank-biserial $r = 0.95, 0.78, 0.75$; on fuel all three contrasts are at adjusted $p = 0.003$ ($r = 0.95$ vs savings, 0.95 vs GA, 0.87 vs StdABC). The Nemenyi CD at $k = 4, N = 12$ is 1.35 (Figure 3). The IABC mean rank differs from those of StdABC and GA on distance and from all three baselines on fuel by more than the CD. The fuel gap to StdABC (1.38) barely crosses the critical line (0.03 above CD), whereas the distance gap to savings (1.17, Holm-significant) does not. The evidence for superiority rests on Holm-significant pairs with large effect sizes; the more conservative Nemenyi does not separate IABC from savings on distance.

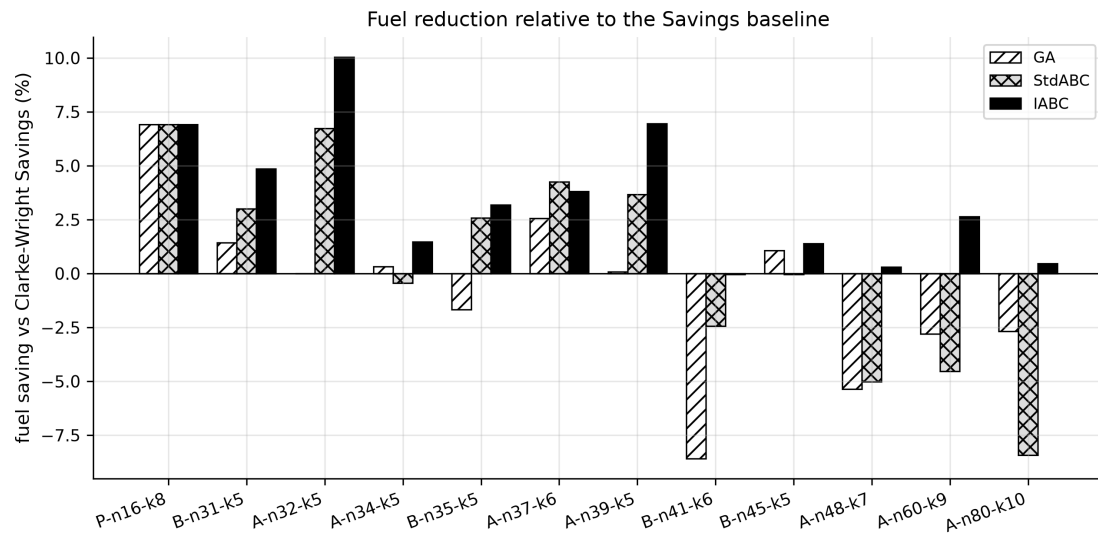


Figure 2. Mean fuel saving of each metaheuristic relative to the Clarke-Wright baseline by instance. Positive values indicate lower fuel. The GA and standard ABC turn negative on the larger instances, whereas the IABC stays positive on 11 of 12 instances (one essentially null case, -0.04% on B-n41-k6).

Table 2. Friedman Omnibus test and mean algorithm ranks ($N = 12$ instances).

Objective	chi-square	df	p	IABC	StdABC	Savings	GA
Distance Z_1	15.31	3	0.002	1.33	3.17	2.50	3.00
Fuel Z_2	14.90	3	0.002	1.29	2.67	2.92	3.12

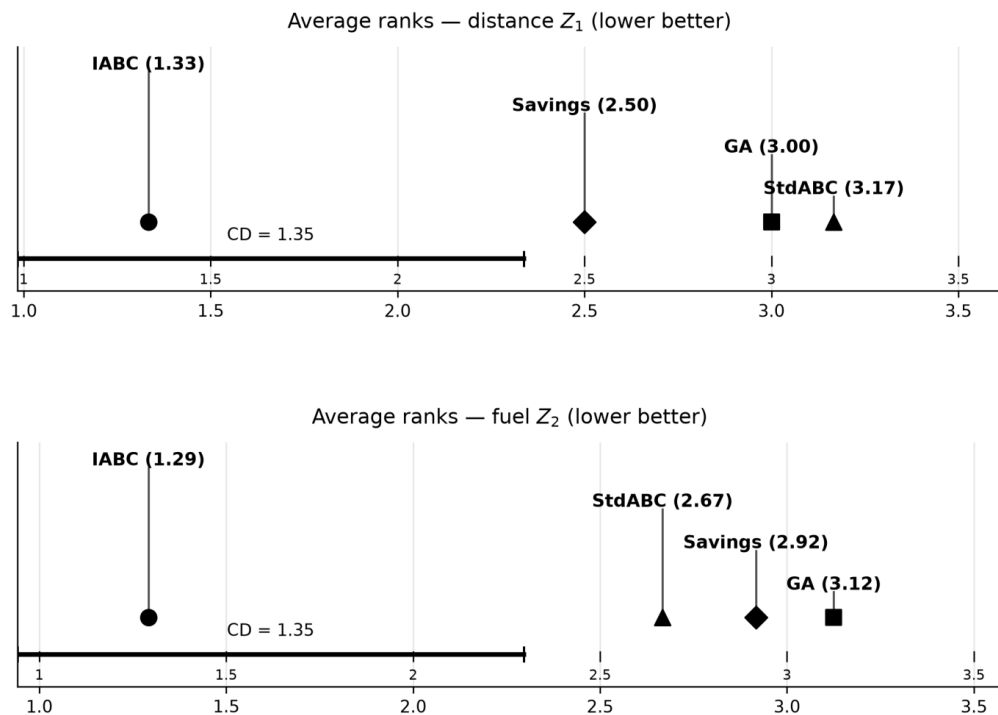


Figure 3. Friedman/Nemenyi critical-difference diagrams for distance and fuel ($k = 4$ algorithms, $N = 12$ instances; $CD = 1.35$). Lower rank is better.

5.4 Component Ablation

Table 3 isolates each component over 12 runs on P-n16-k8, A-n32-k5, and A-n60-k9, reporting mean percentage change in Z_1 and Z_2 relative to the full IABC (positive = worse); these span small, medium, and large sizes. The load-dependent model dominates: replacing it with a flat fuel rate raises fuel by 8.52%, 8.19%, and 2.93% (mean +6.55%), and distance-only optimization ($w_1 = 1$) raises fuel by 3.80%, 5.83%, and 1.26% (mean +3.63%), direct evidence that a distance objective mis-specifies fuel. The remaining components are marginal: removing the forward-insertion scout worsens both objectives slightly on average (+0.74% distance, +0.78% fuel), while G2 and the dynamic penalty are neutral (within 0.4%). Section 5.7 examines whether they pay off under tight capacity and finds no numerical advantage at the sizes tested.

Table 3. Component ablation: Mean percentage change relative to the full IABC.

Configuration	Mean change in Z_1 (%)	Mean change in Z_2 (%)	Configuration	Mean change in Z_1 (%)	Mean change in Z_2 (%)
Full-IABC	0.00	0.00	Fixed-penalty	0.36	0.19
No-dual-group(G2)	0.00	-0.15	Distance-only ($w_1 = 1$)	0.26	3.63
No-forward-scout	0.74	0.78	Fixed-fuel-rate	-0.05	6.55

5.5 Sensitivity to the Fuel Coefficients

Because the fuel coefficients are literature-order parameters, we re-ran A-n32-k5 with all coefficients scaled jointly by 0.8 and 1.2 under the same 12-run protocol. The relative fuel saving is essentially unchanged (10.09%, 10.04%, and 10.42% for scales 0.8, 1.0, 1.2; range 0.38 pp), and scale 1.0 (10.04%) reproduces Table 2. The saving is driven by the load-versus-arc-length routing decision rather than the absolute emission factor, supporting robustness of the qualitative conclusion.

5.6 The Weight-Dependent Distance-Fuel Frontier

Table 4 and Figure 4 trace the trade-off by sweeping w_1 in $\{0, 0.25, 0.5, 0.75, 1\}$ over ten runs on P-n16-k8, B-n31-k5, and A-n60-k9. On P-n16-k8 the frontier is flat up to $w_1 = 0.75$ (450 km, 116.73 L), with fuel penalty only at the pure-distance endpoint (121.26 L), so fuel improves at no distance cost on easy instances. On A-n60-k9 a genuine compromise emerges: moving from $w_1=1$ to 0 adds 39.3 km (1401.5 to 1440.8) but cuts 6.9 L (388.43 to 381.57), with a knee near $w_1=0.5 \rightarrow 0.75$. The sweep approximates the supported content of the Pareto front (Section 6.4). The three instances span small ($n = 15$), medium ($n = 31$), and large ($n = 60$) sizes, so the frontier analysis covers the full-size range of the benchmark rather than a single scale. Solution quality, gaps, and runtimes across all twelve sizes are reported in Table 2.

5.7 Exact Validation and Tight-Capacity Stress Test

To verify that the metaheuristic reaches the true optimum, Table 5 compares the IABC with exact single-commodity MILPs (SciPy/HiGHS) on P-n16-k8. A first MILP minimizing distance certifies $Z_1 = 450$. The particular distance-optimal route it returns consumes 118.34 L. This value is not the minimum fuel attainable at that distance, merely the fuel of one of the many routes that attain 450; because many routes share the optimal 450 yet differ in fuel, a second lexicographic MILP fixes distance at 450 and minimizes fuel, certifying 116.73 L. The IABC distance-only run ($w_1 = 1$) also reaches 450 but uses 121.26 L, whereas the bi-objective run ($w_1 = 0.5$) attains (450, 116.73 L) exactly. No heuristic solution therefore falls below a proven optimum: the IABC fuel value equals the certified lexicographic optimum, and the difference between 118.34 L and 116.73 L reflects the different objectives of the two MILPs rather than a super-optimal heuristic solution. Distance minimality thus does not imply fuel minimality (116.73 vs 121.26 L at equal distance), and the IABC optimum is certified on this instance (Figure 5).

Table 4. Weight-dependent distance-fuel frontier (mean over 10 runs).

Instance	w_1	Mean Z_1 (km)	Mean Z_2 (L)	Instance	w_1	Mean Z_1 (km)	Mean Z_2 (L)
P-n16-k8	0.00	450.0	116.73	B-n31-k5	0.75	673.0	173.79
P-n16-k8	0.25	450.0	116.73	B-n31-k5	1.00	673.8	174.97
P-n16-k8	0.50	450.0	116.73	A-n60-k9	0.00	1440.8	381.57
P-n16-k8	0.75	450.0	116.73	A-n60-k9	0.25	1420.1	382.95
P-n16-k8	1.00	450.0	121.26	A-n60-k9	0.50	1408.3	384.71
B-n31-k5	0.00	674.1	173.94	A-n60-k9	0.75	1403.2	386.20
B-n31-k5	0.25	674.8	174.16	A-n60-k9	1.00	1401.5	388.43
B-n31-k5	0.50	673.8	173.99				

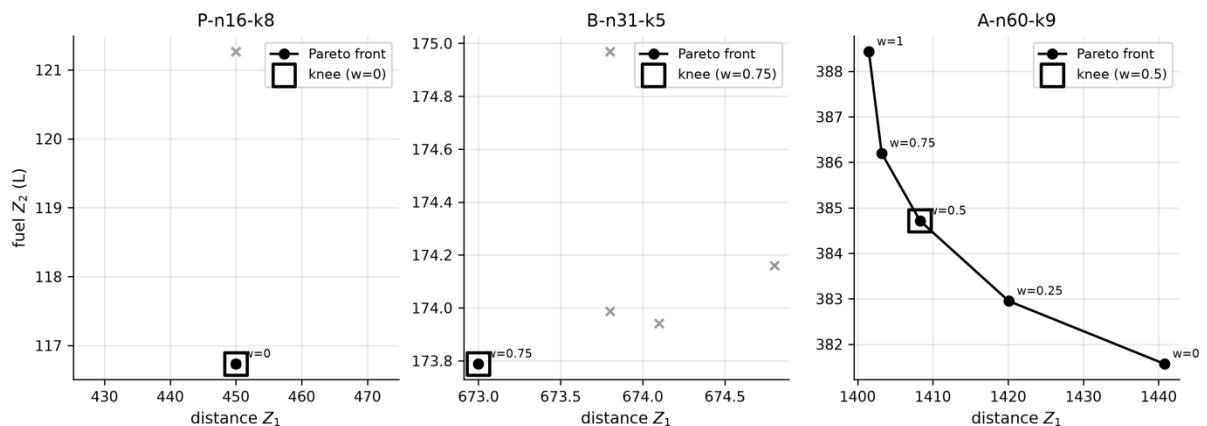


Figure 4. Non-dominated distance-fuel solutions as the weight w_1 varies from 0 to 1 on P-n16-k8, B-n31-k5, and A-n60-k9. The knee of each frontier is marked.

Table 5. Exact versus metaheuristic solutions on P-n16-k8.

Method	Z_1 (km)	Z_2 (L)	CO ₂ (kg)	Status
MILP-exact	450	118.34	311.24	Optimal (HiGHS)
MILP-lexicographic	450	116.73	307.01	Optimal (HiGHS)
IABC-distance ($w_1 = 1$)	450	121.26	318.92	Best/mean, 10 runs
IABC-biobjective ($w_1 = 0.5$)	450	116.73	307.01	Best/mean, 10 runs

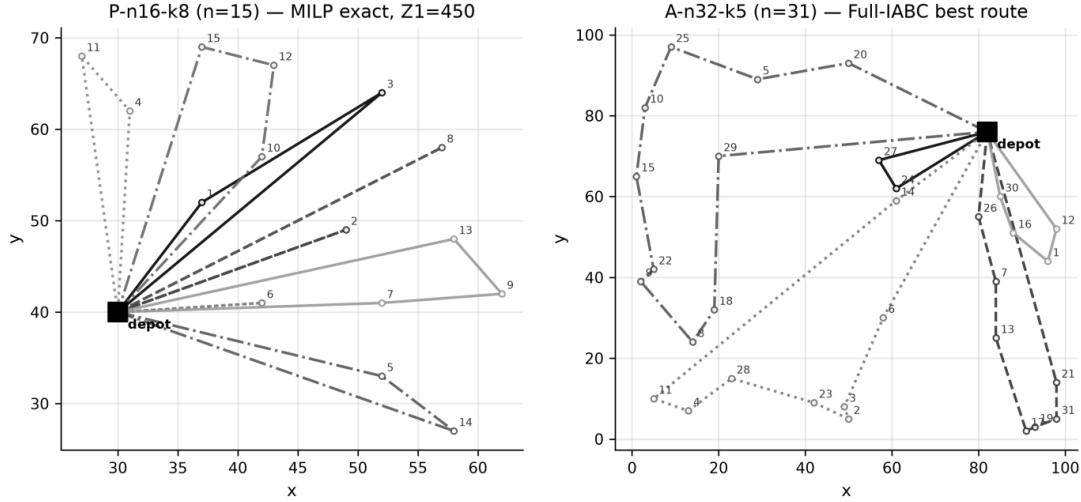


Figure 5. Best feasible routes for P-n16-k8 from the exact MILP (left) and for A-n32-k5 from the IABC (right). The square is the depot, circles are customers sized by demand, and distinct line styles and grey shades denote vehicles.

Table 6. Tight-capacity stress test at $Q' = 0.85 Q$ (10 runs).

Instance	Capacity	Variant	Mean Z_1	Mean Z_2 (L)	Mean vehicles	Feasible
A-n32-k5	0.85 Q	Dynamic penalty	893.0	232.80	6.0	100%
A-n32-k5	0.85 Q	Fixed penalty	892.5	233.22	6.0	100%
A-n60-k9	0.85 Q	Dynamic penalty	1620.6	433.62	10.9	100%
A-n60-k9	0.85 Q	Fixed penalty	1614.5	433.47	10.7	100%

Finally, Table 6 stresses feasibility by reducing capacity to 85% of nominal on A-n32-k5 and A-n60-k9 (10 runs per instance). Both dynamic and fixed penalties kept 100% feasibility, with no significant difference in distance or number of vehicles. The dynamic penalty therefore shows no advantage at these sizes. Its role is a robustness margin keeping the early search broad while ensuring late feasibility.

6. DISCUSSION

6.1 Summary of Findings

The IABC matched the BKS in four of twelve instances and cut mean fuel by 3.50% on 11 of 12 instances. As Section 5.4 shows, the benefit traces mainly to the load-aware objective rather than the search enhancements, and the lexicographic check of Section 5.7 certifies that the IABC attains the distance-fuel optimum on P-n16-k8.

6.2 Theoretical Implications

The findings extend green routing in two directions. Empirically, they add ABC-based evidence to the claim, previously established mainly with GA, tabu, and PSO, that distance is a mis-specified environmental objective. The exact comparison at identical distance controls for routing length entirely. Methodologically, they show how a load-sensitive term can be placed directly inside the bee fitness alongside lightweight feasibility machinery, and how the weighted-sum normalization of Section 3.4, coupled with weight sweeping and non-dominated filtering, approximates the supported decision-support content of a Pareto method without NSGA-II's non-dominated sorting and crowding-distance maintenance. The ablation results reinforce this conclusion: removing the load-aware objective causes large deteriorations, whereas removing the added operators does not, locating the green gain in the objective design rather than the operators, and cautioning against attributing improvements to generic operator novelty.

Relative to recent state-of-the-art work, the contribution is positioned as follows. Guo *et al.* [13] redesign ABC with adaptive phases for a single-objective low-carbon routing problem on electric industrial vehicles. The present IABC instead keeps the standard discrete ABC structure and adds a bi-objective, load-aware fitness validated on the public Augerat benchmark family with exact certification. Boonmee *et al.* [26] minimize CO₂ in a special CVRP with an exact Gurobi model on a real beverage case, whereas our contribution is a stochastic algorithm for the standard benchmark setting that exposes the

distance-fuel trade-off rather than a single emission optimum. On the other hand, Morsidi [27] proposes a memetic algorithm for the multi-depot VRP with time windows and reports routing-efficiency gains. By contrast, the present study isolates the environmental dimension under capacity constraints.

6.3 Practical Implications

For fleet operators, fuel and CO₂ can be reduced without adding distance or vehicles, by sequencing deliveries so that the heaviest segments are shortest. The maximum observed saving (10% on A-n32-k5) illustrates the best case, while tightly constrained instances, including one null case, bound the realistic gain conservatively. The weight frontier lets a manager choose an explicit economic-environmental balance. Robustness to $\pm 20\%$ fuel-coefficient error means the recommendation does not depend on precise engine data. Per-run times of about two seconds (0.80–2.01 s) make the method usable in operational re-planning.

6.4 Limitations and Future Research

Several limitations bound these conclusions. The benchmark covers twelve Augerat instances from one family. A full 73-instance A/B/P evaluation and other families with more runs are needed before generalizing, and one instance returned a null saving. The fuel coefficients are literature-order values. The linear model omits speed, gradient, congestion, and heterogeneous fleet, and time windows, pickups, and electric vehicles are out of scope. Weighted-sum scalarization cannot recover non-convex Pareto regions. The baselines are StdABC [9], a GA, and Clarke-Wright savings. Future work should scale the benchmark, calibrate the fuel model with fleet-card data, embed the load-aware fitness in an NSGA-II-style multi-objective bee algorithm, re-examine G2 and the dynamic penalty on large tight instances, and benchmark against recent adaptive bee variants. The model reports CO₂ only and neglects other greenhouse gases such as CH₄ and N₂O. A CO₂-equivalent treatment with full emission factors is left to future extensions. Benchmarking the IABC against PSO and differential evolution under the same budget is also planned.

7. CONCLUSIONS

We formulated a bi-objective green CVRP minimizing distance and load-dependent fuel consumption, solved by a modified ABC with scattered construction-based initialization, a dual-group neighbourhood, forward-insertion scouts, and an iteration-dependent capacity penalty. Across twelve Augerat instances, the IABC matched the BKS distance in four cases, remained fully feasible, and cut mean fuel by about 3.5% versus savings. As certified in Section 5.7, it attains the lexicographic distance-then-fuel optimum on P-n16-k8. The load-aware objective is the dominant source of benefit where the weight frontier offers an explicit economic-environmental trade-off and the fuel saving is robust to coefficient uncertainty. With a larger, calibrated benchmark and a full emissions model, the same load-aware rule can be transferred to other fleets without changing routes or fleet size.

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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APPENDIX

Main comparison over 12 independent runs ($w_1 = 0.5$).

Instance	Algorithm	Best Z_1	Mean Z_1	SD Z_1	Mean fuel Z_2 (L)	Mean CO ₂ (kg)	Fuel saving (%)	Gap to BKS (%)	CPU (s/run)
P-n16-k8	Savings	478	478	0.00	125.39	329.8	—	6.22	0.00
	GA	450	450	0.00	116.73	307.0	6.91	0.00	0.14
	StdABC	450	450	0.00	116.73	307.0	6.91	0.00	0.68
	IABC	450	450	0.00	116.73	307.0	6.91	0.00	0.80
B-n31-k5	Savings	678	678	0.00	182.81	480.8	—	0.89	0.00
	GA	679	692	11.26	180.20	473.9	1.43	3.00	0.27
	StdABC	672	682	5.42	177.31	466.3	3.01	1.56	1.26
	IABC	672	674	2.14	173.91	457.4	4.87	0.22	1.40
A-n32-k5	Savings	839	839	0.00	230.42	606.0	—	7.02	0.00
	GA	839	866	25.60	230.43	606.0	-0.01	10.52	0.28
	StdABC	784	819	20.40	214.90	565.2	6.74	4.41	1.29
	IABC	784	797	15.84	207.29	545.2	10.04	1.68	1.44
P-n16-k8	Savings	478	478	0.00	125.39	329.8	—	6.22	0.00
	GA	450	450	0.00	116.73	307.0	6.91	0.00	0.14
	StdABC	450	450	0.00	116.73	307.0	6.91	0.00	0.68
	IABC	450	450	0.00	116.73	307.0	6.91	0.00	0.80
B-n31-k5	Savings	678	678	0.00	182.81	480.8	—	0.89	0.00
	GA	679	692	11.26	180.20	473.9	1.43	3.00	0.27

	StdABC	672	682	5.42	177.31	466.3	3.01	1.56	1.26
	IABC	672	674	2.14	173.91	457.4	4.87	0.22	1.40
A-n32-k5	Savings	839	839	0.00	230.42	606.0	—	7.02	0.00
	GA	839	866	25.60	230.43	606.0	-0.01	10.52	0.28
	StdABC	784	819	20.40	214.90	565.2	6.74	4.41	1.29
	IABC	784	797	15.84	207.29	545.2	10.04	1.68	1.44
A-n34-k5	Savings	798	798	0.00	216.63	569.7	—	2.57	0.00
	GA	796	798	0.62	215.92	567.9	0.33	2.54	0.30
	StdABC	789	811	16.03	217.59	572.3	-0.44	4.22	1.30
	IABC	785	792	3.76	213.43	561.3	1.48	1.74	1.50
B-n35-k5	Savings	979	979	0.00	268.20	705.4	—	2.51	0.00
	GA	960	1022	39.50	272.68	717.2	-1.67	7.07	0.30
	StdABC	963	986	13.04	261.26	687.1	2.59	3.29	1.39
	IABC	959	976	9.21	259.68	682.9	3.18	2.19	1.54
A-n37-k6	Savings	984	984	0.00	277.71	730.4	—	3.69	0.00
	GA	981	984	2.02	270.60	711.7	2.56	3.70	0.29
	StdABC	980	1008	15.60	265.89	699.3	4.26	6.26	1.26
	IABC	969	996	20.07	267.15	702.6	3.80	4.94	1.44
A-n39-k5	Savings	900	900	0.00	247.91	652.0	—	9.49	0.00
	GA	889	907	17.32	247.72	651.5	0.08	10.33	0.29
	StdABC	837	899	26.83	238.81	628.1	3.67	9.31	1.27
	IABC	827	849	14.98	230.69	606.7	6.95	3.33	1.43
B-n41-k6	Savings	896	896	0.00	231.01	607.6	—	8.08	0.00
	GA	853	932	55.96	250.86	659.8	-8.59	12.42	0.31
	StdABC	847	885	22.26	236.64	622.4	-2.44	6.73	1.34
	IABC	840	881	19.28	231.11	607.8	-0.04	6.23	1.54
B-n45-k5	Savings	756	756	0.00	209.92	552.1	—	0.67	0.00
	GA	751	752	1.60	207.68	546.2	1.07	0.09	0.33
	StdABC	762	802	28.45	210.01	552.3	-0.04	6.83	1.46
	IABC	751	754	6.39	206.99	544.4	1.39	0.33	1.62
A-n48-k7	Savings	1102	1102	0.00	297.48	782.4	—	2.70	0.00
	GA	1109	1152	34.04	313.44	824.3	-5.36	7.41	0.36
	StdABC	1129	1174	25.88	312.39	821.6	-5.01	9.42	1.55
	IABC	1100	1101	1.66	296.56	779.9	0.31	2.58	1.78
A-n60-k9	Savings	1420	1420	0.00	394.14	1036.6	—	4.87	0.00
	GA	1412	1466	49.69	405.20	1065.7	-2.81	8.27	0.42
	StdABC	1483	1542	32.35	412.04	1083.7	-4.54	13.92	1.75
	IABC	1393	1408	12.29	383.72	1009.2	2.64	3.98	2.01
A-n80-k10	Savings	1864	1864	0.00	520.01	1367.6	—	5.73	0.00
	GA	1861	1947	55.79	533.99	1404.4	-2.69	10.41	0.40
	StdABC	2040	2104	38.88	563.82	1482.8	-8.42	19.36	1.55
	IABC	1856	1857	2.23	517.65	1361.4	0.46	5.31	1.80