SN Computer Science (2024) 5:79
https://doi.org/10.1007/s42979-023-02385-w

ORIGINAL RESEARCH

Meliorated Crab Mating Optimization Algorithms for Capacitated Vehicle Routing Problem

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Received: 1 June 2023 / Accepted: 4 October 2023

Abstract

This study proposes a new metaheuristic optimization algorithm, inspired by crabs mating in nature, with five versions. For these crab versions, first, the code of the crab mating optimization algorithm was written, inspired by Chifu's crab mating optimization paper. It has been observed that the original crab mating algorithm gives successful results; however, works very slowly and there are some parameters that are not used in the algorithm, and the mating probability of crabs converges to either 100% or 0%. Considering that the crab mating algorithm gives good results, new crab versions have been developed from this algorithm. The improved crab algorithms are compared with 4 popular metaheuristic algorithms for 20 different benchmark functions on metrics, such as mean, standard deviation, optimality, accuracy, run time, and the number of function evaluations (NFE). According to the results obtained, the proposed crab versions give as good results as the popular algorithms. In the last part of the study, the proposed algorithms were adapted for capacitated Vehicle Routing Problem (VRP) which is one of the real-world optimization problems, and their performances on this problem were compared among themselves. As a result of this comparison made on the VRP, the Meliorated Adaptive Crab mating optimization algorithm (MAC) algorithm gave more successful results in terms of speed and performance than the other proposed crab versions. Due to the performance of the proposed algorithms, we expect these algorithms to be applied to different optimization problems.

Keywords Metaheuristic · Optimization · Crab mating · Vehicle routing

Introduction

Metaheuristic algorithms are alternative methods to solve optimization problems instead of mathematically based exact optimization methods. In these algorithms, some methods are used such as backtracking, branch-and-bound, and dynamic programming methods [1]. It is easy to adapt metaheuristic algorithms for solving real optimization problems. At the same time, these algorithms are easy to understand. Many metaheuristic algorithms have been developed by inspired biological or physical processes from daily life and nature. Genetic Algorithm (GA) [2, 3], Simulated Annealing (SA) algorithm [4, 5], Artificial Bee Colony (ABC) algorithm [6–9], Particle Swarm Optimization (PSO) algorithm [10, 11], Differential Evolution (DE) algorithm [12–14], Ant Colony Optimization (ACO) algorithm [15, 16] can be given as examples of classic metaheuristic algorithms.

Another metaheuristic algorithm inspired by nature is the crab mating algorithm [17]. This algorithm is inspired by the life cycle and mating processes of crabs in nature. When crabs in nature are examined, it is seen that crabs are a type of crustacean that lives in water or on land. Crabs, which have more than 800 species, are found in all oceans, but there are also species that can live in freshwater and on land. Crabs, like many animals, have mating seasons. During this period, male crabs perform some visual movements called crab dance to impress female crabs. The probability of male crabs influencing female crabs is directly proportional to their size. The sensing capacity of female crabs is also effective in mating. During the mating period, male crabs can mate with up to three female crabs, but the sperm quality decreases as the male crab matures. When mating takes place, some eggs of the female crabs are fertilized and the female crab keeps these eggs inside until the embryo formation is completed. Then the embryos are released into the water [17–19].

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Published online: 08 December 2023

There are four main periods in the life of crabs. Figure 1 shows the evolution of crabs—zoea, megalopae, juvenile, and adult crab. The zoea period lasts from 31 to 49 days. During this period, the legs of the baby crabs begin to come out. While the megalopae period lasts between 31 and 49 days, the larvae begin to take on the appearance of crab during this period. While juvenile crabs migrate to less salty waters, they become adult crabs at this stage [20].

In this study, five new crab algorithm versions, inspired by the nature of crabs, are proposed such as Meliorated Crab mating optimization algorithm (MC), Meliorated Adaptive Crab mating optimization algorithm (MAC), Meliorated Fully Adaptive Crab mating optimization algorithm (MFAC), Meliorated Normalized and Adaptive Crab mating optimization algorithm (MANAC), Meliorated Normalized and Fully Adaptive Crab mating optimization algorithm (MANFAC). The proposed algorithms and some popular metaheuristic algorithms have been tested and compared on 20 benchmark functions. Then the proposed algorithms were adapted to the Vehicle Routing Problem (VRP) which is one of the real-world optimization problems, and their performances were evaluated.

In the second part of this study, the properties of the proposed algorithms; in third section, the benchmark functions used; in fourth section, the properties of the Capacitated Vehicle Routing Problem; and in the fifth part, the results are given, respectively.

Crab Mating Optimization Algorithm

The algorithms developed in this study were inspired by the original crab mating optimization algorithm. Since the code of the crab mating optimization algorithm is not given in Chifu's Crab mating optimization algorithm article [17], the code of the crab mating optimization algorithm was written in Matlab for this study. It has been observed that the crab mating algorithm gives successful results, although it has a handicap in run time. Inspired by these observations and the nature of crab mating, five novel versions of crab optimizer are proposed within the scope of this study. In Table 1, the terminological adaptation of crab mating behaviors to optimization problems is given.

Meliorated Crab Mating Optimization Algorithm (MC)

In MC first, the crab population was divided into two parts as male population and the female population, and the female population was ranked by fitness values. After these pre-processes, the mating step of the crabs was started. The probability of mating with each female crab for each male crab in the population was calculated with Eq. (1), and the crab pairs with a value higher than the threshold value were mated. In this equation, P denotes the mating probability of the crab pair, C_m shows the number of times the male crab mates with the females, $F(m)$ denotes the fitness values of male crabs, and the α denotes the female crab's receptivity degree.

$$P = e^{F(m) \times C_m \times \alpha^{-1}} \tag{1}$$

As the mating number of male crabs increases, their sperm qualities decrease. For the algorithm to work faster, each male crab was allowed to mate with at most half of the female crab population. The juvenile crabs obtained from these mating with the best fitness values were replaced with

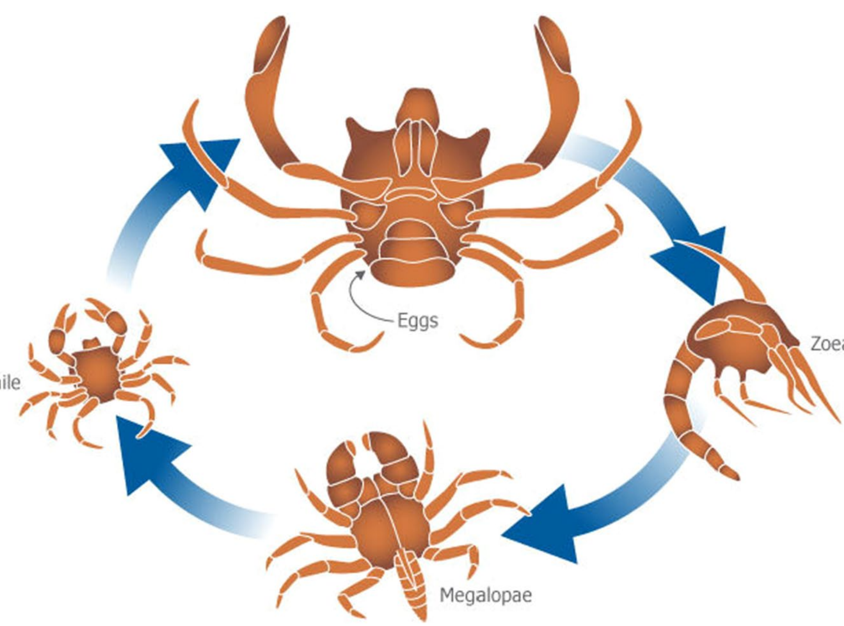


Fig. 1 Crab life cycle [21]

Table 1 The terminological adaptation of crab mating behaviors to optimization problems

Mating behavior of crabs	Optimization problem
Female population	A set of solutions of the optimization problem
Male population	A set of solutions of the optimization problem
Probability of mating	Probability computed by considering the fitness value of the male
Mating process	Crossover between a male and a female
Eggs	Clones of the best individual resulted after crossover
Number of eggs	Depends on the number of female crabs and
Deposited by each female	The fitness of the female crabs considered
Number of fertilized eggs	Depends on the fitness of the male and the mating history of the male

the parents with the worst fitness values in the population. During crab matings, the crossover operator is implemented in the same manner as the original algorithm. This results in selected male and female crabs exchanging genetic information to create offspring in the crossover process. The resulting offspring are then subjected to mutation in the subsequent stage, introducing small random changes in their genetic information and adding diversity to the population.

The pseudo-code of the MC is presented in Algorithm 1. Parameters used in pseudo-code are the number of population (Ps), number of the female population (NoF), number of the male population (NoM), female receptivity degree (α), crossover points (C_p), mutation points (M_p). In MC algorithm α, C_p and M_p values are fixed parameters.

Algorithm 1: Pseudo Code of MC Algorithm

```
procedure MC ALGORITHM(Ps, NoF, NoM, α, Cp, Mp)
    C_m = 0
    FemalePop = Initialize(NoF, Ps)
    MalePop = Initialize(NoM, Ps)
    FemalePop = Sort(FemalePop)
    while iteration < Maxiteration do
        for all m ∈ MalePop do
            for all f ∈ FemalePop do
                if C_m > (Ps < 2) + 1 then
                    P = MatingProb(m, f, α)
                    if P > Threshold then
                        Ch = Crossover(m, f, C_p)
                        C_m = C_m + 1
                        Clones = MakeClones(Ch, M_p)
                    end if
                end if
            end for
            C_m = 0
        end for
        FemalePop = FemalePop ∪ Half(Clones)
        FemalePop = Rank(FemalePop)
        MalePop = MalePop ∪ Half(Clones)
        MalePop = Rank(MalePop)
        FemalePop = Eliminate(FemalePop)
        MalePop = Eliminate(MalePop)
    end while
    return GetHighestFitness(FemalePop, MalePop)
end procedure
```

As can be seen from 11. and 12. lines of Algorithm 1, if the mating probability exceeds a predefined threshold, a standard crossover procedure between the male and the selected female is performed. In MakeClones procedure, the two offsprings resulting from the crossover are subjected to mutation. Eliminate procedure in lines 24 and 25 of the algorithm removes the crabs with the lowest cost value from the population for the next step.

Meliorated Adaptive Crab Mating Optimization Algorithm (MAC)

The MAC algorithm is based on the adaptive mechanisms for C_p and M_p parameters. The MAC algorithm has the features described in the MC and its code is the same as the pseudo-code given in Algorithm 1. The difference between the MAC and the MC is that the mutation and crossover coefficients are calculated adaptively as given in Eqs. (2)–(3). Here, C_{p_r} and M_{p_r} represent the adaptation coefficients. By choosing $C_{p_{min}} = 0.25$, $C_{p_r} = 0.55$, the crossover value was changed between 0.25 and 0.80, by choosing $M_{p_{min}} = 0.10$ and $M_{p_r} = 0.15$, the mutation value was changed between 0.10 and 0.25. In these equations, r_1 and r_2 represent the random numbers in [0,1].

$$C_p = C_{p_{min}} + r_1 \times C_{p_r} \tag{2}$$

$$M_p = M_{p_{min}} + r_2 \times M_{p_r} \tag{3}$$

Meliorated Fully Adaptive Crab Mating Optimization Algorithm (MFAC)

The MFAC algorithm is based on the adaptive mechanisms for C_p and M_p, α parameters. The MFAC is also an improved algorithm based on the MC. At the same time, it has the adaptive mutation and crossover features applied in the MAC, given

Table 2 Benchmark functions

Name	Formula
Ackley	$f(x) = -a \exp\left(-b\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(cx_i)\right) + a + e$
Bird	$f(x) = \sin(x_1)e^{(1-\cos(x_2))^2} + \cos(x_2)e^{(1-\sin(x_1))^2} + (x_1 - x_2)^2$
Booth	$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$
Cross	$f(x) = \left(\mid \sin(x_1)\sin(x_2)e^{\mid\frac{100-\sqrt{x_1^2+x_2^2}}{\pi}\mid} + 1 \mid\right)^{-0.1}$
Penholder	$f(x) = -\exp\mid\exp\left(\mid\frac{-\sqrt{x_1^2+x_2^2}}{\pi} + 1\mid\right)\cos(x_1)\cos(x_2)\mid^{-1}$
Cube	$f(x) = 100(x_2 - x_1^3)^2 + (1 - x_1)^2$
Testtubeholder	$f(x) = -4\mid\exp\mid\cos\left(\frac{1}{200}x_1^2 + \frac{1}{200}x_2^2\right)\mid\sin(x_1)\cos(x_2)\mid$
Giunta	$f(x) = 0.6 + \sum_{i=1}^{d}\left[\sin^2\left(1 - \frac{16}{15}x_i\right) - \frac{1}{50}\sin\left(4 - \frac{64}{15}x_i\right) - \sin\left(1 - \frac{16}{15}x_i\right)\right]$
Goldstein-Price	$f(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)]$ $\cdot[30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$
Himmelblau	$f(x) = (x_1^2 + x_2 - 11)^2 + (x_1 + x_2^2 - 7)^2$
Holdertable	$f(x) = -\mid sin(x_1)cos(x_2)e^{\mid 1-\frac{\sqrt{x_1^2+x_2^2}}{\pi}\mid}\mid$
Leon	$f(x) = 100(x_2 - x_1^3)^2 + (1 - x_1)^2$
Matyas	$f(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$
Mccormick	$f(x) = \sin(x_1 + x_2) + (x_1 - x_2)^2 - 1.5x_1 + 2.5x_2 + 1$
Rastrigin	$f(x) = 10d + \sum_{i=1}^{d}\left(x_i^2 - 10\cos(2\pi x_i)\right)$
Rosenbrock	$f(x) = \sum_{i=1}^{d-1}\left[100(x_{i+1} - x_i^2) + (x_i - 1)^2\right]$
Schweffel	$f(x) = 418.9829d - \sum_{i=1}^{d} x_i sin\sqrt{\mid x_i \mid}$
Sinenvsin	$f(x) = 0.5(d - 1) + \sum_{i=1}^{d}\frac{sin(\sqrt{(x_k^2+x_{k+1}^2)})^2 - 0.5}{(0.0001(x_k^2+x_{k+1}^2)+1)^2}$
Sixhumpcamel	$f(x) = (4 - 2.1x_1^2 + \frac{x_1^4}{3})x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2$
Styblinski-Tang	$f(x) = \frac{1}{2}\sum_{i=1}^{d}[x_i^4 - 16x_i^2 + 5x_i]$

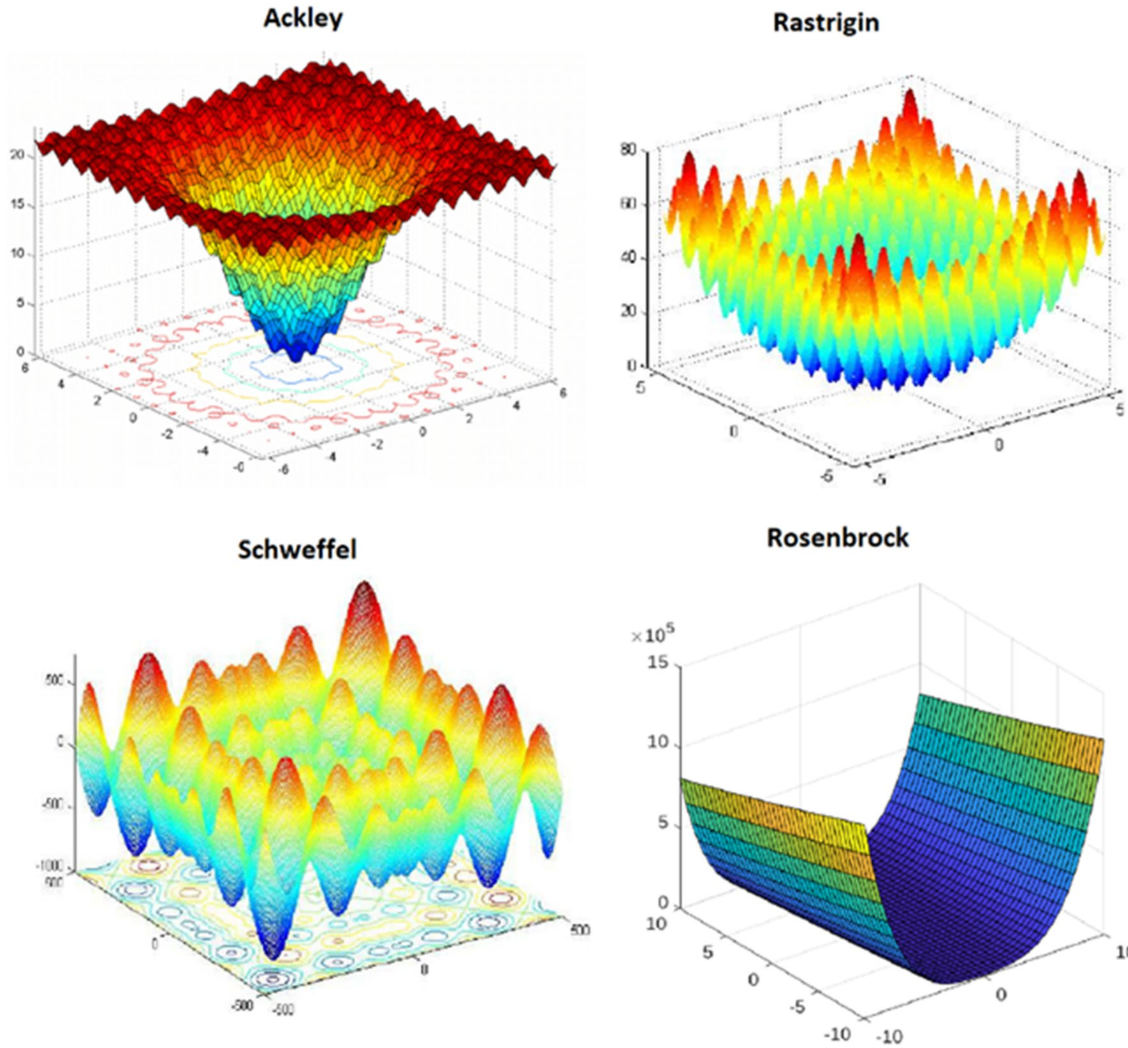


Fig. 2 3D graphs of Ackley, Rastrigin, Schweffel, Rosenbrock functions

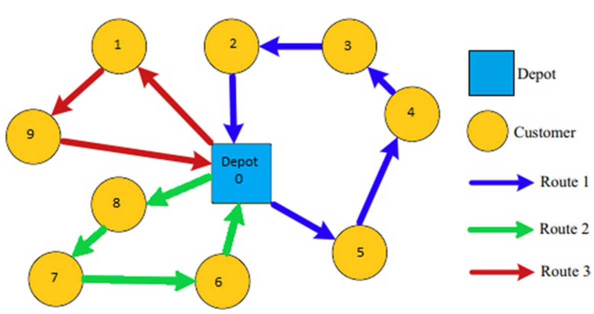


Fig. 3 An example of VRP

in Eqs. (2)–(3). In addition to these, the receptivity degree representing the perception of females was also made adaptive using Eq. (4). By determining $\alpha_{min} = 100$ $\alpha_r = 400$, it was ensured that the receptivity degree changed between 100 and 500.

$$\alpha = \alpha_{min} + r_3 \times \alpha_r \quad (4)$$

Meliorated Normalized and Adaptive Crab Mating Optimization Algorithms (MANAC)

The main goal in MANAC is adaptive mechanisms for C_p and M_p using Eqs. (2)–(3) and normalizing the P value as in Eq. (6). α parameter is used as a fixed value in MANAC. In the MANAC algorithm, the P mating probability values used to decide which crabs will mate were normalized by Eqs. (5)–(6). In Eq. (5), the $F_N(m)$ value shows the normalized fitness value of the male crab selected for mating, M_{min} shows the lowest fitness value among male crabs, and M_{max} shows the highest fitness value. In Eq. (6), α denotes the female receptivity degree and C_m denotes the mating counter.

$$F_N(m) = \frac{F(m) - M_{min}}{M_{max} - M_{min}} \tag{5}$$

$$P = e^{-|F_N(m) \times C_m \times \alpha^{-1}|} \tag{6}$$

Meliorated Normalized and Fully Adaptive Crab Mating Optimization Algorithms (MANFAC)

The MANFAC is based on the adaptive mechanisms for C_p, M_p, α parameters, and normalized the P value as in Eq. (6). The MANFAC algorithm includes all the features of MANAC algorithm. In addition to the MANAC algorithm, the receptivity degree of females was used as a variable in the range of 100–500 using Eq. (4) in the MANFAC algorithm.

Benchmark Functions

Twenty benchmarks with different properties, whose mathematical formulas are given in Table 2, were chosen to test the performances of the proposed crab versions. From these benchmarks, Ackley, Holdertable, Rastrigin, Penholder, Schweffel, Testtubeholder functions have more than one local minimum. The surfaces of Booth, Cube, Himmelblau, Matyas, Mccormick functions plate-shaped, and Leon, Rosenbrock, Sixhumpcamel surfaces are valley shaped. Figure 2 shows the 3D graphs of Ackley, Rastrigin, Schweffel, Rosenbrock functions used in this study.

Vehicle Routing Problem

Vehicle Routing Problem (VRP), which is one of the combinatorial optimization problems, involves designing the most suitable set of roads for vehicle groups to serve a certain customer cluster. In classical VRP, each node is visited only once, by only one vehicle, and each vehicle has a limited capacity [22–24]. Figure 3 shows an example of a VRP with a depot, nine customers, and three routes/vehicles [25]. In Fig. 3, the blue square shows the warehouse where the products will be received, the yellow circles show the customers where the products will be delivered, and the red, blue, and green arrows show the routes that the vehicles will follow.

In solving such a problem, the main objective is to minimize the time and distance traveled. The objective function and model constraints are given as follows [22]:

$$\begin{aligned}
&\text{minimize } \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} d_{ij}x_{ij}^{k}\\
&\text{subject to } \sum_{i=1}^{n} x_{0j}^{k} = 1, \quad k \in [1,m]\\
&\sum_{i=0}^{n} x_{ip}^{k} - \sum_{j=0}^{n} x_{pj}^{k} = 0, \quad p \in [0,n]; k \in [1,m]\\
&\sum_{k=1}^{m} y_{i}^{k} = 1, \quad i \in [1,n]\\
&\sum_{i=0}^{n} q_i y_{i}^{k} \le a_k, \quad k \in [1,m]\\
&y_{i}^{k} \le \sum_{i=0}^{n} x_{ji}^{k}, \quad i \in [1,n]; k \in [1,m]\\
&b_{i}^{k} + s_i + t_{ij} - M_{ij}(1 - x_{ij}^{k}) \le b_{j}^{k}, \quad i,j \in [1,n]; k \in [1,m]\\
&M_{ij} = l_i + t_{ij} - e_j, \quad i,j \in [1,n]\\
&e_i \le b_{i}^{k} \le l_i, \quad i \in [1,n]; k \in [1,m]\\
&y_{i}^{k} \ge 0, \quad i \in [1,n]; k \in [1,m]\\
&b_{i}^{k} \ge 0, \quad i \in [1,n]; k \in [1,m]\\
&x_{ij}^{k} \in \{0,1\}, \quad i,j \in [0,n], \quad k \in [1,m]
\end{aligned} \tag{7}$$

The model's decision variables are given below:

x_{ij}^{k}: 1, if j is supplied after i by vehicle k; 0, otherwise
b_{i}^{k}: service start time at customer i by vehicle k.
y_{i}^{k}: fraction of customer's demand i delivered by vehicle k
s_i: the service time at customer i
t_{ij}: travel time ($i \ne j$)
d_{ij}: distance traveled
q_i: the demand at point i
a_k: capacity of vehicle k
M_{ij}: constant with a large enough number
e_i: the earliest to start to service customer i
l_i: and latest time to start to service customer i

Table 3 Parameters of the improved crab optimizer versions

Algorithm	Parameter		
	C_p	M_p	α
MC	0.75	0.15	200
MAC	[0.25–0.80]	[0.10–0.25]	200
MFAC	[0.25–0.80]	[0.10–0.25]	[100–500]
MANAC	[0.25–0.80]	[0.10–0.25]	200
MANFAC	[0.25–0.80]	[0.10–0.25]	[100–500]

Table 4 Mean (Std Dev) results for benchmarks with 50 runs

FN	MC	MAC	MFAC	MANAC	MANFAC	PSO	ABC	SA	TACO
F1	1.55e−1(1.22e−1)	1.38e−1(8.77e−2)	1.32e−1(7.91e−2)	1.81e−1(1.08e−1)	1.88e−1(1.37e−1)	2.43e−1(6.11e−1)	5.01e−10(1.61e−9)	3.06e0(2.18e0)	2.33e−1(3.93e−1)
F2	1.05e2(5.33e0)	1.04e2(6.83e0)	1.06e2(4.67e0)	1.05e2(5.33e0)	1.05e2(5.33e0)	− 1.06e2(4.66e0)	− 1.07e2(4.67e−3)	− 1.06e2(1.21e0)	− 9.39e1(1.40e1)
F3	3.94e−4(4.39e−4)	3.68e−4(3.73e−4)	4.89e−4(4.32e−4)	5.77e−4(6.35e−4)	5.02e−4(5.10e−4)	6.11e−3(1.52e−2)	1.44e−3(1.91e−3)	3.32e−1(5.34e−1)	1.53e−2(6.32e−2)
F4	4.85e−5(5.80e−8)	4.85e−5(5.58e−8)	4.85e−5(3.68e−8)	4.85e−5(3.87e−8)	4.85e−5(4.11e−8)	4.85e−5(3.06e−9)	4.85e−5(6.34e−10)	4.85e−5(3.01e−8)	4.85e−5(5.06e−9)
F5	− 9.63e−1(4.44e−3)	− 9.64e−1(3.98e−6)	− 9.64e−1(4.05e−6)	− 9.64e−1(4.27e−6)	− 9.64e−1(4.20e−6)	− 9.52e−1(1.68e−2)	− 9.64e−1(1.05e−8)	− 9.63e−1(3.49e−4)	− 9.56e−1(1.18e−2)
F6	1.73e−3(1.57e−3)	1.80e−3(1.84e−3)	1.57e−3(1.59e−3)	1.39e−3(1.29e−3)	1.56e−3(1.46e−3)	2.30e−1(7.27e−1)	3.38e−2(4.44e−2)	3.03e−1(7.00e−1)	3.04e0(9.00e0)
F7	− 1.09e1(7.98e−3)	− 1.09e1(6.72e−3)	− 1.09e1(5.46e−3)	− 1.09e1(4.18e−3)	− 1.09e1(4.23e−3)	− 1.08e1(1.02e−1)	− 1.09e1(1.23e−3)	− 1.08e1(5.32e−2)	− 1.08e1(4.07e−2)
F8	6.45e−2(1.45e−6)	6.45e−2(1.56e−6)	6.45e−2(1.73e−6)	6.45e−2(1.65e−6)	6.45e−2(1.15e−6)	6.45e−2(7.48e−5)	6.45e−2(6.28e−12)	6.48e−2(5.60e−4)	6.45e−2(9.39e−6)
F9	6.24e0(1.60e1)	6.24e0(1.60e1)	6.24e0(1.60e1)	3.00e0(1.79e−3)	3.00e0(2.31e−3)	5.16e0(7.40e0)	3.00e0(3.90e−3)	5.02e0(4.30e0)	3.25e0(1.71e0)
F10	1.48e−3(1.40e−3)	1.26e−3(1.37e−3)	1.55e−3(1.23e−3)	1.59e−3(1.41e−3)	1.47e−3(1.47e−3)	4.98e−3(1.66e−2)	6.08e−4(1.12e−3)	4.84e−2(1.01e−1)	2.65e−3(6.39e−3)
F11	1.83e1(2.67e0)	-1.91e1(6.28e−1)	-1.92e1(3.49e−3)	-1.92e1(7.85e−2)	-1.92e1(1.31e−3)	-1.46e1(4.86e0)	-1.92e1(1.40e−4)	-1.92e1(2.74e−2)	-1.87e1(1.66e0)
F12	1.99e−5(1.86e−5)	3.01e−5(2.88e−5)	1.71e−5(1.45e−5)	2.24e−5(2.38e−5)	3.01e−5(2.51e−5)	2.76e−2(8.00e−2)	8.28e−4(7.32e−4)	2.02e−2(3.29e−2)	3.26e−3(1.06e−2)
F13	1.31e−5(1.36e−5)	1.47e−5(1.26e−5)	1.78e−5(1.51e−5)	1.65e−5(1.28e−5)	1.48e−5(1.90e−5)	5.21e−6(1.36e−5)	1.91e−4(1.64e−4)	1.39e−2(2.14e−2)	4.83e−4(1.66e−3)
F14	− 1.73e0(7.51e−1)	− 1.85e0(4.29e−1)	− 1.79e0(6.00e−1)	− 1.85e0(4.44e−1)	− 1.86e0(3.75e−1)	− 1.85e0(4.44e−1)	− 1.91e0(1.14e−5)	− 1.90e0(2.46e−2)	− 1.73e0(2.55e−1)
F15	4.84e−2(1.98e−1)	9.54e−3(8.59e−3)	7.43e−3(6.68e−3)	9.09e−3(9.20e−3)	1.20e−2(1.02e−2)	8.75e−1(8.52e−1)	1.06e−3(6.21e−3)	8.22e−1(7.75e−1)	6.28e−2(1.07e−1)
F16	9.07e−5(1.07e−4)	1.05e−4(9.45e−5)	8.32e−5(8.94e−5)	8.40e−5(8.65e−5)	9.33e−5(8.83e−5)	1.26e−2(1.82e−2)	1.49e−3(1.44e−3)	3.18e−2(3.90e−2)	1.40e−2(4.57e−2)
F17	1.49e2(1.04e2)	1.47e2(1.01e2)	1.30e2(9.53e1)	1.17e2(1.00e2)	1.22e2(9.67e1)	1.19e2(1.06e2)	3.88e−2(1.39e−1)	3.87e1(5.11e1)	1.65e−1(2.49e−1)
F18	− 1.49e0(2.29e−8)	− 1.49e0(5.06e−8)	− 1.49e0(1.72e−8)	− 1.49e0(8.41e−8)	− 1.49e0(2.44e−8)	− 1.49e0(8.63e−3)	− 1.49e0(1.31e−5)	− 1.48e0(2.02e−2)	− 1.49e0(2.95e−5)
F19	− 1.03e0(2.47e−4)	− 1.03e0(1.98e−4)	− 1.03e0(1.88e−4)	− 1.03e0(2.95e−4)	− 1.03e0(1.60e−4)	− 1.03e0(1.69e−3)	− 1.03e0(5.98e−6)	− 1.02e0(1.75e−2)	− 5.60e−1(4.31e−1)
F20	3.75e1(3.05e0)	3.78e1(2.86e0)	3.78e1(2.86e0)	3.83e1(2.72e0)	3.83e1(2.32e0)	− 3.85e1(2.14e0)	− 3.92e1(1.49e−12)	− 3.91e1(1.25e−1)	− 3.67e1(2.53e0)

Table 5 NFE and run-time results for benchmarks with 50 runs

FN	MC	MAC	MFAC	MANAC	MANFAC	PSO	ABC	SA	TACO
F1	19906.36 (1.280)	19905.12 (1.290)	19946.20 (1.330)	20000.00 (1.211)	20000.00 (1.155)	2847.60 (0.146)	16106.38 (0.916)	20000.00 (1.384)	19216.80 (3.444)
F2	2096.04 (0.157)	2107.96 (0.174)	4038.56 (0.273)	20000.00 (0.861)	20000.00 (0.869)	2418.00 (0.080)	21024.28 (0.766)	20000.00 (0.974)	12386.40 (1.689)
F3	19903.60 (0.796)	19897.04 (1.087)	19929.16 (0.973)	20000.00 (1.002)	20000.00 (1.012)	2246.80 (0.070)	20998.62 (0.782)	20000.00 (0.929)	11724.00 (1.576)
F4	218.80 (0.014)	210.80 (0.013)	216.00 (0.014)	214.40 (0.015)	217.60 (0.014)	483.60 (0.016)	1144.54 (0.041)	20000.00 (1.000)	20000.00 (3.044)
F5	20000.00 (0.803)	20000.00 (0.799)	20000.00 (0.844)	20000.00 (0.800)	20000.00 (0.806)	1672.40 (0.052)	20994.26 (0.791)	20000.00 (0.903)	4252.80 (0.376)
F6	19569.56 (0.810)	19594.76 (1.043)	19595.68 (1.036)	20000.00 (1.074)	20000.00 (1.049)	2642.40 (0.138)	21005.96 (0.984)	20000.00 (1.121)	13507.60 (2.418)
F7	12040.84 (0.603)	12036.44 (0.613)	16288.28 (0.779)	20000.00 (0.917)	20000.00 (1.005)	2242.40 (0.086)	21001.90 (0.878)	20000.00 (0.992)	10045.20 (1.900)
F8	20000.00 (1.018)	20000.00 (1.073)	20000.00 (0.876)	20000.00 (0.872)	20000.00 (0.869)	1580.40 (0.055)	4518.52 (0.206)	20000.00 (1.180)	20000.00 (3.197)
F9	18930.64 (0.935)	18907.64 (0.953)	19046.96 (1.021)	20000.00 (1.233)	20000.00 (1.049)	2314.00 (0.133)	21006.12 (0.940)	20000.00 (1.063)	17722.40 (2.699)
F10	19856.52 (0.961)	19846.32 (0.922)	19886.04 (1.029)	20000.00 (0.937)	20000.00 (0.977)	2375.60 (0.096)	21003.40 (0.919)	20000.00 (1.056)	14014.80 (2.220)
F11	8607.60 (0.408)	8368.84 (0.407)	12614.72 (0.570)	20000.00 (0.866)	20000.00 (0.849)	2328.80 (0.085)	21007.52 (0.840)	20000.00 (0.987)	7590.00 (1.026)
F12	19976.20 (0.800)	19978.24 (0.803)	19982.52 (0.815)	20000.00 (0.828)	20000.00 (0.847)	2132.00 (0.069)	21008.78 (0.766)	20000.00 (0.864)	8322.00 (1.121)
F13	19991.20 (1.108)	19990.20 (1.151)	19992.12 (1.100)	20000.00 (1.098)	20000.00 (1.097)	1599.60 (0.071)	20997.34 (1.029)	20000.00 (1.149)	8992.80 (1.392)
F14	19994.08 (0.997)	19994.08 (1.103)	19995.52 (1.099)	20000.00 (1.096)	20000.00 (1.097)	1844.80 (0.067)	20792.98 (0.786)	20000.00 (0.934)	12383.60 (1.669)
F15	19881.36 (1.045)	19885.56 (1.068)	19939.08 (1.080)	20000.00 (1.106)	20000.00 (1.115)	2517.20 (0.117)	20999.68 (1.018)	20000.00 (1.182)	15695.60 (2.211)
F16	19941.68 (0.863)	19942.72 (0.884)	19953.40 (0.877)	20000.00 (0.915)	20000.00 (0.916)	2161.60 (0.079)	20999.32 (0.832)	20000.00 (0.963)	11180.80 (1.417)
F17	5521.12 (0.341)	5375.68 (0.326)	6209.84 (0.375)	20000.00 (1.022)	20000.00 (0.998)	2694.40 (0.119)	20996.84 (0.954)	20000.00 (1.073)	14093.60 (1.996)
F18	20000.00 (0.900)	20000.00 (0.920)	20000.00 (0.910)	20000.00 (1.046)	20000.00 (1.026)	2041.60 (0.076)	21050.16 (0.879)	20000.00 (1.018)	20000.00 (2.771)
F19	19963.88 (0.823)	19967.40 (0.908)	19967.00 (0.891)	20000.00 (0.877)	20000.00 (0.874)	2080.00 (0.069)	21141.18 (0.796)	20000.00 (0.954)	6508.00 (0.884)
F20	4039.56 (0.253)	4042.72 (0.259)	7878.28 (0.447)	20000.00 (0.997)	20000.00 (1.014)	2122.80 (0.084)	10767.42 (0.497)	20000.00 (1.014)	13120.00 (1.874)

Results and Discussion

In this section, first, the proposed crab variant algorithms and Simulated Annealing (SA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Touring Ant Colony Optimization (TACO) algorithms are compared in 20 benchmark functions. In the second part of this section, the five proposed crab versions were applied to the capacitive Vehicle Routing Problem and compared with each other.

This study compares various algorithms based on several performance metrics, including statistical results such as mean and standard deviation, optimality, accuracy, run time, and number of function evaluations (NFE). The mean results metric represents the average of the best solutions obtained. NFE and run-time metrics provide information about the computational efficiency of the algorithms. In addition, comparisons are made using optimality metrics, which measure the relative closeness of an objective function value of a candidate solution to the global solution given in Eq. (8), and accuracy metrics, which define the relative proximity

Table 6 Optimality results for benchmarks with 50 runs

FN	MC	MAC	MFAC	MANAC	MANFAC	PSO	ABC	SA	TACO
F1	0.993	0.994	0.994	0.992	0.992	0.989	0.991	0.863	0.990
F2	0.994	0.990	0.996	0.994	0.994	0.996	0.995	0.998	0.954
F3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F4	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F5	0.999	1.000	1.000	1.000	1.000	0.988	1.000	1.000	0.992
F6	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F7	0.999	1.000	1.000	1.000	1.000	0.995	1.000	0.995	0.996
F8	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000
F9	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F10	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F11	0.954	0.993	1.000	0.999	1.000	0.760	0.998	0.999	0.971
F12	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F13	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F14	0.996	0.999	0.997	0.999	0.999	0.999	0.996	1.000	0.996
F15	0.999	1.000	1.000	1.000	1.000	0.989	1.000	0.990	0.999
F16	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F17	0.911	0.913	0.923	0.930	0.927	0.929	0.998	0.977	1.000
F18	1.000	1.000	1.000	1.000	1.000	0.998	1.000	0.985	1.000
F19	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F20	0.990	0.991	0.991	0.995	0.995	0.996	0.995	1.000	0.985

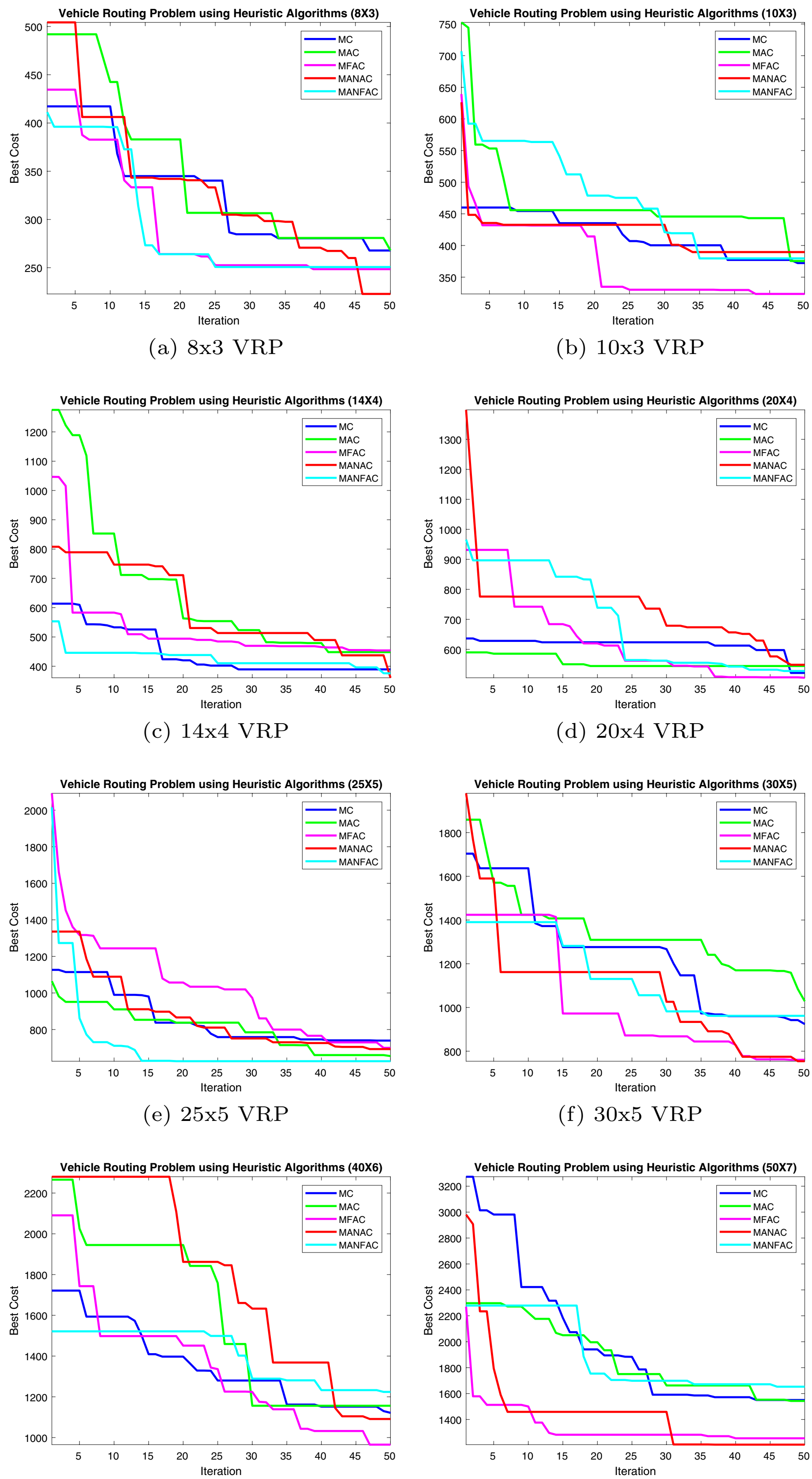
Table 7 Accuracy results for benchmarks with 50 runs

FN	MC	MAC	MFAC	MANAC	MANFAC	PSO	ABC	SA	TACO
F1	1.000	1.000	1.000	1.000	1.000	0.999	0.813	0.992	1.000
F2	0.999	0.999	0.999	0.999	0.999	1.000	0.876	0.997	0.987
F3	1.000	1.000	1.000	0.999	1.000	0.998	0.753	0.987	0.998
F4	0.933	0.933	0.932	0.932	0.933	0.932	0.922	0.932	0.933
F5	0.493	0.553	0.544	0.474	0.579	0.549	0.536	0.515	0.583
F6	0.998	0.998	0.998	0.998	0.998	0.972	0.751	0.967	0.923
F7	0.943	0.942	0.965	0.957	0.960	0.899	0.748	0.908	0.924
F8	1.000	1.000	1.000	1.000	1.000	1.000	0.969	0.996	0.999
F9	0.985	0.985	0.985	1.000	1.000	0.988	0.762	0.990	0.999
F10	1.000	1.000	1.000	1.000	1.000	1.000	0.908	0.998	1.000
F11	0.991	0.998	0.999	0.999	1.000	0.956	0.789	0.999	0.994
F12	0.998	0.998	0.998	0.998	0.998	0.937	0.569	0.951	0.983
F13	0.999	0.999	0.999	0.999	0.999	1.000	0.751	0.979	0.998
F14	0.981	0.995	0.991	0.989	0.996	0.990	0.694	0.989	0.969
F15	0.998	1.000	1.000	1.000	1.000	0.960	0.754	0.973	0.999
F16	0.999	0.998	0.998	0.998	0.998	0.973	0.675	0.957	0.982
F17	0.760	0.734	0.718	0.771	0.769	0.775	0.530	0.910	0.999
F18	0.967	0.967	0.967	0.968	0.967	0.966	0.752	0.954	0.967
F19	1.000	1.000	1.000	1.000	1.000	1.000	0.773	0.998	0.976
F20	0.932	0.943	0.943	0.966	0.966	0.971	0.814	0.995	0.943

of a solution's position to the global solution position given in Eq. (9). In these equations, x_0, f_0 represent the obtained result and its fitness value, $\hat{x}_0$, $\hat{f}_0$ are the theoretical solution and objective value of the problem, and $\bar{x}$, $\bar{f}$, $\underline{x}$, and $\underline{f}$ denote the upper and lower limits of solution and its fitness [26].

$$\text{Optimality} = 1 - \frac{\left\| f_0 - \hat{f}_0 \right\|}{\left\| \bar{f} - \underline{f} \right\|} \in [0, 1] \quad (8)$$

Fig. 4 Convergence curves obtained by crab versions

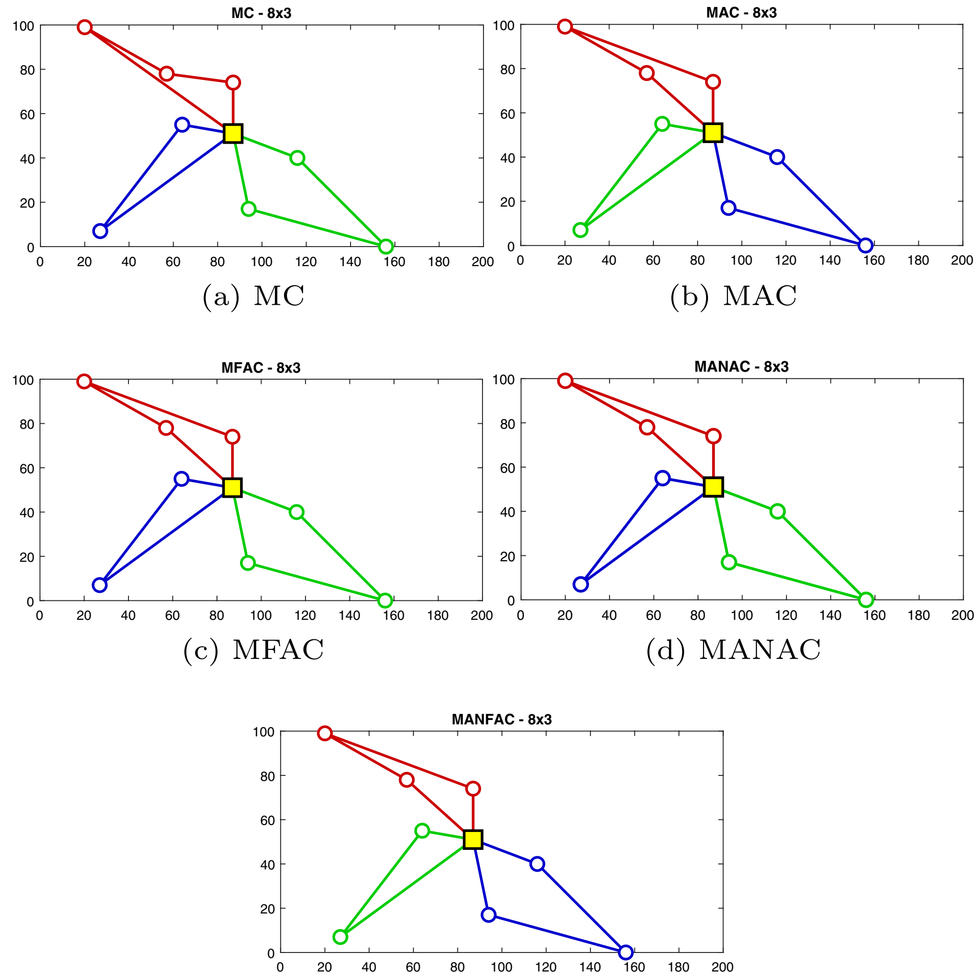


(a) 8x3 VRP (b) 10x3 VRP

(c) 14x4 VRP (d) 20x4 VRP

(e) 25x5 VRP (f) 30x5 VRP

(g) 40x6 VRP (h) 50x7 VRP



(a) MC (b) MAC (c) MFAC (d) MANAC (e) MANFAC

Fig. 5 Best results of the crab versions (8 × 3 VRP)

$$\text{Accuracy} = 1 - \frac{\|x_0 - \hat{x}_0\|}{\|\bar{x} - \underline{x}\|} \in [0, 1] \quad (9)$$

Benchmark Tests

All algorithms' codes have been run on a computer with 8GB of RAM with Intel Core (TM) i5-5300 processor. All algorithms have been run 50 times. Each algorithm searches the solution based on two stopping criteria, first maximum iteration number is 1000; second, the Value To Reach (VTR) parameter. VTR parameter which is used as the stopping condition given in Eq. (10) is 10e-6.

$$\text{VTR} = | F(X_{best}) - F(X_{worst}) | \quad (10)$$

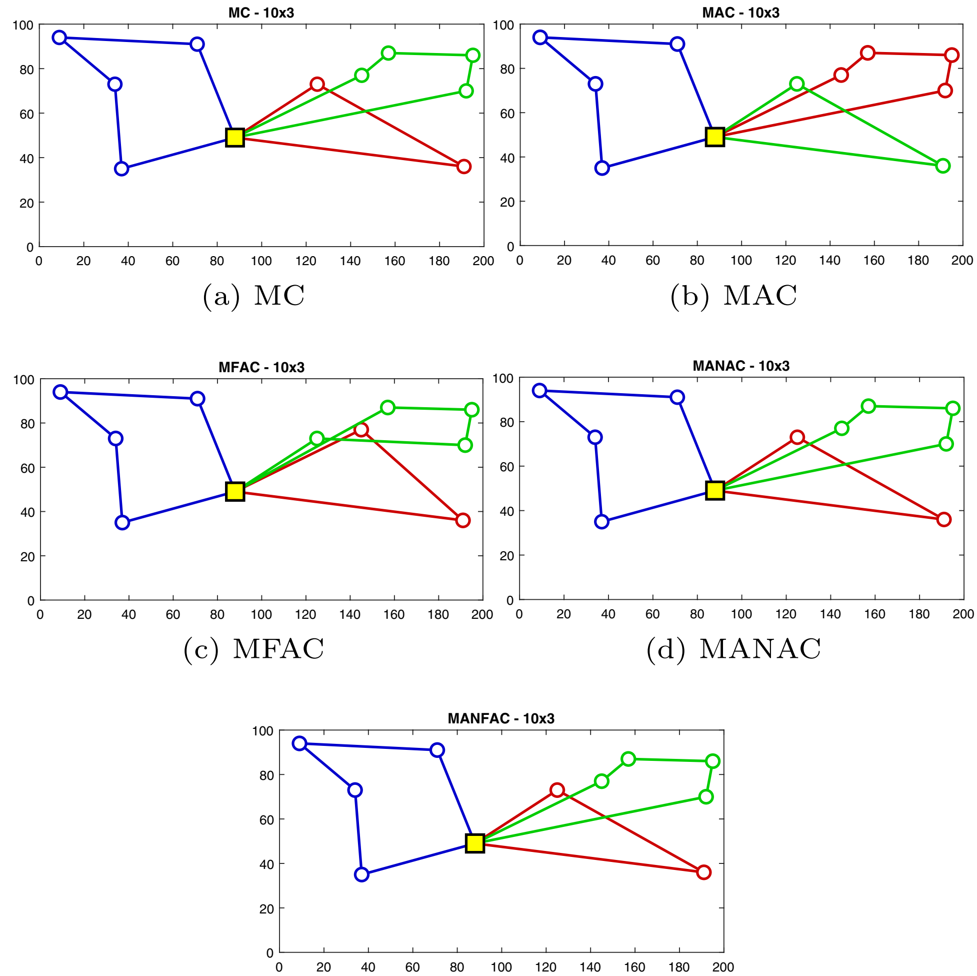
The values of the female receptivity degree (α), crossover points (C_p), and mutation points (M_p) of the crab versions are given in Table 3. In all algorithms, the crab population is 20.

The crab versions (MC, MAC, MFAC, MANAC, MANFAC) and some popular metaheuristic algorithms (PSO, ABC, SA, and TACO) are compared with Mean, Std Dev, NFE, run time, optimality, accuracy metrics, and the results are given in Tables 4, 5, 6, 7.

From the results obtained, it can be observed that the performances of the proposed crab versions are promising. It is seen that the proposed crab algorithms give good results as compared to popular algorithms in terms of accuracy, optimality, and mean metrics considered. When the speeds of all algorithms in comparison are evaluated, they lag behind a speed-oriented algorithm such as PSO, but give equal or better results than the other compared algorithms.

Capacitated Vehicle Routing Problem Tests

As explained in Sect. "Vehicle Routing Problem", VRP involves finding the most suitable route options for vehicle groups belonging to a particular customer cluster. The codes



(a) MC (b) MAC (c) MFAC (d) MANAC (e) MANFAC

Fig. 6 Best results of the crab versions (10 × 3 VRP)

of the crab versions proposed in this study were adapted for VRP.

Algorithms adapted for VRP have been observed to have promising results in benchmark tests. To compare the proposed algorithms among themselves, the algorithms are adapted to the VRP. VRP used in this study includes 8 customers on 3 routes (8 × 3), 10 customers on 3 routes (10 × 3), 14 customers on 4 routes (14 × 4), 20 customers on 4 routes (20 × 4), 25 customers on 5 routes (25 × 5), 30 customers on 5 routes (30 × 5), 40 customers on 6 route (40 × 6), and 50 customers on 7 route (50 × 7) models. For all VRP models, the codes of all crab versions have been run on a computer with 8GB of RAM with Intel Core (TM) i5-5300 processor. All algorithms have been run 50 times.

The Capacitated Vehicle Routing Problem (CVRP) is a combinatorial optimization problem in which each vehicle has a limited carrying capacity, and the total weight of the products requested by each customer is specified. The CVRP code was taken from Yarpiz website [27] and improved crab versions were tested. The cost function of the capacitated VRP used in this study is given below [27]:

$$f = (1 + \beta\overline{CV})\left(\eta \sum D + (1 - \eta)MaxD\right) \tag{11}$$

where f denotes the cost function, D represents the distance, $MaxD$ is the maximum distance of route between depot and customers, β denotes the penalty parameter, η is the weight factor, and CV is the constraint violation. This CV measure penalizes solutions in which the ratio of the capacity used for the vehicle routes exceeds the maximum capacity of the vehicles. In other words, the CV penalizes solutions that violate the capacity constraints. The magnitude of the penalty is proportional to the degree to which the capacity constraints are violated, and the resulting value of the CV affects the suitability of the solution. If the CV is zero, the solution satisfies all of the capacity constraints. The η was chosen as 0.5 and β as 10 in this study. This section presents the results of the tests conducted, which are displayed in tables and figures. An example of the

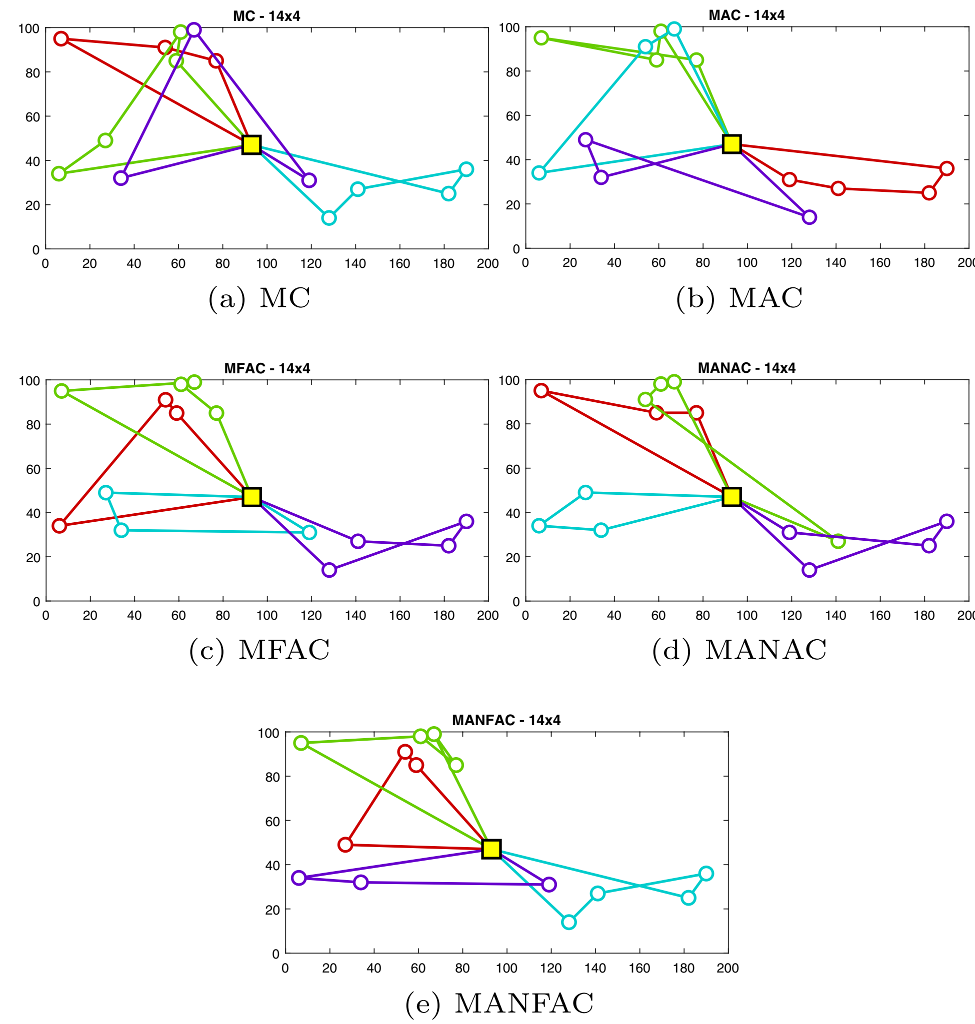


Fig. 7 Best results of the crab versions (14 × 4 VRP)

convergence curves achieved by the crab versions in each iteration of a single run is shown in Fig. 4. It is worth noting that the convergence curves obtained by the crab versions may vary for each Vehicle Routing Problem (VRP) and for each iteration. Hence, Fig. 4 is provided as a representation of a typical iteration, rather than an exhaustive display of all possible variations.

The curves in these figures demonstrate the convergence rates of the proposed crab optimization algorithm versions for eight different vehicle routing problems (VRPs). Upon examining the results of 8 × 3 VRP with eight customers on three routes, it is evident that the MANAC algorithm achieves the best performance. The MANAC algorithm can also be declared as the best approach for 14 × 4, 30 × 5, and 50 × 7 VRPs in terms of convergence. For 10 × 3, 20 × 4, and 40 × 6 VRPs, the MFAC algorithm exhibits the best convergence. Moreover, the MANFAC displays the best convergence curve for 25 × 5 VRP.

In Fig. 5, the results found by each crab version for 8x3 VRP are shown. The results here show the best solutions found by the proposed crab version algorithms after 50 runs. The visual representation of the results shows the routes taken by the vehicles, color coded to indicate the connections between the depot and the customers. The sub-figures reveal that, with the exception of the MC algorithm for the 8 × 3 capacitated VRP, all four crab versions yielded identical solutions. Figure 6 shows the best solutions obtained by all crab version algorithms for 10x3 VRP. In the context of this scenario with ten customers and three routes, the MFAC algorithm yielded distinct solutions in two of the routes, diverging from the solutions generated by the other crab-based algorithms. Figures 7 and 8 show the best solutions obtained by each crab variant algorithm for 14 × 4 and 20 × 4 capacitated VRPs. The proposed algorithms were evaluated in 2 different cases, one involving 4 routes

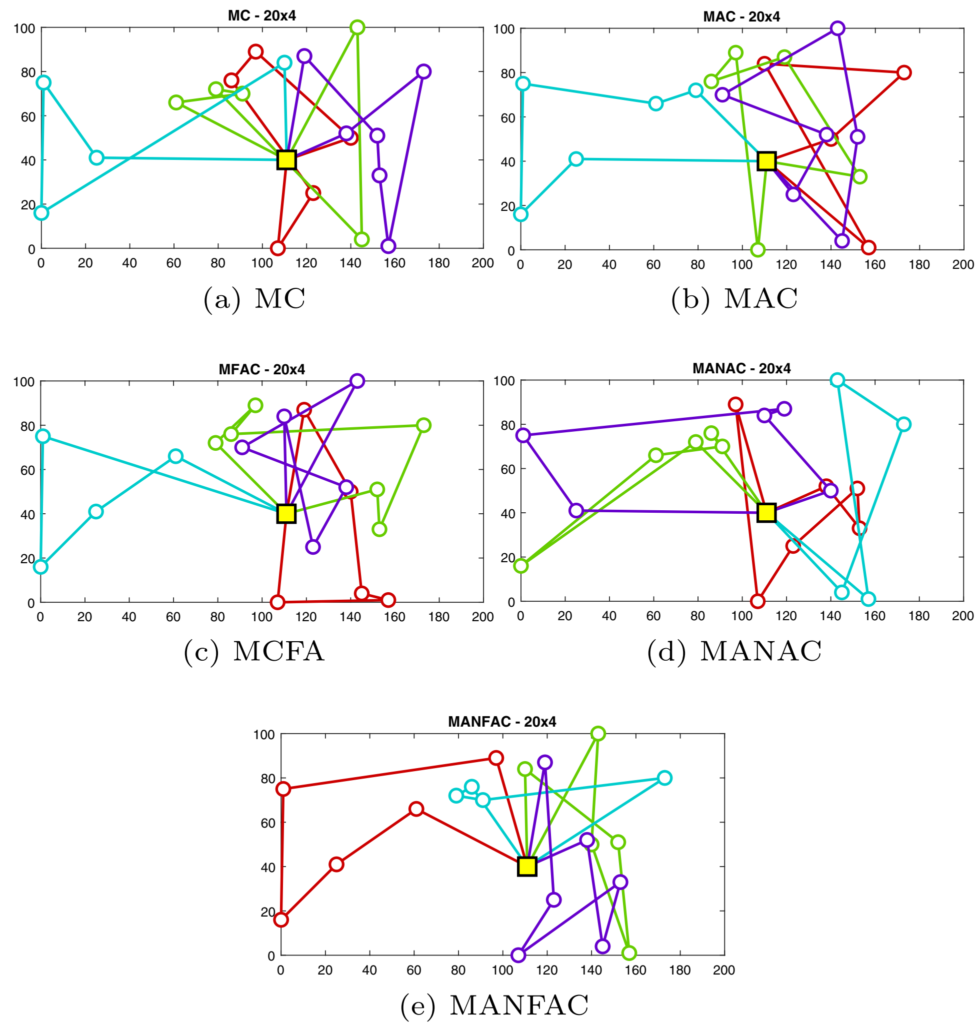


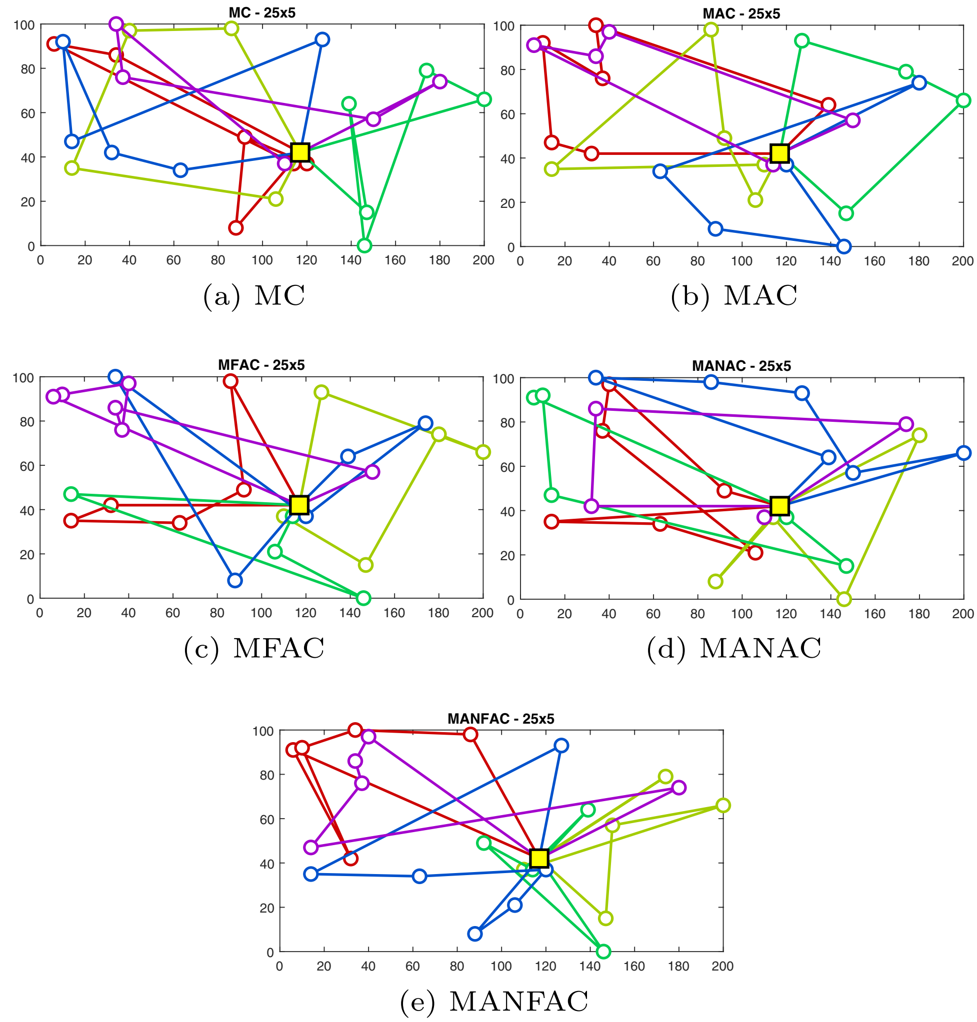
Fig. 8 Best results of the crab versions (20 × 4 VRP)

and 14 customers, and the other involving 4 routes and 20 customers. The algorithms generated distinct routes to fulfill the customers' demands, although some of the routes in the solutions shared similarities. It is worth noting that the increase in the number of customers and routes raises the complexity of the VRP, making it more challenging for the algorithms to identify optimal solutions, thus leading to variations in the results.

For 25 × 5 and 30 × 5 capacitated VRPs, the best results of the crab versions are shown in Figs. 9 and 10. In the given examples, the objective is to assign 25 and 30 customers to 5 different routes, while minimizing the total distance traveled by vehicles to fulfill the demands based on the customers' locations and demand information. For both VRP cases, each solution found with crab variants shows us different routes that meet customer demands.

Figure 11 shows the best solutions for 40 × 6 capacitated VRP which includes 40 customers and 6 routes, using the proposed crab versions. In Fig. 12, the results found by each crab variant are shown for 50 × 6 capacitated VRP. Upon analyzing the best solutions obtained by the proposed crab algorithm versions for both VRP examples, it is apparent that the routes created to satisfy customer demands differ across all algorithms.

Table 8 summarizes the statistical results of VRP of the crab versions for 50 runs. Table 9 gives the statistical results of the run-time metrics for 50 runs. In these tables, the best values are shown in bold. The tables reveal that the enhanced crab optimizer versions demonstrated remarkable performance for all VRPs, achieving results in an expedient manner. In the statistical comparison conducted for eight VRP samples, the MAC and MANAC algorithms yielded the



(a) MC (b) MAC (c) MFAC (d) MANAC (e) MANFAC

Fig. 9 Best results of the crab versions (25 × 5 VRP)

most favorable results in three VRP cases, while the MFAC and MANFAC algorithms produced the best results in one VRP case each, as indicated by the mean values. A careful inspection of the average running times of the algorithms demonstrated that the MAC algorithm exhibited the shortest run time in seven out of the eight VRPs, while the MANAC algorithm yielded the best time for only the 30 × 5 VRP. The running times of the Crab algorithm versions were generally close to each other. In terms of time, it is certainly possible to say that the handicap of the original crab algorithm has been eliminated. Generally, two crab optimization versions, namely the MAC and MANAC algorithms, stand out owing to their successful statistical outcomes.

The study employed the Wilcoxon Rank Sum Test, or the Mann–Whitney U Test, to evaluate the efficacy of the MAC algorithm compared to other algorithms. This non-parametric statistical test determines statistically significant differences in the medians of two independent groups. Our analysis served as a reliable tool for assessing whether the MAC algorithm produced noticeably distinct results in comparison to the other algorithms under scrutiny. Examining the rankings of observations derived from the MAC algorithm against those of rival algorithms enabled us to gain valuable insights into the MAC algorithm's relative performance and effectiveness within the study's context.

Table 10 gives the results of Wilcoxon Rank Sum Test of MAC algorithm with other crab versions. The table of results presented highlights the notable observation that the majority of P values computed are consistently below the conventional threshold of significance at 0.05. The pattern of $p < 0.05$ observed throughout indicates convincing statistical proof to refuse the null hypothesis, hence

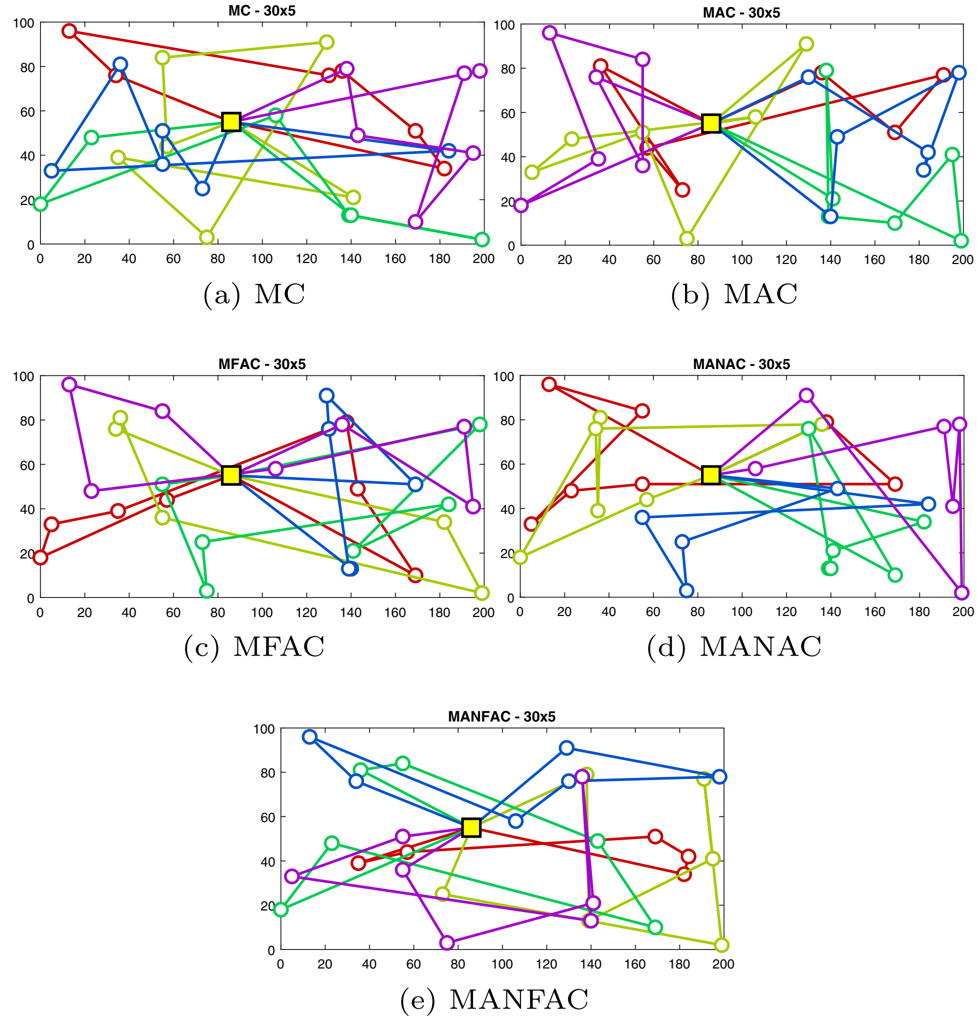


Fig. 10 Best results of the crab versions (30 × 5 VRP)

detecting the existence of significant disparities between the MAC algorithm and the other algorithms examined. These results highlight the resilience and efficacy of the MAC algorithm in attaining specific outcomes when contrasted with its counterparts in the study. A notable observation in the table results regards the comparison between the MAC algorithm and MANAC. In contrast to other comparisons, the calculated P values exceed the conventional significance threshold of 0.05 on a consistent basis. This observation suggests that there are no statistically significant differences in performance between the MAC algorithm and MANAC. These results suggest that although the MAC algorithm may differ significantly from other algorithms in the study, it is comparable to MANAC, indicating possible resemblances in their outcomes or capabilities within the specific context of this analysis.

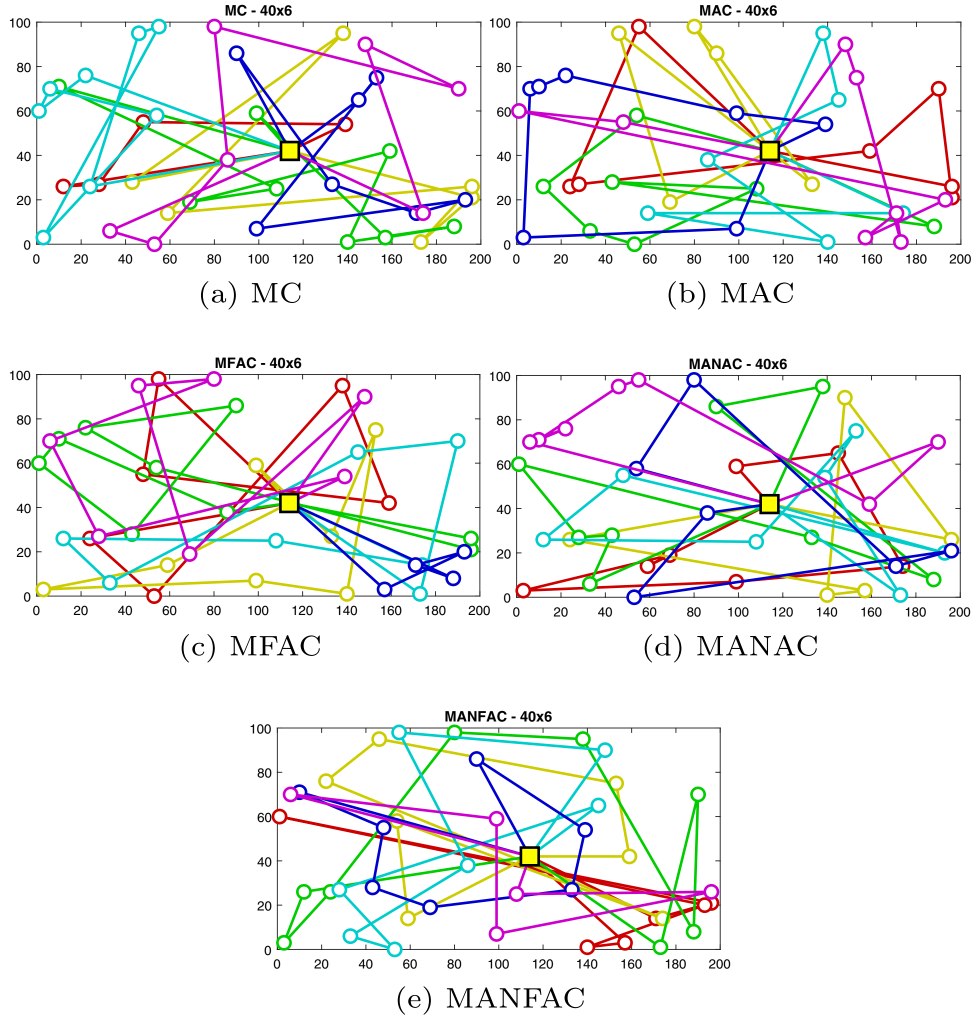


Fig. 11 Best results of the crab versions (40 × 6 VRP)

Conclusion

In this study, five novel versions of the crab optimizer are proposed, inspired by the life and mating of crabs. The first of these five novel versions, the Meliorated Crab mating optimization algorithm (MC), focuses on mating male crabs with half of the population, not the entire population. The second crab optimizer Meliorated Adaptive Crab mating optimization algorithm (MAC) is based on the adaptive mechanisms for crossover points (C_p) and mutation points (M_p). The third proposed algorithm, the Meliorated Fully Adaptive Crab mating optimization algorithm (MFAC), focuses on the adaptive mechanisms for C_p, M_p, and the receptivity degree (α) parameters. The main goal in Meliorated Normalized and Adaptive Crab mating optimization algorithms (MANAC) is to adaptive mechanisms for C_p and M_p and normalize the probability of matching value (P value). The last novel version is Meliorated Normalized and Fully Adaptive Crab mating optimization algorithms (MANFAC) which has adaptive mechanisms for C_p, M_p, α parameters, and normalized P value.

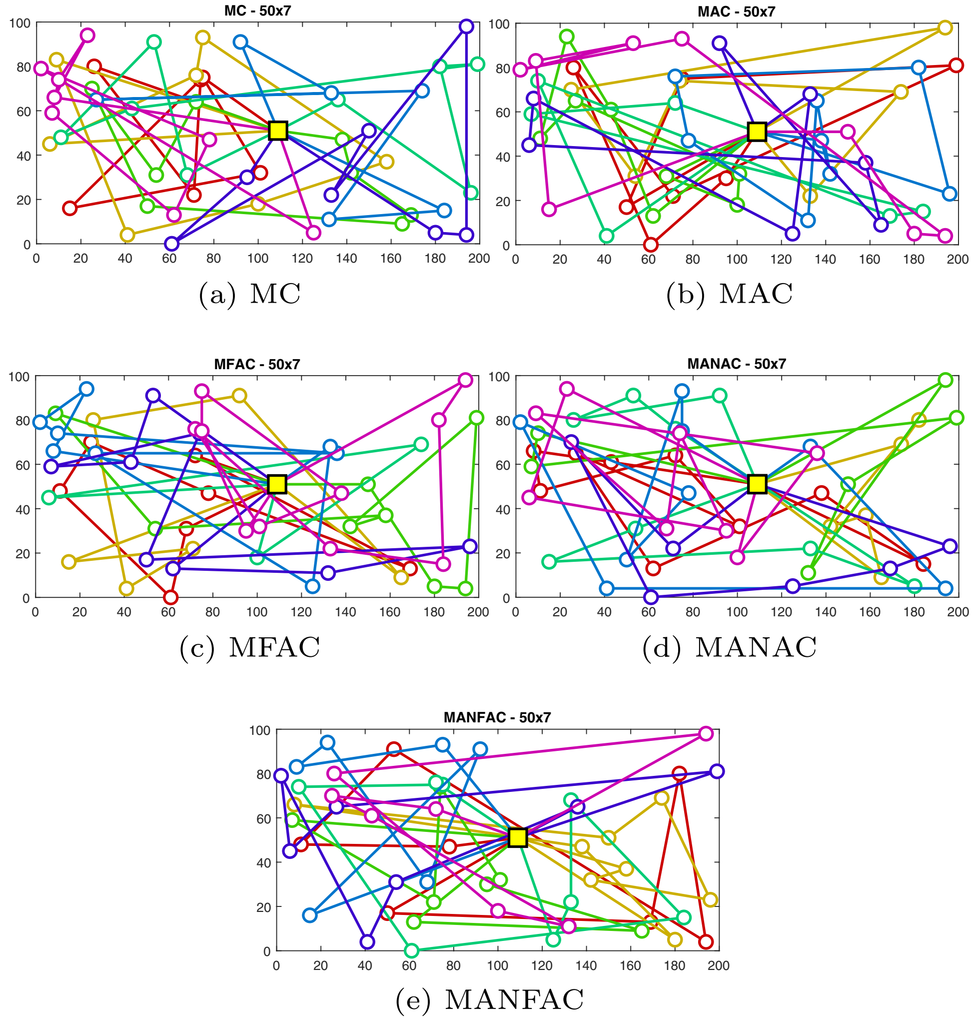


Fig. 12 Best results of the crab versions (50 × 7 VRP)

All these improved versions of the crab optimizer are compared with PSO, ABC, SA, and TACO algorithms over 20 different benchmark functions. According to the comparison, the proposed crab versions give competitive results as the other algorithms compared in accuracy, optimality, run time, and meaningful metrics. In terms of run-time scores, while improved crab versions were faster than TACO, they gave similar results to SA and ABC algorithms, but they were slower than the PSO algorithm.

The five crab optimizer versions, whose benchmark results were seen as promising, were adapted to the real-life problem, the capacitated Vehicle Routing Problem (VRP), and the solution results were compared. In the algorithms compared with the best cost metric in eight different models of the VRP, it was observed that the MAC and MANAC algorithms have more successful results in three VRPs and the MFAC and MANFAC algorithm in one VRP, while the MAC algorithm achieved faster results in seven of the eight VRPs. From the obtained results, it is observed that MAC has the best results among the other improved crab versions for VRP. Another result has been observed that adapting the mutation and crossover coefficients in the proposed algorithms has a positive effect on the performance of the algorithms. However, a positive effect of the adaptive structure of the receptivity value on the results was not observed.

Table 8 The statistical results of the crab versions

VRP	Metric	MC	MAC	MFAC	MANAC	MANFAC
8 × 3	Best	220.245	**220.163**	**220.163**	**220.163**	**220.163**
	Average	260.935	**248.221**	253.326	256.188	262.277
	Worst	336.452	315.572	**310.095**	396.788	318.500
10 × 3	Best	**284.979**	**284.979**	290.231	**284.979**	**284.979**
	Average	353.086	353.704	341.854	348.136	**340.394**
	Worst	487.454	440.150	411.428	**407.742**	412.788
14 × 4	Best	318.676	305.786	**295.510**	300.260	311.322
	Average	431.128	400.944	410.107	**396.614**	401.095
	Worst	683.336	**487.621**	596.020	493.127	500.036
20 × 4	Best	449.762	401.370	**397.150**	422.803	426.757
	Average	520.719	523.900	510.893	**508.477**	510.591
	Worst	621.249	844.884	**593.878**	825.755	659.057
25 × 5	Best	501.409	**467.493**	518.116	539.302	478.889
	Average	677.063	**620.714**	646.815	632.281	652.928
	Worst	1.013.847	**769.127**	816.448	847.618	956.476
30 × 5	Best	653.014	**576.631**	655.311	630.810	694.382
	Average	844.737	820.196	828.431	**816.544**	834.818
	Worst	1.206.305	**1.045.454**	1.216.811	1.391.850	1.099.109
40 × 6	Best	822.094	**756.294**	828.072	860.971	875.732
	Average	1.078.715	**1.016.145**	1.038.223	1.027.348	1.057.351
	Worst	1.552.320	1.422.553	1.341.323	**1.320.654**	1.446.589
50 × 7	Best	**922.771**	966.664	955.127	952.287	987.768
	Average	1.263.603	1.243.118	**1.213.737**	1.230.534	1.225.132
	Worst	1.614.118	1.675.448	**1.533.482**	1.680.806	1.793.904

Table 9 The statistical results of the run time of the crab versions

VRP	Metric	MC	MAC	MFAC	MANAC	MANFAC
8 × 3	Best	0.109	0.109	0.234	**0.094**	0.109
	Average	0.231	**0.194**	0.404	0.208	0.210
	Worst	0.938	**0.594**	1.219	0.625	0.625
10 × 3	Best	0.125	**0.094**	0.234	**0.094**	0.109
	Average	0.201	**0.173**	0.344	0.185	0.176
	Worst	0.438	**0.313**	0.578	0.547	0.391
14 × 4	Best	0.156	**0.141**	0.281	0.156	**0.141**
	Average	0.219	**0.177**	0.358	0.185	0.184
	Worst	0.391	**0.250**	0.516	0.281	0.281
20 × 4	Best	0.188	**0.156**	0.359	0.172	**0.156**
	Average	0.257	**0.211**	0.421	0.220	0.211
	Worst	0.391	0.313	0.531	0.313	**0.297**
25 × 5	Best	0.297	**0.219**	0.484	**0.219**	**0.219**
	Average	0.345	**0.268**	0.549	0.276	0.282
	Worst	0.484	**0.328**	0.734	0.406	0.391
30 × 5	Best	0.375	**0.281**	0.578	**0.281**	**0.281**
	Average	0.420	0.341	0.680	**0.339**	0.347
	Worst	0.609	0.594	0.922	0.547	**0.516**
40 × 6	Best	0.609	**0.438**	0.969	0.469	0.469
	Average	0.701	**0.524**	1.046	0.538	0.531
	Worst	1.016	**0.719**	1.328	0.797	0.844
50 × 7	Best	0.844	**0.594**	1.219	0.641	0.625
	Average	0.926	**0.696**	1.400	0.721	0.698
	Worst	1.188	0.938	1.656	1.078	**0.859**

Table 10 Wilcoxon Rank Sum Test results of MAC algorithm

VRP	MC	MFAC	MANAC	MANFAC
8 × 3	0.0152	0.4857	0.3250	0.0080
10 × 3	0.0317	0.0612	0.4179	0.0329
14 × 4	0.0037	0.0140	0.5695	0.0061
20 × 4	0.0364	0.1606	0.0682	0.2745
25 × 5	0.0135	0.0122	0.5602	0.0253
30 × 5	0.0157	0.0430	0.3647	0.0120
40 × 6	0.0267	0.0323	0.5147	0.0323
50 × 7	0.0145	0.0430	0.6417	0.0051

Data availability The datasets used during the current study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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