An evolutionary algorithm for the solution of multi-objective optimization problem

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ABSTRACT

Worldwide, COVID-19 widespread has a significant impact on a great number of people. The hospital admittance issue for patients with COVID-19 has been optimized by previous research. Identifying the symptoms that can be used to determine a patient's health status, whether they are dead or alive is a difficult task for medical professionals. To solve this issue, the multi-objective group counseling optimization (MOGCO) algorithm was used to control this problem. First, the zitzler-deb-thiele (ZDT)-2 benchmark function is used to evaluate the MOGCO, multi-objective particle swarm optimization (MOPSO), and non-dominated sorting genetic algorithm (NSGA) II. In comparison to MOPSO and NSGA-II, MOGCO is closest to the Pareto front line according to graphic statistics on different fitness evolution values such as 4000, 6000, 8000, and 10000. As a result, MOGCO is used for COVID-19 data optimization. Moreover, six symptoms (heart rate, oxygen saturation, fever, body pain, flue, and breath) were optimized to see if the COVID-19 patients were still alive. The information was gathered from GitHub. Based on the minimum and maximum values of these symptoms obtained by the suggested method, the optimum study shows that COVID-19 patients can remain alive.

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1. INTRODUCTION

Choosing the best solution from a group of alternatives is the process of optimization. It is a technique for choosing inputs that will produce the best possible solution. This can apply to a variety of things, such figuring out how to use available resources as effectively as possible. According to the authors [1], there are two categories of optimization issues: single-objective and multi-objective problems. The single-objective and multi-objective issues have been used to solve by a variety of evolutionary techniques. The author suggests the metaheuristic algorithms are another name for evolutionary algorithms [2]. In this article, the proposed method is used to apply the multi-objective group counselling optimization (MOGCO) algorithm to optimize the alive state of patients through multi-objective symptoms of COVID-19 dataset on different fitness values. This research is useful for medical doctors to save the lives of COVID-19 patients in today's era using the MOGCO optimization algorithm. Many patients have been unable to receive hospital services during the COVID-19 time. The patient's temperature, oxygen saturation and age-related issues were three main problems raised at this time. When COVID-19 patients are hospitalized, these three significant issues are controlled by MOGCO algorithms.

The patient death and survival rates are calculated using this method. We explain the evaluation criterion that was used to evaluate the proposed and tested algorithms. The performance of new and existing approaches is compared using the zitzler-deb-thiele (ZDT)-2 benchmarked function [3]. In this paper, following steps are used to implement this algorithm, first one is population size created by the model using the input data from the excel file and storing the proposed solution in the population table. In the second step, the model then creates new patients for the upper case and lower case of the COVID-19 patients. In the third step, the outcome of the generated individual is recovered. In step four, this process is repeated until the number of generations is complete [4], [5]. Various multi-objective evolutionary algorithms have been proposed, recently developing evolutionary algorithms to solve multiobjective optimization issues. Most algorithms were developed with two parallel goals in mind, rapid convergence to the Pareto-optimal front and a good distribution of solutions along the front. Each algorithm makes use of a particular combination of efficient techniques to achieve those goals [6].

The main benefit of using evolutionary algorithms (EAs) to solve multi-objective optimization problems is their ability to find many Pareto-optimal runs. This capacity is also present in particle swarm optimizers (PSO) and there have been several proposals to extend PSO to handle multi-objective situations [7]. The PSO versions and a complete learning particle swarm optimizer (CLPSO) have been shown to perform better in the single-objective domain [8]. Some authors used a multi-objective optimization algorithm to overcome the issues of multi-objective optimization problem by using the evolutionary method. By using the multi-objective optimization they suggest an evolutionary algorithm (EA) [9]. The authors proposed a method for multi-objective optimization that could be used in hospitals to diagnose and treat COVID-19 disease, a very serious condition that needs to be treated as soon as possible. The author of this study used two-optimization methods first one is multi-objective problem (MOP) and the second one is the Pareto optimization (PO). The PO algorithm handles patients with COVID-19. For the purpose of analyzing the PO algorithm, the authors used a data set of 254 patients.

These patients' dataset has been obtained from the Saudi Arabian King Faisal hospital. The main goal of this algorithm is to select the best hospital in the smallest period of time based on the patient's condition. However, these algorithms are not suitable to minimize hospital admission times. The study's author is trying to use the meta heuristic approach. The quantum-behaved algorithm for solving the problem of multi-objective. The authors of this literature review represented a novel cultural multi-objective quantum particle swarm optimizers (MOQPSO) procedure for multi-objective problems. To solve the multi-objective problem by using a mechanism like quantum particle swarm optimizers (QPSO), a novel practice optimization was presented on the base of some methods MOQPSO. But it does not focus on solving the problem of a dynamic environment [10], [11].

For the purpose of multi-objective optimization of the home healthcare problem. The main objective of this algorithm for decrease the total working time of patients like a patient going to the hospital and then admitting time and care take time. Patients have faced most of the problems like a travel time, during visit, and based on the availability [12]. To resolve the energy and throughput challenges through optimization. The transmission error rate and the total amount of packets that have been received depend on which types of problems and challenges. The authors of this study proposed an optimization problem with multiple-objects for home health care with sensor devices. The most of wireless senior network (WSN) are used for five detection, health care system and other security issues in different situations. But these wearable devices are rechargeable and take resources and budget [13].

The researcher of this study proposed a multi-objective optimization model in the health care system. It just multi-objective optimization to help waste management network design with a sustainability perspective [14]. The researcher tries to get an accurate result with the multi-objective grasshopper optimization algorithm (MOGOA). But it does not use the same rules and techniques for solving the multi-objective problems [15]. Researchers have used a different objective model like a susceptible, infected, dead, and recovered. This model was based on robust multi-objective optimization stochastic fractal search. They were used a China datasets of COVID-19 patients to solve the nominal and robust problems [16]. In multi-objective optimization problems, noise parameters are used to maximize the value, however this study is not considered as a dynamic analysis of COVID-19 patients [17].

2. RELATED WORKS

Authors of this study presented a technique in which they created a group counseling optimizer that is based on a new population and uses a novel methodology. Similarly, they used group counselling optimization (GCO) to find a solution to the issue of human behavior. By using the method, the authors verified seven benchmark functions. The comparison of learning particle swarm complicated optimization and group guiding revealed higher efficiency and power than others. Numerous methods for multi-objective optimization problems have been presented by the enters. The processes MOGCO, multi-objective comprehensive learning particle swarm optimizer (MOCLPSO), non-dominated sorting genetic algorithm

(NSGA), NSGA-II, attributed multi-objective comprehensive learning particle swarm optimizer (AMOCLPSO), and multi-objective particle swarm optimization (MOPSO) all require a long time to complete. The process of calculating ideal results takes time and greater fitness development value. However, we attempt to employ the MOGCO method to resolve multi-objective issues in the suggested system multi-objective optimization problems can be solved with the MOGCO.

MOGCO performs multi-objective optimization using a variety of benchmark measurements and functions [18], [19]. Nowadays, optimization issues are frequently solved using evolutionary algorithms. Numerous evolutionary algorithms, such as the evolutionary genetic algorithm (GA), evolutionary strategies (ES), differential evolution (DE), evolutionary programming (EP), and genetic programming (GP), have been effectively applied in real-world settings. These processes fall under the category of evolutionary algorithms [20]. The multi-objective extensively the speeds of each parameter using a randomly chosen particle drawn from the total population [21]. This technique helps to speed up the algorithm. Optimization for particle swarms makes use of liner summation. Utilizing the randomly selected particle from the entire population, we can determine the speed of dimension. When dealing with many competing objectives, conventional optimization techniques like linear programming and the weighted sum methodology are useless. The use of evolutionary algorithms is made to address such issues. The non-dominated solutions to multi-objective optimization problems are numerous. Optimizing the particle swarm with several objectives also enhances performance. The multi-objective exhaustive uses a randomly selected particle from the entire population to update the speed of each dimension [22]. To enhance the effectiveness of an evolutionary multiobjective optimization (EMO) approach, the majority of the author created a novel method to preserve variation, such as the Pareto repository evolutionary strategy's adaptive grid (PAES). PSO is a novel algorithm inspired by bird flock choreography that has been demonstrated to perform well in a variety of optimization scenarios, but it hasn't been extended to manage various objectives. New methods and data structures have been developed for handling unrestrained external archived achievement [23].

A unique algorithm influenced by a bird swam arm choreographer has been demonstrated to perform well in numerous optimization circumstances, but it has not been expanded to handle various objectives. Novel methods and data structures for managing unconstrained external archival performance [24]. To demonstrate that the accuracy of the proposed calculation has already been fully evaluated. The system's damage and total security cost are reduced by the suggested model. Our experimental data for this method are compared to the outcomes for the same problem utilizing NSGA-II and MOCLPSO. To showd that on well-known benchmark problems including Schaffer (SCH), Kurosawa (KUR), and zitzler-deb-thiele (ZDT), as well as MOPSO and NSGA-II, the proposed approach beat them (NSGA-II) [25]. This approach is used to manage security issue while attempting to reduce costs. For further network optimization, the author of this study compares the two primary approaches, NSGA-II as well as MOCLPSO.

The approach, suggested by Kim *et al.* [26], used the PSO version of the MOCLPSO technique (swarm optimization variant). A random molecule is chosen to enhance the speed of the old molecular for each area, enabling it to search through more possible regions of the search space [27]. The MOCLPSO is no match for this PSO. Most often, PSO includes other sorts of plans, including the best (lbest) and best (gbest). For example, a person may use their best personal circumstances and the best local conditions, or they may use their best local circumstances and the top local conditions that have existed. If the research area is challenging, the PSO can basically be placed at the best local position based on lbest or gbest. In order to address that, a CLPSO-calculation was developed with three special pbest, gbest, and irregular update speed conditions. The probability boundary personal computer (PC) was used to determine the number of ages for which randomly selected particles were used for each aspect. The multi-objective version of CLPSO called MOCLPSO stands for multi-objective complete learning development swarm improvement [28]. Choosing the optimum locations throughout the world is still difficult, despite the fact that these techniques improve PSO implementation in complicated multimodal circumstances. Molecule swarm analysis with multi-objective continuous learning (A-MOCLPSO). We employ the best area of a randomly selected component from the total population to refresh each aspect's speed, as opposed to the global or local best areas [29].

According to Wunsch [30], a quick and efficient multi-objective algorithm can be used to solve any kind of problem. Every aspect of life, such as technology, transportation, and finance, has been using multi-objective optimization. Vector optimization and the Pareto optimization technique are other names for multi-objective optimization. Because of its population-based approach, it is used to determine the most appropriate solution for each issue. They suggested a group counselling optimization to address issues that group counselling faces in addressing human social behavior. Group therapy optimization is extended to address the constrained optimization problem for the first time. By presenting the benchmark, the first three results from restricted group optimization, then another, the efficiency of confining group counselling optimization is evaluated in the 2010 competition. These four test issues are used by the author of their literature review. Constern, SRN, and TNK water come first. The Pareto approach for optimization techniques is not appropriate in CONSTER, and there is another issue with SRN. It is employed in original research. In TNK issues, the constraint limit is applied.

The previous issue was the water problem, which had five objectives and seven regulations. It uses five objectives to try and solve the issue. The total population size across all issues is 100. But the main problem with this paper is that [31]. The same mathematics issues were employed to make numerous criterion decisions in multi-objective situations. Since problems are something that everyone encounters every day. Multi-objective approach and recommended a priority evolutionary algorithm for multi-objective optimization problems. They employ a variety of strategies and procedures in an effort to deal with the problem. There have been various ways to address the same problem. Because there are many ways to handle a single issue, good approaches and methods should always be used. Everyone tries to select an efficient approach to one issue. Single and multi-objective problems are solved by optimization. In the single-objective optimization method, the problem is solved using just one objective. The second way is the multi-objective optimization algorithm, which uses the greatest number of objectives to solve the problem [32]. Multiple-objectives are solved through multi-objective challenges. For the optimization process, they used a space manoeuvre vehicle flow optimization technique.

The paper suggested the hp-a daptive pseudo spectral approach for addressing the multiple-objective situations by Missouris *et al.* [33], They presented an optimization issue for space maneuva vehicles (SMV). The violation learning differential evolution (VLDE) algorithm is made to handle non-local image dehazing (NLD) issues in the three-dimensional SMV framework. A learning mechanism is applied to the algorithm to increase computation time. For the violations degree, with violation degree, and the satisfying degree, these author presents some limitations, some regulations, and rules. After comparing the testing procedure with SMV, researchers utilised a new convergent testing. SMV performs better in terms of convergence time and convergence ability. However, there are certain flaws in the VLDE technique used to address make significant. The issue is that it does not concentrate on addressing really challenging and difficult issues [34].

3. METHOD

Recently years, COVID-19 diseases have become a serious problem for the whole world. This research is helpful for medical practitioners to save the lives of COVID-19 patients in today’s era using the MOGCO optimization algorithm (Figure 1). MOGCO algorithm to check the symptoms (fever, oxygen saturation, breath, heart rate, body pain, and flue) of COVID-19 patients.

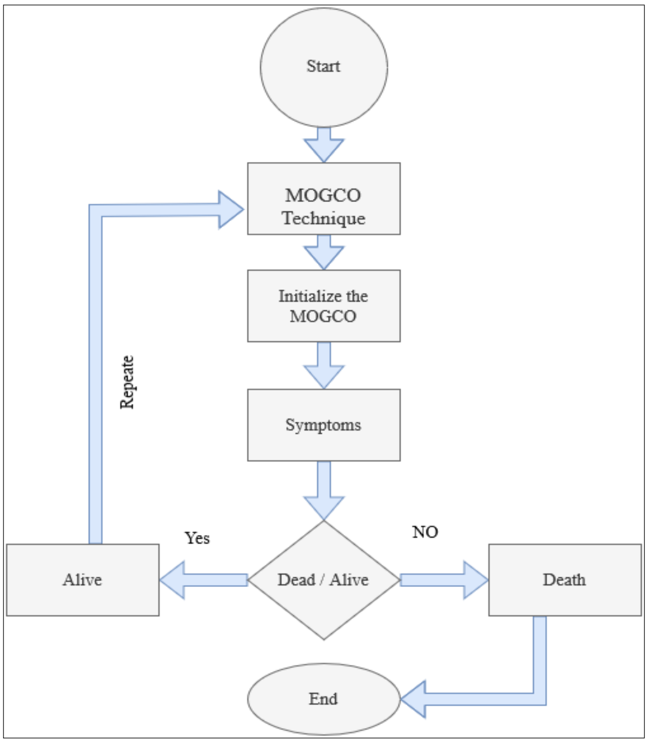

Figure 1. Proposed framework

After that, the proposed algorithm checked the condition dead and alive. If the condition is alive, then the process is repeated. In this study work, COVID-19 patient data is measured. The data set is collected from the GitHub https://github.com/ProDeSquare/COVID_data or https://surl.prodesquare.com/l/COVID_data. The description of the COVID-19 patient's data set is given in Table 1.

Table 1. Explanation of COVID-19 patient's data set

No. of samples	No. of features	No. of classes
2511	6	2

3.1. Evaluation metrics

The evaluation parameter that was used to test the proposed and existing algorithms is described in this section. The performance of the suggested approaches is compared using the ZDT2 benchmarked function (Figure 2) [35]. Benchmark test functions have been used in the works to estimate the performance of meta heuristic algorithms. Effective approaches for solving real-world problems are algorithms that perform well on a set of arithmetical optimization tasks.

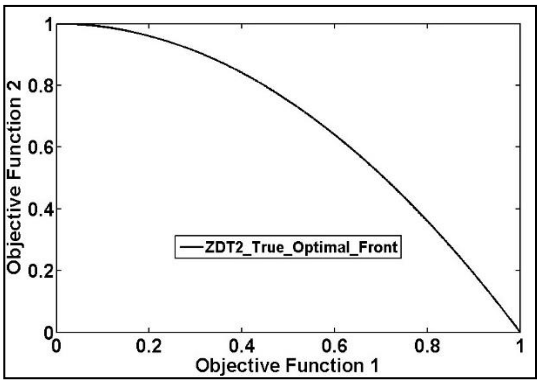

Figure 2. True Pareto front of ZDT2 function

The algorithms are tested using the performance metric to choose which algorithm performs better. In the region x = 0, both objective functions are reducing, whereas in the region $x \geq 1$, they are increasing. F1 (x) increases and F2 (x) decreases between 0 and 1. Between maximum 1 and minimum 0 exists in this area as a tradeoff [36].

3.2. Tools and technology

The proposed algorithm is implemented using MATLAB R2013b running on Microsoft Windows 10 pro 64 bits operating system. The desktop PC was built with 6.00 GB physical memory, (RAM), Intel (R) core i5 1.70 GHz processor central processing unit (CPU). For the implementation of an optimization model for the classification of COVID-19 patients used the languages PHP, SQL, sublime, and XAMPP.

4. PROPOSED WORK

This section describes the suggested algorithm's step-by-step operations. Figure 3 shows the overall work of proposed method. The MOGCO method is used to implement this model practice. On the COVID-19 data, the proposed model is tested. The GitHub is used to gather the patient's datasets. The proposed method works according to the following steps:

Step 1: The model first creates the population size by saving the chosen solution in the population table using the input data from the excel file.
Step 2: The model then produces new patients for the upper case and lower case of the COVID-19 patients in the second step.
Step 3: If the generated individual's outcome is recovered in the third phase, the control proceeds on to the next iteration; otherwise, the control goes back and generates brand-new people.
Step 4: The fourth step includes maintaining this procedure until all generations have been created.

The population size (p/P) and generation size (g/G) are shown in Figure 3 all population iterations must have completed. The model builds a new individual for upper case and lower case COVID-19 patients in each population iteration based on a particular population.

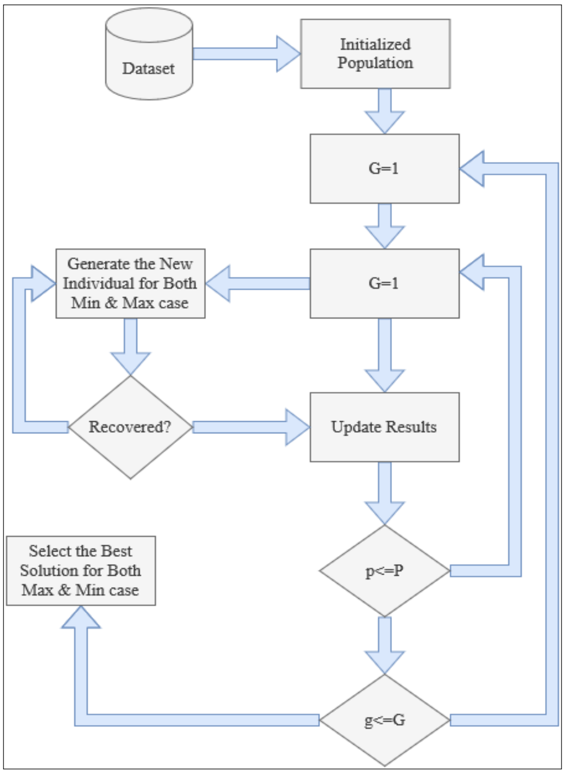

Figure 3. Propose flow chart of optimization model for classification of COVID-19 patients

5. RESULTS AND DISCUSSION

The results of proposed and existing algorithms on benchmarked function of COVID-19 datasets. Using the ZDT2 benchmark function, a multi-objective group counselling optimizer is test. The final outcome shows that the proposed method is a very feasible and successful approach for multi-objective optimization problems.

i) Random initialized the population POP.
ii) Find the fitness of each individual.
iii) Store the best position and objective function of each individual while stopping criteria is not met do
    a. Compute the changes in an individual position using the method.
    b. Counseling strategies.
    c. Compute the new position of each individual.
    d. Maintain the position of each individual within the search space.
    e. Evaluate the new position of each individual.
    f. Update the personal best position of each individual end
iv) Select the best solution.

The proposed algorithm is examined for the fitness evolution values 4000, 6000, 8000, and 10000; the results are shown according to the algorithm as shown in Figures 4(a)-(d). The algorithm is tested on the ZDT2 benchmark function. According to the results, the Pareto front formed with the fitness evolution value of 10000 is the best one, as shown in Figure 4(d). The results also indicate that the algorithm's efficiency is unaffected by an increase in the fitness evolution values. According to Figure 4(d), the MOGCO produced the solutions with the best spread and convergence at the genuine Pareto front for fitness evolution values of 10000.

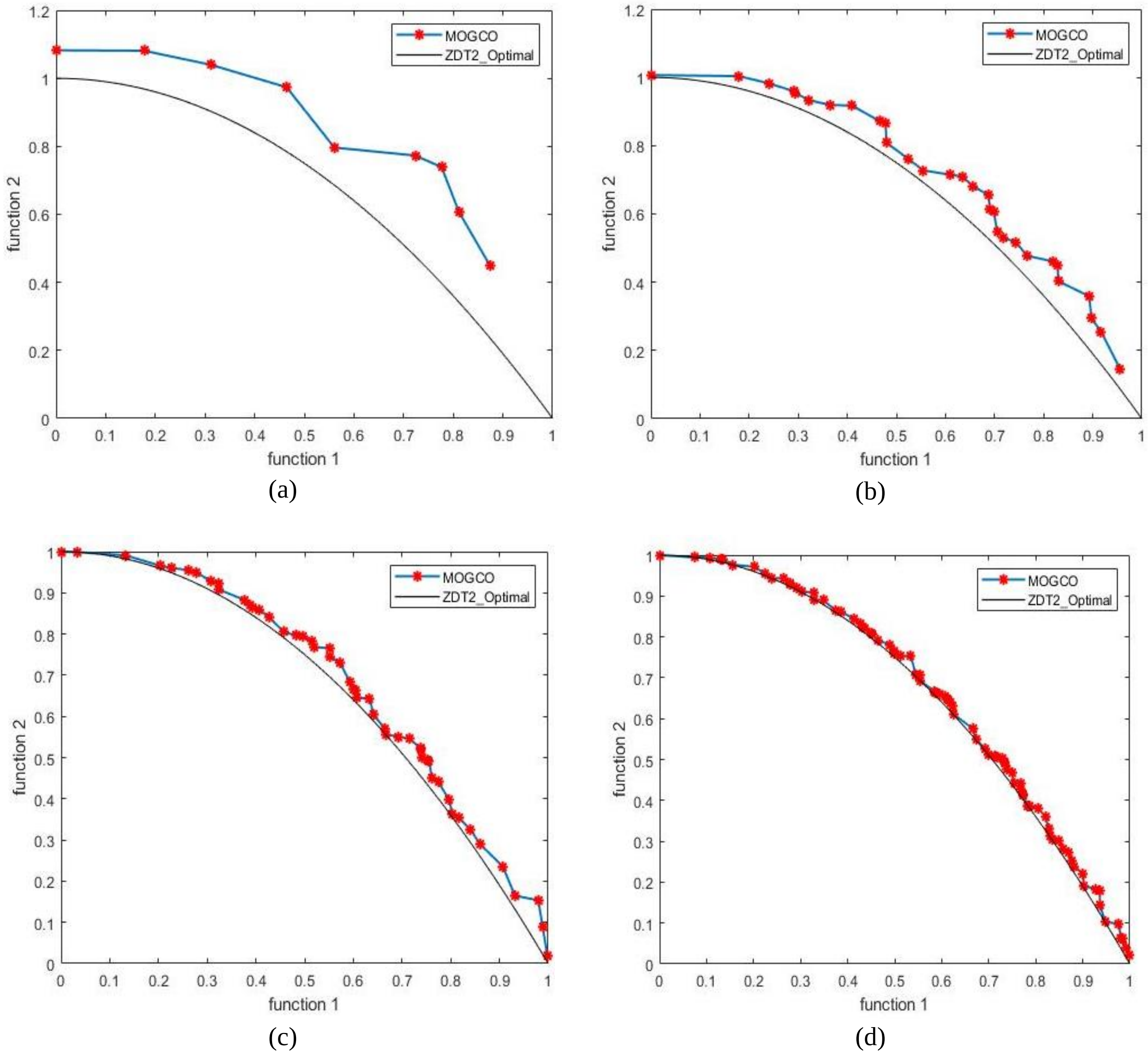

Figure 4. Results of MOGCO for ZDT2 on fitness evolution value: (a) 4000, (b) 6000, (c) 8000, and (d) 10000

The algorithm tested on 3000 patients' data with the following parameters: heart rate, oxygen saturation, fever, breath, body pain, and flue. The parameter is used in the data set for the survival of COVID-19 data by using the optimization algorithm based on MOGCO is shown in Table 2. The results of the optimization algorithm for the survival of COVID-19 patients are presented in Table 3.

Table 2. Following parameters are used in data set

S. No	1	2	3	4	5	6
Parameter	Heart Rate	Oxygen Saturation	Fever	Body Pain	Flue	Diff Breath

Table 3. The results of optimization algorithm for COVID-19 patients

S. No	1	2	3	4	5	6
Parameter	Heart Rate	Oxygen Saturation	Fever	Body Pain	Flue	Diff Breath
Maximum	199	94.15	104	Yes/No 51%/49%	Yes/No 50%/50%	No/Yes 55%/45%
Minimum	41	84.825	98	Yes/No 47%/53%	Yes/No 49%/51%	No/Yes 48%/52%

Table 3 displays that the results are produced for two limits upper limit and lower limit. The upper limit is the maximum value for each parameter, display that this is the maximum value for the parameter up to that the patient can be alive. And the lower limit is the minimum value for each parameter, showing that this is the minimum value for the parameter till that the patient can live. If the value of the parameter exceeds the limit the patient can't survive more and will die.

6. CONCLUSION

According to this research, the MOGCO improves NSGA-II and MOPSO, two other population-based evolutionary algorithms. On test function ZDT2, the comparison was done for the fitness evolution values of 4000, 6000, 8000, and 10000. The results show that, in comparison to other algorithms, the MOGCO provides greater resolution around the optimal outcomes and a better distribution of solutions close to the Pareto optimal front. We present a new optimization algorithm for the optimization of COVID-19 patients as our primary contribution in this paper. The method is evaluated using the following metrics from the data of 3000 patients: heart rate, oxygen saturation, fever, breath, bodily pain, and flu. The algorithm created an upper limit and a lower limit for each parameter such that the COVID-19 patient can survive as long as the limit is reached else, the patient will die. To solve this issue, MOGCO is developed a powerful multi-objective counselling optimization method. The information is gathered via Git Hub. In order to comparison the proposed and comparison algorithms were used in fitness evolution values of 4000, 6000, 8000, and 10000.

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