Multi-Objective Evolutionary Computation Solution for Chocolate Production System Using Pareto Method

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Abstract

Solving manufacturing engineering problems normally involves variety of challenges. It is important to maximize profit, improve quality of a product mean while reduce losses and cost. This trade-off plays a vita role in solving many manufacturing optimization problem. The Chocoman Inc, USA produces varieties of chocolate bars, candy and wafer by means of raw materials. The objective of the company is to minimize its cost while maximizing the production of eight products. The formulation of this problem resulted in five functions to be optimized based twenty nine constraints to be satisfied. This is a typical Multi-objective Optimization Problems (MOPs). Many methods attempted to solve this problem. In this paper, we provide a comparison between the Scalarization and Pareto methods based Genetic Algorithms (GAs) to solve the chocolate production problem. GAs provides an outstanding solution.

Keywords: *Multi-objective Optimization Problems (MOPs), Evolutionary Computation, Chocolate Production System, Scalarization Method, Pareto Method, GEATbx, Matlab.*

1. Introduction

Most manufacturing engineering problems involve multiple-objectives. For example, minimize cost, maximize performance, maximize quality, reduce defected products etc. These are difficult but practical problems which normally happen [1]. GA was successfully used to solve variety of problems in system design, optimization and control. Genetic algorithms (GAs) are adaptive search procedures which were first introduced by J. Holland at Michigan University, USA 1975, and extensively studied by K. De Jong, D. Goldberg and others. GA found to be a well-matched tool for this class of problems. GAs is a population based approach which can optimize a complex optimization function given a fitness function to evaluate the goodness of a solution. Two universal approaches to solve multiple-objective optimization were introduced in the literature [2]. The first approach is to combine each individual objective functions into a single composite function [3]. Solving a single objective function problem is visible with many methods such as the utility theory, weighted sum method [4], etc. There were many disadvantages reported on using the given methods. For example, in the case of utility function, finding the accurate weight of the function is not an easy task. Besides, the values of the weight are to be optimized not always robust. It is most likely affected by little uncertainly. The second approach is to find an entire Pareto optimal solution set. A Pareto optimal set is defined as the set of solutions that are non-dominated with respect to each other. The basic concepts of non-dominated and Pareto optimal solutions is explained by the following example. Solution S is said to dominate solution Y if all components of S are at least as good as those of Y, with at least one better component, and S is non-dominated if it is not dominated by any solution. Pareto optimal solution usually provides a more practical solution to engineering problem since they are always a trade-off between key parameters of the problem. The Pareto set size is always a function of the number of objective functions.

In this paper the main motivation for using Evolutionary Algorithms (EA's) to solve multi-objective optimization problems is because EA's deal simultaneously with a set of possible solutions (called population) which allows us to find several members of the Pareto optimal set in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of the traditional mathematical programming techniques. Additionally the EA's does not require problem specific knowledge to carry out a search [2]. Our goal is to solve the well-known chocolate production system problem as a multi-objective optimization problem using Genetic Algorithms. We plan to use the Genetic and Evolutionary Algorithm Toolbox with Matlab (GEATbx) [5] to solve the problem. A comparison between the Scalarization and Pareto methods will be provided.

2. Statement of the problem

The multi-objective optimization problem can be defined as follows [10]. Our objective is to find the vector $\bar{x}^* = [\bar{x}^*, \bar{x}^*, ...\bar{x}^*]^T$ which will satisfy the m inequality constraints:

$$g_i(\bar{x}) \geq 0 \quad i = 1,\ldots,m \tag{1}$$

The p equality constraints:

$$h_i(\bar{x}) = 0 \quad i = 1,\ldots,p \tag{2}$$

and optimize the vector function

$$f(\bar{x}) = [f_1(\bar{x}), f_2(\bar{x}),..., f_k(\bar{x})]^T \tag{3}$$

$\bar{x} = [x_1, x_2,..., x_n]^T$ is the vector of decision variables. In other words, we want the set of all numbers which satisfy Equations (1) and (2) using the particular set $x_1^*, x_2^*, \ldots, x_k^*$ which yields the optimum values of all the objective functions.

3. Multi-objective Optimization Problem

Genetic Algorithm uses computational models of natural evolutionary processes in developing computer based problem solving systems. Solutions are obtained using operations that simulate the evolution of individual structures through mechanism of reproductive variation and fitness based selection. Due to their success at searching complex non-linear spaces and their reported robustness in practical applications, these techniques are gaining popularity and have been used in a wide range of problem domain, one of which is the multi-objective problem [6, 7, 8, 9, 10, 11].

Different methods were used to explore the multi-objective optimization, such as the classic method for integrating several criteria scalarization, also called aggregation of objectives, and the Pareto method. Multiple Pareto-optimal solutions can be captured in the GA population in a single simulation run. A wide number of problems have been solved in various multi-objective optimization applications [12, 13, 14, 15, 16]. New and improved GA implementations studies were also investigated in [17, 18, 19, 20].

3.1 Scalarization method

Multi-objective optimization problems can be solved in numerous ways; a direct one is to combine them into a single scalar value (e.g., adding them together). This techniques are normally known as "aggregating functions", because they combine (or "aggregate") all the objectives of the problem into a single one.

An example of this technique is the fitness function that is used to solve the following problem:

$$J = \sum_{i=1}^{k} w_i f_i(x) \tag{4}$$

where $w_i \rangle 0$ are the weighting coefficients representing the relative importance of the k objective functions of our problem [2]. We usually assume that it has a value of 1 ($\sum_{i=1}^{k} w_i = 1$).

Aggregating functions are a very common tool used to develop a direct implementation for the multi-objective problem were a single objective is used in fitness assignment, so a single objective GA can be used with minimum modifications. The drawback of this technique is that not all Pareto-optimal solutions can be investigated when the true Pareto front is non-convex. That's way, the multi-objective GAs based on the weighed sum approach have difficulty in finding solutions uniformly distributed over a non-convex trade-off surface [21]. When a multi-objective problem is solved by means of single-objective optimization, only a point solution is obtained. The advantage of obtaining several solutions of equal value relating to a target vector is lost. For that reason the user must decide to either use the simple weighted sum or the approximation of the Pareto-optimal solutions [22].

3.2 Pareto method

The MOPs is sometimes combined into a single objective so that traditional optimization and the mathematical programming methods can be used. Alternatively, a Pareto optimal set is found. This is usually achieved by using an evolutionary algorithm such as GA [23]. The definition for such a problem with more than one objective function (say, $f_j, j = 1,..., M$ and $M \rangle 1$), with two solutions x_1 and x_2 can have one of two possibilities: one dominates the other or none dominates the other. A solution x_1 is said to dominate the other solution x_2, if both the following conditions are true [24]:

1. The solution x_1 is no worse (say the operator<denotes worse and > denotes better) than x_2 in all objective, or $f_j(x_1) > f_j(x_2) \quad \forall \quad j = 1....2, M$ objectives.
2. The solution x_1 is strictly better than x_2 in at least one objective, or $f_j(x_1) > f_j(x_2)$ for at least one $j \in \{1,2,...., M\}$.

If any of the above condition is violated, the solution x_1 does not dominate the solution x_2. To solve the production problem with five objective functions using

Scalarization, and Pareto methods, we plan to use the GEATbx Toolbox based on Matlab [5].

4. Chocolate production system

In this section, we provide a description for the famous production system chocolate problem for a chocolate exporting company. The data for this problem have been adopted from the data-bank of Chocoman Inc, USA [25]. The firm Chocoman, Inc. manufactures produced 8 different kinds of chocolate products since there are 8 raw materials to be mixed in different proportions and 9 processes (i.e. facilities) to be utilized. The problem can be presented as multi objective functions with 8 parameters to be optimized and 29 constrained that should be satisfied at the end of the evolutionary process that finds the optimal set of parameters. The objective of this problem is to maximize the five objective functions with eight variables. The decision variables for the chocolate problems are defined as:

x_1 = milk chocolate of 250g to be produced
x_2 = milk chocolate of 100g to be produced
x_3 = crunchy chocolate of 250g to be produced
x_4 = crunchy chocolate of 100g to be produced
x_5 = chocolate with nuts of 250g to be produced
x_6 = chocolate with nuts of 100g to be produced
x_7 = chocolate candy to be produced
x_8 = chocolate wafer to be produced

MAXIMIZATION - FIVE OBJECTIVE FUNCTIONS

F1 **Revenue**

$$F_1 = 375x_1 + 150x_2 + 400x_3 + 160x_4 + 420x_5 + 175x_6 + 400x_7 + 150x_8$$

F2 **Profit**

$$F_2 = 0.25x_1 + 0.1x_2 + 0.25x_3 + 0.1x_4 + 0.25x_5 + 0.1x_6$$

F3 **Market Share for Chocolate Bars**

$$F_3 = 0.25x_1 + 0.1x_2 + 0.25x_3 + 0.1x_4 + 0.25x_5 + 0.1x_6$$

F4 **Units produced**

$$F_4 = x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8$$

F5 **Plant utilization**

$$F_5 = 1.65x_1 + 0.9x_2 + 1.975x_3 + 1.03x_4 + 1.75x_5 + 0.94x_6 + 4.2x_7 + 1.006x_8$$

Subject to the constraints:

C1: $x_1 \leq 0.6x_2$

C2: $x_3 \leq 0.6x_4$

C3: $x_5 \leq 0.6x_6$

C4: $400x_7 + 150x_8 \leq 56.25x_1 + 22.5x_2 + 60x_3 + 24x_4 + 63x_5 + 26.25x_6$

C5: (cocoa usage)

$$87.5x_1 + 35x_2 + 75x_3 + 30x_4 + 50x_5 \quad 20x_6 + 70x_7 + 12x_8 \leq 100000$$

C6: (milk usage)

$$62.5x_1 + 25x_2 + 50x_3 + 20x_4 + 50x_5 \quad 20x_6 + 30x_7 + 12x_8 \leq 120000$$

C7: (nuts usage)

$$0x_1 + 0x_2 + 37.5x_3 + 15x_4 + 75x_5 \quad 30x_6 + 0x_7 + 0x_8 \leq 60000$$

C8: (confectionery sugar usage)

$$100x_1 + 40x_2 + 87.5x_3 + 35x_4 + 75x_5 + 30x_6 + 210x_7 + 24x_8 \leq 200000$$

C9: (flour usage)

$$0x_1 + 0x_2 + 0x_3 + 0x_4 + 0x_5 + 0x_5 + 0x_6 + 0x_7 + 72x_8 \leq 20000$$

C10: (aluminum foil usage)

$$500x_1 + 0x_2 + 500x_3 + 0x_4 + 0x_5 + 0x_6 + 0x_7 + 250x_8 \leq 500000$$

C11: (paper usage)

$$450x_1 + 0x_2 + 450x_3 + 0x_4 + 450x_5 \quad 0x_6 + 0x_7 + 0x_8 \leq 500000$$

C12: (plastic usage)

$$60x_1 + 120x_2 + 60x_3 + 120x_4 + 60x_5 + 120x_6 + 1600x_7 + 250x_8 \leq 500000$$

C13: (cooking facility usage)

$$0.5x_1 + 0.2x_2 + 0.425x_3 + 0.17x_4 + 0.35x_5 + 0.14x_6 + 0.6x_7 + 0.096x_8 \leq 1000$$

C14: (mixing facility usage)

$$0x_1 + 0x_2 + 0.15x_3 + 0.06x_4 + 0.25x_5 \quad 0.10x_6 + 0x_7 + 0x_8 \leq 200$$

C15: (forming facility usage)

$$0.75x_1 + 0.3x_2 + 0.75x_3 + 0.30x_4 + 0.75x_5 + 0.30x_6 + 0.90x_7 + 0.36x_8 \leq 1500$$

C16: (grinding facility usage)

$$0x_1 + 0x_2 + 0.25x_3 + 0x_4 + 0x_5 + 0x_6 \quad 0x_7 + 0x_8 \leq 200$$

C17: (wafer making facility usage)

$$0x_1 + 0x_2 + 0x_3 + 0x_4 + 0x_5 + 0x_6 \quad 0x_7 + 0.3x_8 \leq 100$$

C18: (cutting facility usage)

$$0.5x_1 + 0.1x_2 + 0.1x_3 + 0.1x_4 + 0.1x_5 \quad 0.1x_6 + 0.2x_7 + 0x_8 \leq 400$$

C19: (packaging facility usage)

$$0.25x_1 + 0x_2 + 0.25x_3 + 0x_4 + 0.25x_5 + 0x_6 + 0x_7 + 0.1x_8 \leq 400$$

C20: (packaging 2 facility usage)

$$0.05x_1 + 0.3x_2 + 0.05x_3 + 0.3x_4 + 0.05x_5 + 0.3x_6 + 2.50x_7 + 0.15x_8 \le 1000$$

C21: (labor usage)

$$0.3x_1 + 0.3x_2 + 0.05x_3 + 0.3x_4 + 0.3x_5 \; 0.3x_6 + 2.50x_7 + 0.25x_8 \le 1000$$

C22: (demand for MC 250) $x_1 \le 500$

C23: (demand for MC 100) $x_2 \le 800$

C24: (demand for CC 250) $x_3 \le 400$

C25: (demand for CC 100) $x_4 \le 600$

C26: (demand for CN 250) $x_5 \le 300$

C27: (demand for CN 100) $x_6 \le 500$

C28: (demand for Candy) $x_7 \le 200$

C29: (demand for Wafer) $x_8 \le 400$

The parameters $x_1 .... x_8$ must be nonnegative (i.e. $x_1 .... x_8 \ge 0$. This problem has been solved in [30] using a newly developed Matlab toolbox called Hybrid Optimization Genetic Algorithms (HOGA). Comparatively; we solve the same problem by using different toolbox (i.e. GEATbx) [5] using two famous methods. They are the Scalarization and the Pareto methods.

5. Experimental Setup and Results

The Genetic and Evolutionary Algorithm Toolbox for use with Matlab (GEATbx) [5] contains a broad range of tools for solving real-world optimization problems. They not only cover pure optimization, but also the preparation of the problem to be solved. We can use the GEATbx as follows:

Creating m-file1

- Write the objective function to describe the problem
- Write the problem constraints

Parameters setting:

- Number Variable Default :8
- for Scalarization method, Number Objective Default: 1
- for Pareto method , the Number Objective Default: 5
- Variable Bound (Min): 0, 0, 0, 0, 0, 0, 0, 0
- Variable Bound (Max): 500, 800, 400, 600, 300, 500, 200, 400

- Save m-file1.
- Create m-file2.

Write the function which operates m-file1

Parameters setting:

- Population size: 20, 50, 100
- Termination Max Generations: 20
- Selection Mechanism: Stochastic Universal Sampling (SUS)
- Selection Pressure: 1.7
- Recombination Name: Recombination discrete
- Recombination Rate: 0.6
- Mutation mechanism: real value Mutation
- Generation Gap: 0.9
- Mutation Rate: 0.01
- Saving m-file2
- When using Scalarization method, we give an equal weight of 0.2 for each objective function.

5.1 Scalarization method Results

The firm Chocoman, Inc. manufactures 8 different kinds of chocolate products since there are 8 raw materials to be mixed in different proportions and 9 processes to be utilized. The objective of the company is to maximize its profit, which is, alternatively, equivalent to maximizing the gross contribution to the company in terms of US$. Thus, we need to find the optimal product mix within a set of constraints in the technical, raw material and market consideration. The goal of this problem is to maximize the objective function subject to a given set of constraints. In [30], the goal was to maximize the objective function presented below subject to the same constraints:

$$\begin{aligned} Z &= 180x_1 + 83x_2 + 153x_3 + 72x_4 + 130x_5 + 70x_6 \\ &+ 208x_7 + 83x_8 - 0.18x_{12} - 0.16x_{22} - 0.15x_{32} \\ &- 0.14x_{42} - 0.13x_{52} - 0.14x_{62} - 0.12x_{72} - 0.17x_{82} \end{aligned} \tag{5}$$

Depending on Scalarization method which converts the problem from multi-objective function to single objective function; this problem can be solved by running the GEATbx for 20 generations. The obtained results using Scalarization were compared with Sequential Quadratic Programming (SQP) presented in [30]. The computed values of the parameters $x_1 .... x_8$ along with the optimal value of the objective function are presented in Table 1.

We note that the optimal value of the objective function using Scalarization method is 150440 which are better than the optimal value 147000 which was obtained by using SQP [3]. In Figure 1 we show the convergence process by showing the relationship between the generations and the optimal objective function value. It is shown that the function to be maximized reached the optimal value after 20 generations.

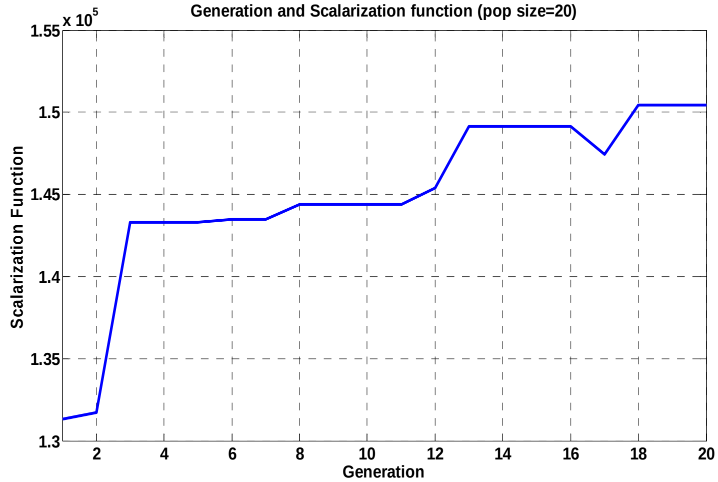

Fig 1. Optimal function value using Scalarization method

5.2 Pareto method results

The goal of this problem is to maximize the five objective functions that were presented previously depending on the Pareto method; this problem can be solved by running the GEATbx at different population sizes 20, 50, and 100. The sizes of the populations were selected arbitrary. In each case, we run GEATbx to find the optimal value of each function using various population sizes. The convergence process is shown in each case. The obtained results for each function F1,…, F5 is shown in Figures 2, 3, 4, 5 and 6. By the end of the evolutionary process, all curves convergence to the domain of the optimal solution. Although, the developed results with population size 100 looks the best. This gives us an indication which is increasing the population size might help in improving the performance of the developed results.

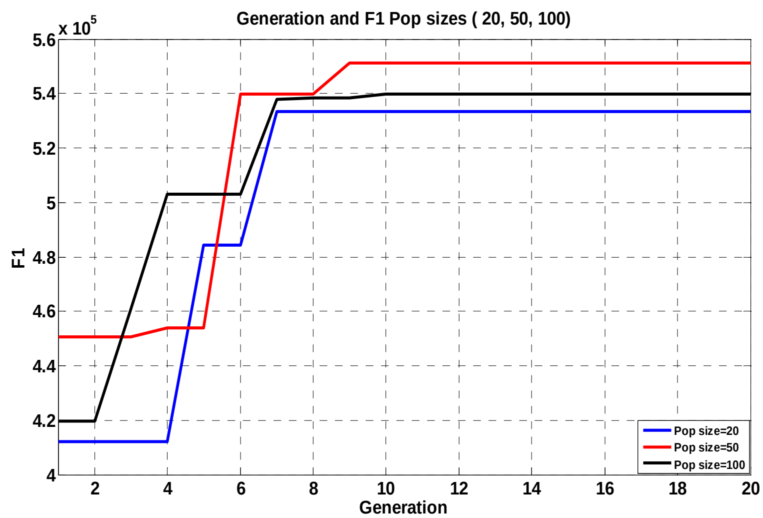

Fig 2. Optimal function value curve of F1 at different Pop Sizes

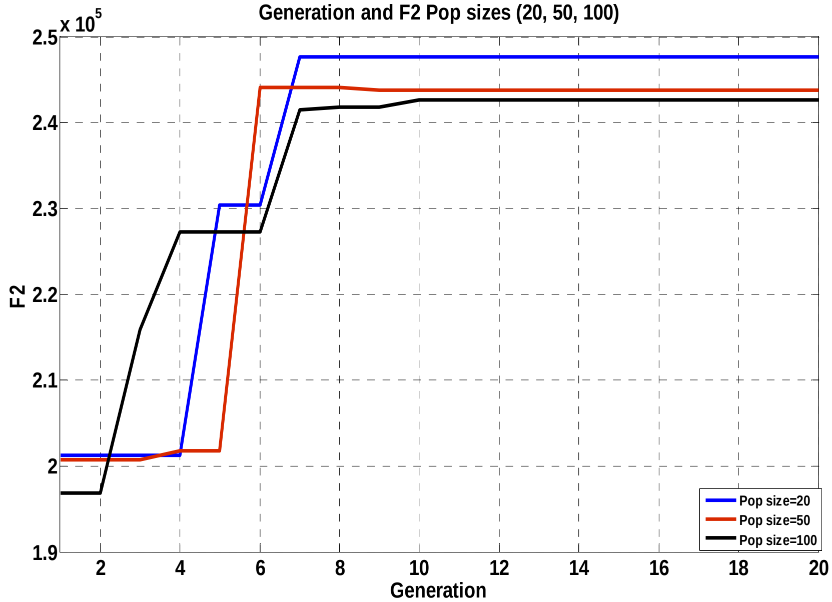

Fig 3. Optimal function value curve of F2 at different Pop Sizes

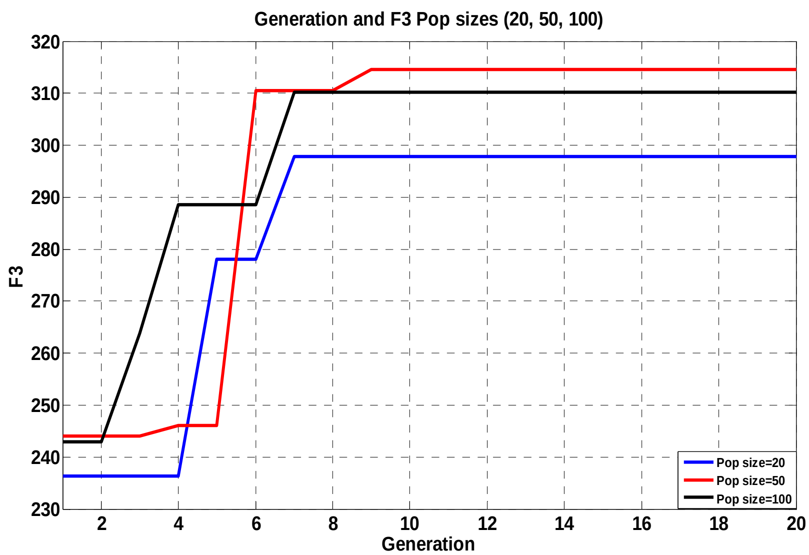

Fig 4. Optimal function value curve of F3 at different Pop Sizes

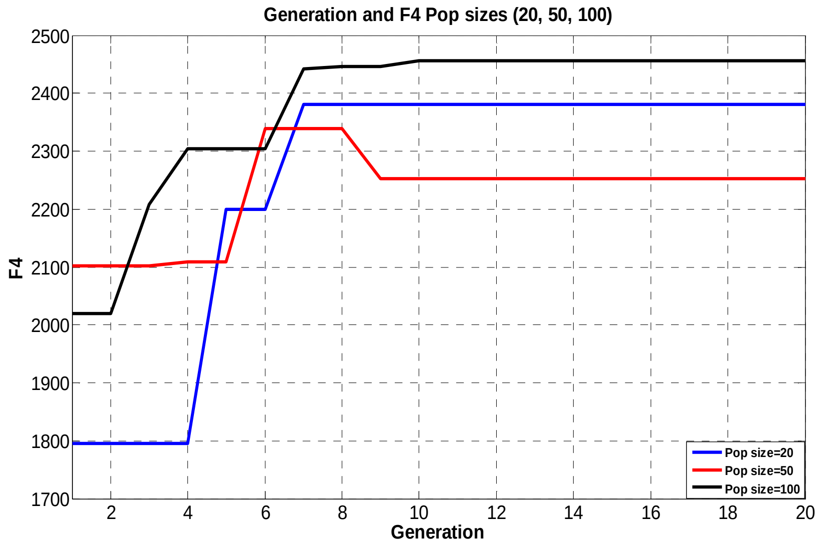

Fig 5. Optimal function value curve of F4 at different Pop Sizes

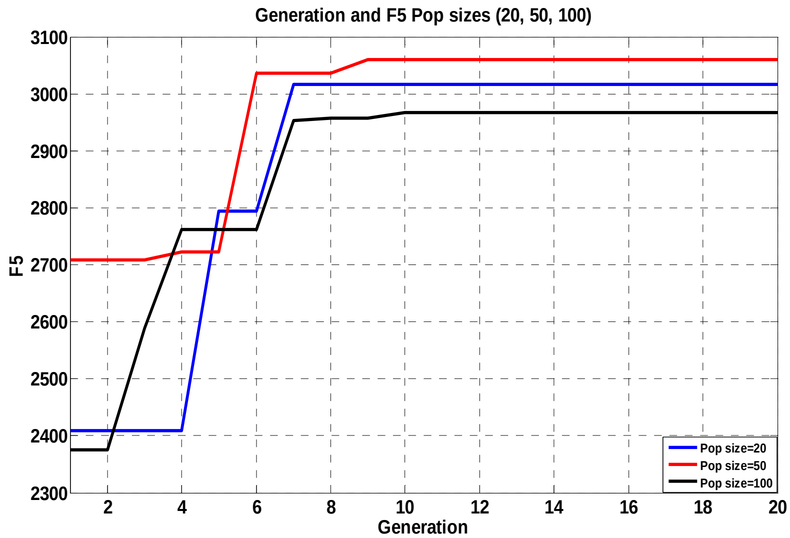

Fig 6. Optimal function value curve of F5 at different Pop Sizes

Table 1. Estimated values of the parameters for the Scalarization method and the Sequential Quadratic Programming (SQP) based GAs method [3]

Parameters	***Scalarization Method***	***SQP-GAs method [30]***
x1	122.65	217.55
x2	700.63	366.11
x3	46.564	246.34
x4	447.97	410.58
x5	279.59	226.05
x6	490.58	489.33
x7	134.83	76.781
x8	124.14	273.99
Optimal Value	150440	147000

Table2. Comparison between various Pop Sizes (20, 50, and 100)

	Pop Size =20	***Pop Size =50***	***Pop Size =100***
F1	533260	539680	539890
F2	247600	244070	242650
F3	297.84	310.51	310.24
F4	2381.2	2338.8	2456.4
F5	3015.7	3036	2967.8
Estimated states values			
x1	393.24	375.19	271.96
x2	739.63	640.27	681.61
x3	32.256	23.099	134.89
x4	328.29	529.72	520.2
x5	138.7	204.72	183.76
x6	500	427.54	424.11
x7	105.22	109.65	44.42
x8	143.85	28.568	195.4

6. Conclusion

In this paper, we provided a solution to the famous production system chocolate problem using both the Scalarization and Pareto methods. We compared our results with the results presented in [3]. Two methods were investigated to solve the production system problem. They are the Scalarization and Pareto methods. The developed results show an improvement in the produced optimal values to solve the MOP for the Chocolate production system than the recent reported results.

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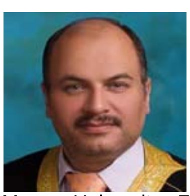

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