Mechatronic Multi-Objective Optimization using a Modified Bacterial Foraging Optimizer

B. Hernández-Ocaña, E.Mezura-Montes and E.A.Portilla-Flores

Abstract—**In this paper we present a proposal based on a modified bacterial foraging optimization algorithm, inspired by the search of nutrients by Escherichia Coli (E. Coli) bacteria, to solve a constrained dynamic multi-objective optimization problem. This proposal focuses on the adaptations made to the algorithm based on bacteria foraging to solve multi-objective problems: Pareto dominance, elitism and crowding distance. The problem tackled in this work is the optimal design of a mechanism so called continuously variable transmission system. The results obtained are feasible and highly competitive, as well as safe to build physically.**

***Index Terms*—Parametric design, bacteria foraging optimization, mechatronics, multi-objective optimization.**

I. Introduction

Real-world optimization problems are complex to solve due to intrinsic sources of difficult such as their dimensionality, the presence of constraints and the number of objectives. Engineering design lies within those type of problems because optimal designs of a diverse group of mechanical systems such as automobiles, airplanes, bulldozers, etc. must be found. Furthermore, the obtained designs may be feasible, easy to reconfigure and safe to build.

There are different methodologies within Engineering Mechatronic framework to solve engineering design problems. Some of the most popular are the concurrent design and the parametric design [1]. Concurrent design combines the optimal physical design with optimal control, while parametric design focuses only in the kinematic design of a mechatronic system. This work focuses on the last one, where a mathematical model of the system in order to propose an optimization problem is developed. This mathematical model is based on a set of parameters which describes the whole system and their values must be sought so as to optimize the design criteria. Such optimization problems may have more than one objective to be optimized and they are usually in conflict. Also, the optimization problem can be even more complex if the objective functions or the design constraints are dynamic. In this case, the problem is known as a constrained dynamic optimization problem (CDMOP) [2]. Mathematical programming methods (MPMs) can be used to solve these problems [3]. However, they often require the transformation of the original model with the risk of losing data in the process. Furthermore, they are sensitive to the initial conditions of the search [4]. Therefore, alternative approaches, such as metaheuristic algorithms, can be used instead.

Metaheuristic algorithms (MAs) are black-box approaches which can find good solutions in a reasonable time for complex optimization problems such as those previously mentioned. Some of these algorithms are based on nature, i.e., they mimic natural behaviors such as natural evolution or cooperation among simple animals such as birds or insects.

When solving CDMOPs, most MPMs provide a single solution. In contrast, MAs work with sets of solutions and they return a collection of solutions in a single run. In this way, the designer is provided with different design options [5]. This is the main motivation of this work, where a novel nature-inspired metaheuristic based on the foraging behavior of bacteria is designed to solve a CDMOP based on a real-world kinematic model of a continuously variable transmission (CVT) system.

The employed algorithm is called modified bacterial foraging optimization algorithm (MBFOA) [6], which was originally proposed to solve single-objective optimization problems. MBFOA is a simplification of the Bacterial Foraging Optimization algorithm proposed by Passino in [7] and emulates the entire bacterial foraging process which consists of the following processes: chemotaxis (tumbling and swimming movements), reproduction and elimination-dispersion.

The paper is organized as follows: section II formally states a CDMOP and describes the CVT system kinematic model. Section III presents the MBFOA and its adaptations to now solve a CDMOP, while Section IV shows and discusses the experiments and results. Finally, section V summarizes the conclusions and establishes the future work.

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II. CONSTRAINED DYNAMIC MULTI-OBJECTIVE OPTIMIZATION PROBLEM

A CDMOP is formally defined as follows:

Minimize or Maximize

$$\phi(x,p,t)=[\phi_1,\phi_2,..,\phi_n]^T \quad (1)$$

$$\phi_i=\int_{t_0}^{t_f} L_i(x,p,t)dt \quad i=1,2,..,n$$

Under p and subject to:

$$\dot{x}=f(x,p,t) \quad (2)$$

$$g(x,p,t)\le 0 \quad (3)$$

$$h(x,p,t)=0 \quad (4)$$

$$x(0)=x_0$$

In the problem stated by (1) to (4): p is the vector of design parameters which belongs to the mechanical and control structure, x is the vector of the state variables and t is the time variable. On the other hand, some performance criteria L must be selected for the mechatronic system. The dynamic model in (2) describes the state vector x at time t. Also, the inequality and equality design constraints of the mechatronic system in (3) and (4) must be satisfied. Therefore, the parameter vector p, which is a solution of the previous problem, will be an optimal set of structure and controller parameters which minimize the performance criteria selected for the mechatronic system and subject to the constraints imposed by the dynamic model and design [8].

A real-world instance of a CDMOP is a CVT tipping unilateral pedaling gear shift system. The main function of such system is to convert the swing pedal input into a rotational motion of the drive wheel of the vehicle. A detailed description of the model can be found in [9]. Figure 1 represents the four-bar CVT where the five design parameters are: the ground bar x_1, the length of the crank bar x_2, the length of the coupling bar x_3, the length of the rocker bar x_4 and the angle between the reference bar and the horizontal axis x_5.

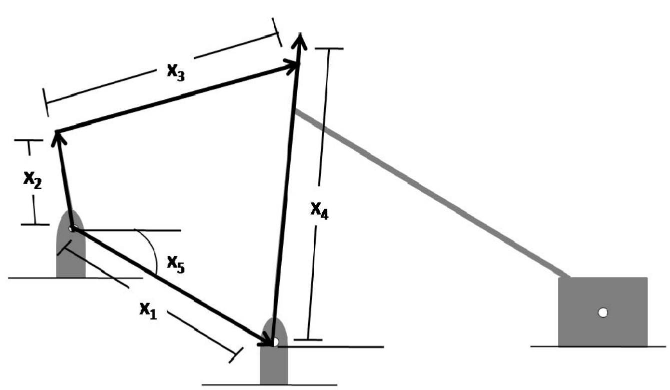

Fig. 1. CVT system

The CVT problem is defined as follows:

$$\phi_1(X)=(\theta_{4\,\max}-\theta_{4\,\min})^2 \quad (5)$$

$$\phi_2(X)=(\gamma\max-\frac{\pi}{2})^2+(\gamma\min-\frac{\pi}{2}) \quad (6)$$

Where ϕ_1 represents the output of the system, which aims to be maximized and ϕ_2 minimizes the deviation of the transmission angle, i.e., it improves the quality of the performance of the CVT system.

The constraints are:

$$g_1(X)=x_2+x_3-x_1-x_4\le 0 \quad (7)$$

$$g_2(X)=x_1-x_3\le 0 \quad (8)$$

$$g_3(X)=x_4-x_3\le 0 \quad (9)$$

$$g_4(X)=x_1-0.5\le 0 \quad (10)$$

$$g_5(X)=0.05-x_1\le 0 \quad (11)$$

$$g_6(X)=x_2-0.5\le 0 \quad (12)$$

$$g_7(X)=0.05-x_2\le 0 \quad (13)$$

$$g_8(X)=x_3-0.5\le 0 \quad (14)$$

$$g_9(X)=0.05-x_3\le 0 \quad (15)$$

$$g_{10}(X)=x_4-0.5\le 0 \quad (16)$$

$$g_{11}(X)=0.05-x_4\le 0 \quad (17)$$

$$g_{12}(X)=x_5-\frac{\pi}{4}\le 0 \quad (18)$$

$$g_{13}(X)=-\frac{\pi}{4}-x_5\le 0 \quad (19)$$

$$h_1(X)=\pi-\theta_{4\,\max}-\theta_{4\,\min}=0 \quad (20)$$

$$g_{14}(X,t)=\frac{\pi}{4}-\mu(x,t)\le 0 \quad (21)$$

The first thirteen are inequality constraints ((7) to (19)) while in (20) and (21) an equality and a dynamic constraint, respectively, are considered.

The limits for each design parameter are defined as: $0.005\le x_1,x_2,x_3,x_4\le 0.5$ and $-45°\le x_5\le 45°$. Design parameter values for x_1,x_2,x_3 and x_4 are in meters and for x_5 they are in radians.

III. MODIFIED BACTERIAL FORAGING OPTIMIZATION ALGORITHM

MBFOA emulates the foraging process of bacteria E. Coli as follows: Within a cycle called generation (G) each bacterium performs a chemotactic step N_c times. After all bacteria went through their chemotactic step, the best bacteria are reproduced while the worst ones are eliminated and new ones are generated at random:

The chemotactic cycle consists on tumble (search direction defined at random) and swim (generation of a new solution, i.e., a new position, by a bacterium) movements carried out by bacteria in the search space with the aim to find nutrients. Furthermore, a swarming mechanism is used. In this cycle, bacteria carry out two actions as they explore the search space:(1) bacteria keep swimming in the same direction while they find nutrients in such direction, or tumble (generate a new search direction) if no more nutrients are found in the current direction, and (2) bacteria follow a leader (the best bacteria in the population) when they perceive a strong chemical segregation which indicates they have to move to high-nutrient regions found by that best bacterium.

The nomenclature used to describe the aforementioned processes in MBFOA and their relationship with the CDMOP described in Section II are the following: a design parameter vector X is equivalent to the position θ of bacterium i, in generation G and chemotactic step j:$\theta^i(j,G)$. S_b is the number de bacteria of the population. Two operators are used to perform the actions of the chemotactic cycle:

(a) The tumble-swim operator, originally proposed by Passino [7] where a random search direction (tumble) is calculated and a new solution (swim) is generated, is defined in (21):

$$\theta^i(j+1,G) = \theta^i(j,G) + C(i)\delta(i) \qquad (21)$$

where $\theta^i(j+1,G\ )$is the new position of bacterium i (new solution), $\theta^i(j,G)$ is the current position of bacterium i, $C(i)$ is the stepsize vector which includes the stepsizes for the design parameters and each of its values is computed at the beginning of the process as proposed in [6] and indicated in (22):

$$C(i) = R * \left(\frac{\Delta Xk}{\sqrt{n}}\right), k = 1,...,n \qquad (22)$$

Where ΔX_k is the difference between upper and lower limits of design parameter k, n is the number of design parameters and R is a user-defined percentage of the value used by the bacteria as stepsize. $\delta(i)$ is the random search direction vector which represents the tumble movement as show in (23) where $\Delta(i)$ is a n-dimensional randomly generated vector with each of its elements $\Delta_k(i) \in [-1,1]$,k=1,...,n.

$$\delta(i) = \frac{\Delta(i)}{\sqrt{\Delta(i)^T \Delta(i)}} \qquad (23)$$

(b) The swarming operator, where a bacterium follows the best bacterium in the population, is presented in (24), where $\theta^i(j+1,G)$ is the new position of bacterium i, $\theta^i(j,G)$ is the current position of bacterium i, $\theta^B(G)$ is the current position of the best bacterium in the population so far at generation G and F defines the step size to the best bacterium.

$$\theta^i(j+1,G) = \theta^i(j,G) + F(\theta^B(G) - \theta^i(j,G)) \qquad (24)$$

The swarming operator is employed twice within the chemotactic cycle for each bacterium. In the remaining steps, the tumble-swim operator is used. The aim is to get a good balance between exploration and exploitation of the search space.

To deal with the constraints of the problem, three feasibility rules [10] are used as criteria in the selection between current and new positions of bacteria as follows: (1) between two feasible bacteria, the one with the best objective function value is preferred, (2) between a feasible and an infeasible bacteria, the feasible one is preferred and (3) between two infeasible bacteria, the one with the lowest sum of constraint violation is preferred.

The reproduction process consists on sorting the bacterial population with respect to the feasibility rules, then the worst half of the population is eliminated and the first half of the population is cloned to maintain the same population size for the next generation. Finally, the process of elimination-dispersal kills the worst bacterium in the population and a new one, generated at random, replaces it.

Recalling from Section II, the problem tackled in this paper is a CDMOP and MBFOA was designed to solve constrained single-objective optimization problems. Therefore, the following modifications were made to MBFOA so as to adapt it to solve the CDMOP presented in such section.

Pareto dominance [11] was coupled with the feasibility rules as criteria for selecting non-dominated feasible solutions, i.e., for a multi-objective problem, those feasible solutions with the best trade-off among objectives in conflict are preferred. Moreover, the concept of elitism in multi-objective optimization is different with respect to single-objective optimization, where only the best solution is stored. For this work, an external file stores all feasible non-dominated solutions and precisely the contents of this file are reported as the output of the algorithm [12].

The swarming operator is slightly modified in such a way that the best bacterium is chosen from the external file instead of choosing the best one from the current population. The criterion to choose the best bacterium from the file is the (highest) crowding distance value, i.e., the solution located in the least explored region of the Pareto front (the Pareto front is the set of objective function values of those non-dominated solutions in the file). If the external file is empty, $\theta^B(G)$ is chosen based on the criteria explained above from the current population. Finally, the reproduction process consists on eliminating the second worst bacterium and replacing it with a copy of the best bacterium in the current population, while the worst bacterium is also eliminated and replaced with one generated at random.

The pseudocode of this version of MBFOA is presented in Fig 2.

```
Begin
  external-file=0
  Generate an initial population of solutions θ^i(j,0)
  at random ∀i, i=1,...,S_b
  Evaluate each θ^i(j,0) ∀i, i=1,...,S_b, in φ_n and constraints
  For i=1 to S_b do
    If θ^i(j,0) is feasible
      update external-file with θ^i(j,G) by using Pareto
      dominance
    end If
  end For
  For G=1 to GMAX do
    For i=1 to S_b do
      For j=1 to N_c do
      Perform chemotactic step j for bacterium θ^i(j,0)
      by using Pareto dominance and feasible
      end For
    end For
    For i=1 to S_b do
      If θ^i(j,0) is feasible
        update external-file with θ^i(j,G) by using Pareto
        dominance
      end If
    end For
  Compute crowding distance for solutions in the external-file.
  Reproduction:Delete the penultimate bacteria and duplicate
  one of the best bacteria from the external-file.
  Elimination-dispersal:Eliminate the worst bacteria and
  generate a new random.
  End For
End
```

Fig. 2. Pseudocode of MBFOA. Input parameters are: population size S_b, number of chemotactic steps N_c, scaling factor *F*, stepsize percentage *R* and generation number *GMAX*.

IV. EXPERIMENTS AND RESULTS

Three experiments were performed to analyze the performance of MBFOA in the solution of the CVT system optimal design problem. The parameter values used in all experiments were obtained after a trial-and-error process and are the following: S_b=200, N_c=20, *GMAX*=25, *F*=1.7, *R*= 0.0018. 10 independent executions of the algorithm were computed in each experiment and each execution carried out 500, 000 evaluations. The tumble-swim operator worked in all chemotactic steps for each bacterium with the exception of steps 15 and 20, where the swarming operator was employed instead.

The first experiment consisted on analyzing the ability of the algorithm to generate feasible solutions, i.e., solutions which satisfy the constraints of the problem. Therefore, in Figure 2, the average number of feasible solutions on 10 independent executions is plotted. It is clear that MBFOA is able to generate feasible solutions early while at the end, almost all the population is feasible.

The second experiment studied the capability of MBFOA to generate feasible non-dominated solutions, i.e., sub-optimal solutions to the CDMOP, which represent potential designs to be given to the designer. Figure 3 shows the average number of feasible non-dominated solutions on 10 independent runs. After generation 20, MBFOA is able to consistently add feasible non-dominated solutions. However, the number of those solutions is significantly lower with respect to the number of feasible solutions reported in Figure 2. This suggests that the feasible region for the CVT system is easier to reach, but moving within it so as to find sub-optimal solutions is considerably more difficult.

Finally, the third experiment was designed to analyze the final results obtained by the MBFOA on the CVT system optimal design. In Figure 3 the filtered Pareto front from 10 independent runs is shown. Furthermore, in Table I the parameter design values and the objective function values are summarized. From an analysis of the expert designer, all solutions found are feasible and are physically capable to be built. Furthermore, the designer can choose the most adequate design from the set of 34 solutions found. It is worth noticing that this problem cannot be solved by using a MPM because of the presence of the dynamic constraint in (21). Therefore, no comparison is presented in this work.

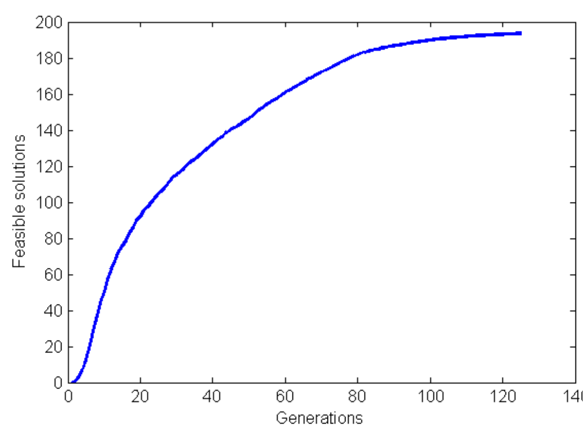

Fig. 2.Average number of feasible solutions per generation on 10 independent runs.

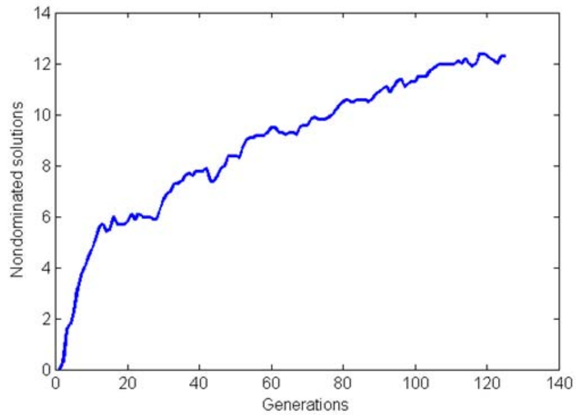

Fig. 3.Average number of feasible non-dominated solutions on 10 independent runs.

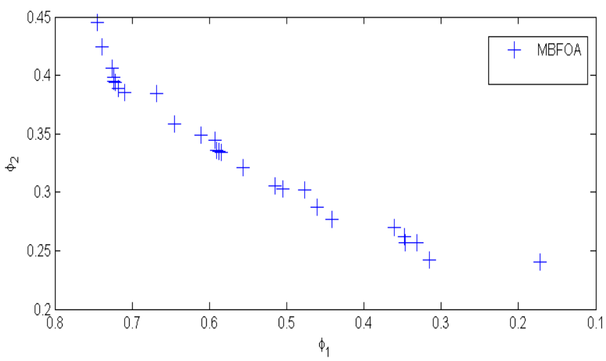

Fig. 4.Filtered Pareto front obtained by MBFOA for the CVT system optimal design from 10 independent runs.

Table I. Details of the set of non-dominated feasible solutions found by MBFOA in the third experiment

x_1	x_2	x_3	x_4	x_5	f_1	f_2
0.49994348	0.08502299	0.49994921	0.20697951	-0.1905838	0.7452421	0.44529109
0.49113015	0.07316047	0.49114296	0.17808611	-0.16651035	0.73851585	0.42475994
0.482173	0.06302829	0.48218214	0.15419758	-0.14673845	0.72577408	0.40599695
0.48246548	0.06305104	0.4824675	0.15425746	-0.1466981	0.72571349	0.40593083
0.49029065	0.0555809	0.49186602	0.13597058	-0.11433606	0.72421035	0.3985347
0.48786372	0.0556154	0.48790573	0.13586271	-0.1272941	0.72400083	0.39466553
0.4878994	0.05561222	0.48794294	0.13585997	-0.12719326	0.72394378	0.3946351
0.48789223	0.05561918	0.48795103	0.13589145	-0.12717765	0.72381017	0.39462314
0.48869009	0.05576938	0.48872866	0.13626943	-0.1274327	0.72368359	0.39458659
0.48784244	0.05563358	0.48789428	0.13595034	-0.12724055	0.72354505	0.39451108
0.48767559	0.05543859	0.4880018	0.13563593	-0.12483498	0.72209104	0.39435134
0.49038743	0.05335721	0.49040773	0.13081951	-0.12211977	0.7173778	0.38863994
0.49990106	0.05419802	0.49995305	0.13358034	-0.1221807	0.7095171	0.38494843
0.47978321	0.05312118	0.48485219	0.1356473	-0.08961977	0.66788371	0.38442845
0.48704915	0.05421461	0.48726535	0.1399373	-0.13135853	0.64537109	0.35865459
0.48968283	0.05805262	0.48968444	0.15401398	-0.14645329	0.61117442	0.34848419
0.48995964	0.06001625	0.48999101	0.16168724	-0.15390245	0.59320663	0.34419227
0.48049652	0.054451	0.48052541	0.14668256	-0.14226072	0.59112912	0.33622524
0.48049849	0.0546063	0.48052401	0.14719254	-0.14281132	0.59044249	0.33616588
0.48022501	0.05455667	0.48022893	0.14735311	-0.14326362	0.58798691	0.33504163
0.48027735	0.05452585	0.48031645	0.147309	-0.14291155	0.58769307	0.33496159
0.47870991	0.05396481	0.47909547	0.14619671	-0.13981395	0.58462773	0.33408716
0.49358552	0.05246295	0.49524342	0.14562067	-0.12597282	0.55637475	0.32128068
0.45735041	0.0520799	0.45736331	0.15007375	-0.15465538	0.51519365	0.30552914
0.48989766	0.0540942	0.49117935	0.15749673	-0.14298954	0.50507901	0.30244873
0.48702447	0.05436296	0.49095248	0.16335404	-0.13318098	0.47691847	0.3018559
0.4897612	0.05626093	0.49024281	0.17155159	-0.1635195	0.46016888	0.2869695
0.49330229	0.05579902	0.4933061	0.17353063	-0.16759252	0.44142453	0.27690643
0.49138995	0.05500243	0.49706509	0.19033046	-0.15505528	0.36087955	0.26967945
0.48686475	0.05676005	0.48965652	0.19992669	-0.18370899	0.3473044	0.26165873
0.49924515	0.05990783	0.49938901	0.21097562	-0.2036491	0.34635903	0.25718036
0.48810797	0.05212362	0.49424043	0.18819579	-0.15204952	0.33100995	0.2568738
0.49992186	0.05733318	0.49995373	0.21142761	-0.2051824	0.31510046	0.2419694
0.49632845	0.0528054	0.49984025	0.26634777	-0.25259647	0.17254579	0.24018371

V. Conclusions and Future Work

A CVT system optimal design problem, defined as a CDMOP, was solved with the Modified Bacterial Foraging Optimization, which was adapted to deal with multiple objectives by using the concept of Pareto dominance and elitism in multi-objective search spaces. Crowding distance was useful to also adapt to chemotactic cycle computed by the bacteria in the population so as to follow a feasible non-dominated bacterium. The results obtained in three experiments suggest that MBFOA is able to quickly generate feasible solutions to the problem. In contrast, feasible non-dominated solutions are consistently found but with more difficulty. Furthermore, the final obtained results were highly competitive and diverse so as to let the designer to choose among a set of feasible and physically valid designs for the CVT system.

The future work will further analyze the chemotactic process, focusing on the relationship between the tumble-swim and the swarming operators. Finally, MBFOA will be used to solve other CDMOPs.

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VII. References

[1] W. Bolton. Mecatrónica: Sistemas de control electrónico en ingeniería mecánica y eléctrica. Alfaomega, Boston Massachusetts, 2 edition, 2001.

[2] Jaime Alvarez-Gallegos, Carlos Alberto Cruz Villar, and Edgar Alfredo Portilla Flores. Evolutionary dynamic optimization of a continuously variable transmission for mechanical efficiency maximization. In Proccedings in Alexander Gelbukh, Alvaro de Albornoz, and Hugo Terashima-Marín, editors, of the 4th Mexican International Conference on Artificial Intelligence (MICAI 2005): Advances in Artificial Intelligence, pages 1093-1102, Monterrey México, 2005.

[3] Jaime Alvarez-Gallegos, Carlos Alberto Cruz Villar, and Edgar Alfredo Portilla Flores. Parametric optimal design of a pinion-rack based continuously variable transmission. In of the 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pages 899-904, Monterey California, 2005.

[4] Edgar A. Portilla-Flores, Efrén Mezura-Montes, Jaime Álvarez Gallegos, Carlos A. Coello Coello, and Carlos A. Cruz-Villar. Integration of structure and control using an evolutionary approach: an application to the optimal concurrent design of a cvt. International Journal for Numerical Methods in Engineering, 8(71):883-901, 2007.

[5] Miguel G. Villarreal Cervantes Carlos A. Cruz Villar, Jaime Alvarez Gallegos. Concurrent redesign of an underactuated robot manipulator. Mechatronics, 19(2):178-183, 2009.

[6] Efrén Mezura-Montes and Betania Hernández-Ocaña. Modified bacterial foraging optimization for engineering design. In Proceedings of the Artificial Neural Networks in Engineering conference (ANNIE 2009),19:357-364.in Cihan H. Dagli et al. (editors), ASMEPress Series,Intelligent Engineering Systems Through Artificial NeuralNetwor, 2000.

[7] Kevin M. Passino. Biomimicry of bacterial foraging for distributed optimizationand control. IEEE Control Systems Magazine, 22(3):52-67, 2002.

[8] Efrén Mezura-Montes, Edgar A. Portilla-Flores, Carlos A. CoelloCoello, Jaime Álvarez-Gallegos and Carlos A. Cruz-Villar, An Evolutionary Approach to Solve a Novel Mechatronic Multiobjective Optimization Problem, in Zbigniew Michalewicz and Patrick Siarry (editors), Advances in Metaheuristics for Hard Optimization, pp: 329-351, Springer-Verlag, Natural Computing Series, 2008, ISBN: 978-3-540-72959-4.

[9] Edgar A. Portilla Flores. Diseño óptimo de un sistema de transmission de variación continua. Technical report, Instituto Politécnico Nacional, CIDETEC, Abril 2010.

[10] Kalyanmoy Deb. An Eficient Constraint Handling Method for Genetic Algorithms. Computer Methods in Applied Mechanics and Engineering, 186(2/4):311:338, 2000.

[11] Kalyanmoy Deb. Multi-Objetive Optimization using Evolutionary Algorithms. John Wiley Sons, LTD, 2002.

[12] C. A. CoelloCoello, D. A. Van Veldhuizen, and G. B. Lamont, Evolutionary Algorithms for Solving Multi-Objective Problems. KluwerAcademicPublishers, June 2002.

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