Advances in Modelling and Analysis B
Vol. 66, No. 1-4, October, 2023, pp. 26-30
Journal homepage: http://iieta.org/journals/ama_b

Comparison of PSO with the Hybrid Algorithms MOORA-PSO and DA-PSO for Decision Making

Ramírez-Ochoa Dynhora-Danheyda, Pérez-Domínguez Luis Asunción*, Martínez-Gómez Erwin Adán

Department of Industrial Engineering and Manufacturing, Institute of Engineering and Technology, Autonomous University of Ciudad Juárez, Juárez 32310, Mexico

Corresponding Author Email: luis.dominguez@uacj.mx

https://doi.org/10.18280/ama_b.661-404

Received: 18 June 2023
Revised: 22 July 2023
Accepted: 10 August 2023
Published: 17 October 2023

Keywords:
DA-PSO, decision-making, MCDM, metaheuristics, MOORA-PSO, PSO, swarm intelligence

ABSTRACT

Technological advances have generated great changes in the optimization of resources, times, and costs, increasing profits and performance. Therefore, decision-making requires a sophisticated and powerful tool that helps the field of decision making. Currently, there is a wide variety of algorithms, but it is difficult to determine which one provides the best results. The materials used in this research contemplate the particle swarm optimization (*PSO*) algorithm in its classical form and the *MOORA-PSO* and *DA-PSO* hybrids. Where these hybrids use the multi-criteria decision-making methods (*MCDM*): Multi-objective optimization using ratio analysis (*MOORA*) and Dimensional Analysis (*DA*). Furthermore, the algorithms are implemented in a computer system. The methodology begins with understanding the algorithms and methods employed. Continue the integration of *PSO* with *MOORA* and *DA*. Followed by the comparison of the algorithms. Ending with the publication of the results and findings found. Therefore, the objective of the research is to compare *PSO* with two hybrids, identifying which algorithm has the greatest potential for decision-making. The results obtained have been successful, demonstrating that the *DA-PSO* hybridization has greater potential for decision-making. In addition, the *MOORA-PSO* hybridization indicates that the initial control parameters are crucial for its performance.

1. INTRODUCTION

The needs of humanity have caused all the industrial revolutions, driving significant changes not only in the activities and processes of companies, but also in the daily life of people [1-3]. As a result of these changes and to maintain competitiveness, companies have faced great challenges that range from meeting the needs of humanity to optimizing resources, simplifying processes, and reducing costs [4-6]. This has meant great technological advances, facilitating access to a large amount of information. But it has also generated a new need, in which the stored information must be classified, analyzed, and interpreted to turn it into valuable information. Similarly, new consumers demand an ever-faster delivery of information, products, and services, forcing the industry to create new strategies and models in response to these demands. Among technological advances, a wide range of decision-making tools can be distinguished [7-9].

Among this variety of tools and mathematical models to solve decision-making problems, there are metaheuristic methods. Within the family of metaheuristics are those that imitate the behavior of living beings to find the best solution [10-12]. Another strategy for solving decision-making problems is the Multi-Criteria Decision Making (*MCDM*) methods. *MCDM* evaluate multiple conditions using algorithms and mathematical tools to come up with the best alternative [13, 14].

For all the above, there is an interest in providing better results to decision makers. Therefore, the novelties and contributions of this work are listed:

(a) Develop two hybrids that minimize the drawbacks of the PSO algorithm and increase the effectiveness of the results.

(b) Compare *PSO* and hybrid algorithms that employ *MCDM* not only to verify their efficiency, but also to identify which one provides robust and reliable results.

(c) Implementation of the algorithms in a computer program to facilitate the changes in the initial parameters and to be able to carry out the comparisons and validations of the results.

The organization of this article includes six main sections. It starts with the introduction and hybrid methods, providing the theoretical and conceptual part of the research. The third section describes the methodology used. Followed by the section containing the experimental setup. And ending with the results and conclusions sections, where the results, findings and future work that could be addressed are discussed.

2. HYBRID METHODS: MCDM + SWARM INTELLIGENCE

In this section are the two hybrid proposals that combine an MCDM and a metaheuristic. The metaheuristic algorithm used is PSO and the MCDM used are DA and MOORA. The algorithm for the *DA-PSO* method can be found in Figure 1, while the *MOORA-PSO* method is in Figure 2.

Algorithm 1: Algorithm structure of the DA-PSO hybrid method

Require: Decision matrix, degree of preference of the criteria and control parameters: ω, c_1, c_2, and the number of iterations to perform (T)
Ensure: best position ($pbest$) and best optimum ($gbest$)
1: Construct the decision matrix, with the degrees of preference for each criterion, and the inertia weight ;
2: Obtain the ideal solution and the similarity index ;
3: Build the successive products and classify the alternatives ;
4: Set learning factors ;
5: Assign the ideal solution and the similarity index, as well as the circulation of each particle ;
6: Determine the first position and velocity of the particles ;
7: Evaluate the fitness function to obtain the best optimum and local position ;
8: Obtain the best global optimum and the best global position ;
9: **while** $t < T$ **do**
   Updates the position and velocity of the particle ;
   Obtain the best position and optimum location ;
   Determine the best position and global optimum ;
10: Return: $pbest$ and $gbest$

Figure 1. Algorithm structure of *DA-PSO* method

Algorithm 2: Algorithm structure of the MOORA-PSO hybrid method

Require: Decision matrix, definition of objectives, degree of preference of the criteria, control parameters: ω, c_1, c_2, and the number of iterations to perform (T)
Ensure: best position ($pbest$) and best optimum ($gbest$)
1: Construct the decision matrix;
2: Define the objectives for each criterion;
3: Develop the normalized decision matrix;
4: Create balanced normalized decision matrix;
5: Estimate the global evaluations of the benefit criteria;
6: Estimate the global evaluations of the cost criteria;
7: Establish the value of the contribution;
8: Determine the first position and velocity of the particles ;
9: Evaluate the fitness function to obtain the best optimum and local position ;
10: Obtain the best global optimum and the best global position ;
11: **while** $t < T$ **do**
   Updates the position and velocity of the particle ;
   Obtain the best position and optimum location ;
   Determine the best position and global optimum ;
12: Return: $pbest$ and $gbest$

Figure 2. Algorithm structure of *MOORA-PSO* method

To update the velocity of the particle we use Eq. (1). And to update the position we use Eq. (2) [15-17].

$$v_N^{\iota}(t+1) = \omega v_N^{\iota}(t) + c_1 r_1 \left(BLP(t\iota) - CP_N^{\iota}(t)\right) + c_2 r_2 \left(BOP(t) - CP_N^{\iota}(t)\right) \quad (1)$$

$$CP_N^{\iota}(t+1) = CP_N^{\iota}(t) + v_{\iota}(t+1) \quad (2)$$

To determine the similarity index (*IS*) we use Eq. (3) [18, 19].

$$IS_i\left(a_i^k, \cdots, a_m^k\right) = \prod_{j=1}^{m} \left(\frac{a_i^k}{S_i^*}\right)^{w_j} \quad (3)$$

To estimate the global evaluations of the criteria, there are two equations. Eq. (4) is used for benefits and Eq. (5) for costs. The results of these two equations are used in Eq. (6) to establish the value of the contribution [9, 20, 21].

$$Nx_i = \xi_{kl}|\epsilon\delta^{max} \quad (4)$$

$$Nx_j = \xi_{kl}|\epsilon\delta^{min} \quad (5)$$

$$Ny_i = \sum_{l=1}^{g} Nx_i - \sum_{l=g+1}^{m} Nx_j \quad (6)$$

3. METHODOLOGY

For the development of the project, the methodology shown in Figure 3 is followed, beginning with a search for the uses of optimization strategies in the literature, as well as their advantages and disadvantages. As a second point, the steps of the *PSO* algorithm are understood. Continuing with the integration of *PSO* with *MOORA* and *DA*. Followed with the comparison of the results of the algorithms. To end with the publication of the results and findings found.

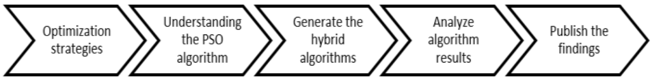

Figure 3. Methodology used for the project

The experimentation is limited to using the PSO algorithm in its classical form and two hybrid methods *MOORA-PSO* and *DA-PSO*. These algorithms are implemented in three computer programs to facilitate the manipulation of input parameters. In addition, the developed programs provide the results in a file that can be manipulated by Microsoft Excel software. These computer programs were developed for the Windows 11 Home Single Language operating system, coded in Python 3.9 and Visual Studio Code 1.55.2.

Regarding the experimental data of this article, it is limited to two cases, the first corresponds to an article in the literature, whose purpose is to have a basis for comparison. And the second case uses data obtained from plastic injection molding simulations of a maquiladora company in Ciudad Juárez, Chihuahua-Mexico.

4. EXPERIMENTAL SETUP

For experimentation, the *PSO* algorithm tested with the 2019 Bansal article [22] is used. The data used for the experimentation correspond to data obtained from plastic injection molding of a maquiladora company in Ciudad Juárez, Chihuahua-Mexico. Among the data, five criteria and nine alternatives are considered (see Table 1). Criteria considered include: warpage (C1), shrinkage (C2), air trap (C3), weld line (C4) and high shear (C5).

Table 1. Matrix of criteria and alternatives of the experiment

	C1	C2	C3	C4	C5
A1	0.502	12.052	41	127	1.108
A2	0.552	13.464	39	119	0.337
A3	0.600	14.747	39	112	0.131
A4	0.647	15.928	37	85	0.039
A5	0.693	17.077	41	125	0.022
A6	0.738	18.219	39	85	0.015
A7	0.820	19.328	39	69	0.010
A8	0.825	20.408	39	52	0.010
A9	0.867	21.422	39	74	0.000

To verify the correct functioning of the algorithms, we developed three computer programs applying each algorithm that ran two experiments with different parameters. For the first experiment, the programs were configured with the following values: the degrees of preference for each criterion (ωC= 0.301, 0.257, 0.086, 0.085, 0.271), the inertial weight (ω=0.3), the learning factors: c_1=c_2=1.5, and the iterations (T=50).

While for the second experiment the configuration was: the degrees of preference for each criterion (ωC=0.123, 0.099, 0.043, 0.343, 0.392), the inertial weight (ω=0.7), the learning factors: c_1=c_2=2 (considering Venter's proposal), and iterations (T=50). It is important to note that the objective function used in the hybrid methods is directly related to the *MCDM* used. Regarding the circulation values of the particles in the swarm (r_1 y r_2), they are updated with the values of the objective function.

5. RESULTS

It is worth mentioning that each experiment was executed 10 times, making a classification according to the results. In addition, a low, medium, and high value was assigned, where the value is low when there are 1 to 3 solution alternatives, medium between 4-6, and high between 7-9.

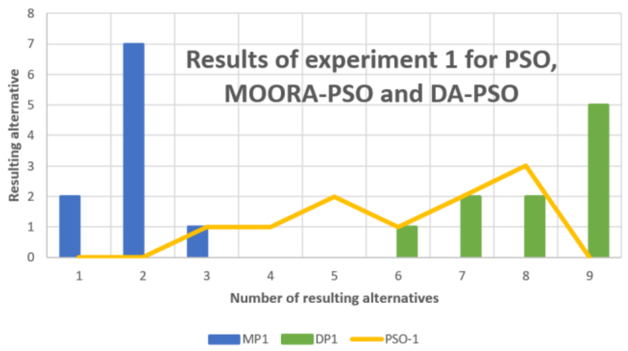

Figure 4. Results of experiment 1

In Figure 4, the results of experiment 1 are observed, the blue color corresponds to the results of the *MOORA-PSO* method, the *DA-PSO* method is green, and the *PSO* algorithm is light orange. Considering the values of this experiment, we obtained the percentage for each algorithm considering the values that were commented at the beginning of this section. For *PSO* it presents 10% low, 40% medium, and 50% high. On the other hand, *MOORA-PSO* shows itself 100% in the bass. While *DA-PSO* gives 10% in the middle and 90% in the high.

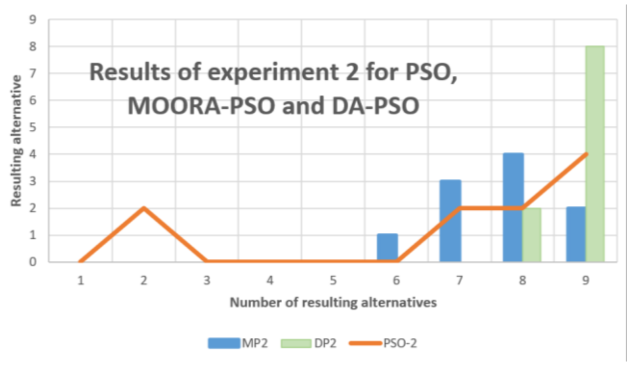

Figure 5. Results of experiment 2

For experiment 2, Figure 5, the color light blue is assigned for the results of the *MOORA-PSO* method, the color light green for the *DA-PSO* method, and orange for the *PSO* algorithm. For this second experiment, we see *PSO* at 20% low, and 80% high. *MOORA-PSO* improves with this build, giving 10% medium, and 90% high. And *DA-PSO* has a high 100%, this shows us that *DA-PSO* better widens your search range and does not fall into premature results.

When analyzing the percentages of the experiments carried out, Table 2, we see that the *PSO* algorithm presents different solution alternatives, leaving its results in a medium-high category. In the case of the *MOORA-PSO* method, the results are extreme, and the results depend on the configuration parameters. On the other hand, the *DA-PSO* algorithm outperforms the *PSO* algorithm, presenting more solution alternatives while remaining in the high category.

Table 2. Results of experiments

Method	Experiment Number	Low	Medium	High
PSO	1	10%	40%	50%
	2	20%	0%	80%
MOORA–PSO	1	100%	0%	0%
	2	0%	10%	90%
DA-PSO	1	0%	10%	90%
	2	0%	0%	100%

6. CONCLUSIONS

As seen in this document, decision-making is a complex process that requires a sophisticated and powerful tool. Hence, the interest, on the part of the authors, to contribute to the field of decision-making. In accordance with the stated objectives, the study has been successful.

With the experimentation carried out, we now have the development and implementation of the *PSO* algorithm and the hybrid methods of *MOORA-PSO* and *DA-PSO*, in three computer programs. These programs made it easy to manipulate the initial values, and the files that the programs output made it easy to compare between methods. However, the amount of information output was not easy to parse in the Excel files. In such a way, that the researchers will focus on the issue of handling large volumes of data for automatic analysis. However, the experiments presented show that, for the *MOORA-PSO* hybrid, the initial control parameters are crucial for its performance. By virtue of what has been studied, we now know that the *MOORA* control parameters are sensitive and affect the result. This guides us to where we should carry out the research and thus improve the *MOORA-PSO* hybrid.

In addition, during the experimentation, we observed that the *DA-PSO* hybridization is a robust method that has potential for decision-making. *DA-PSO* provides additional optimal solutions around the initial solution, demonstrating that *PSO* seasonality can be addressed with this new approach. However, *DA* does not allow fuzzy information to be used, so this will be the next step of the authors to improve the *DA-PSO* hybrid.

Also, it is important to point out that the authors intend to continue with future research based on the results of this study, ranging from the implementation of the programs developed in an intelligent data analysis system, which serves as a basis for the research of other authors. with this approach. In addition, among future works, it is planned to continue with the comparison of the algorithms that are available with new hybrid algorithms, using the bat algorithms (BA) and ant colony optimization (ACO), to find the algorithm to increase the effectiveness of the results.

ACKNOWLEDGMENT

This work is supported by the Autonomous University of Ciudad Juárez, through the Doctorate in Technology. As well as the Secretary of Public Education / Sub-Secretary of Higher Education (*SEP-SES*) and the Technological University of Chihuahua (*UTCH*), for their support through the Professional Teacher Development Program, higher type (*PRODEP*), with concession number: UTCHI-014.

REFERENCES

[1] Rozo-García, F. (2020). Revisión de las tecnologías presentes en la industria 4.0. Revista UIS Ingenierías, 19(2): 177-191. https://doi.org/10.18273/revuin.v19n2-2020019

[2] Omri, N., Al Masry, Z., Mairot, N., Giampiccolo, S., Zerhouni, N. (2020). Industrial data management strategy towards an SME-oriented PHM. Journal of Manufacturing Systems, 56: 23-36. https://doi.org/10.1016/j.jmsy.2020.04.002

[3] Yoo, I., Yi, C.G. (2022). Economic innovation caused by digital transformation and impact on social systems. Sustainability, 14(5): 2600. https://doi.org/10.3390/su14052600

[4] Zhou, G., Luo, S. (2018). Higher education input, technological innovation, and economic growth in China. Sustainability, 10(8): 2615. https://doi.org/10.3390/su10082615

[5] Gunal, M.M., Karatas, M. (2019). Industry 4.0, digitisation in manufacturing, and simulation: A review of the literature. Simulation for Industry 4.0, 19-37. https://doi.org/10.1007/978-3-030-04137-3_2

[6] de Sousa Junior, W.T., Montevechi, J.A.B., de Carvalho Miranda, R., de Oliveira, M.L.M., Campos, A.T. (2020). Shop floor simulation optimization using machine learning to improve parallel metaheuristics. Expert Systems with Applications, 150: 113272. https://doi.org/10.1016/j.eswa.2020.113272

[7] Gunal, M.M. (2019). Simulation and the fourth industrial revolution. In Simulation for Industry 4.0, pp. 1-17. Springer, Cham. https://doi.org/10.1007/978-3-030-04137-3_1

[8] Kulkarni, A., Halder, S. (2020). A simulation-based decision-making framework for construction supply chain management (SCM). Asian Journal of Civil Engineering, 21(2): 229-241. https://doi.org/10.1007/s42107-019-00188-0

[9] Prayoga, N.D., Zarlis, M., Efendi, S. (2022). Weighting comparison analysis ROC and Full consistency Method (FUCOM) on MOORA in decision making. Sinkron: Jurnal Dan Penelitian Teknik Informatika, 7(3): 2024-2032. https://doi.org/10.33395/sinkron.v7i3.11643

[10] Tzanetos, A., Dounias, G. (2021). Nature inspired optimization algorithms or simply variations of metaheuristics? Artificial Intelligence Review, 54(3): 1841-1862. https://doi.org/10.1007/s10462-020-09893-8

[11] Banerjee, A., Singh, D., Sahana, S., Nath, I. (2022). Impacts of metaheuristic and swarm intelligence approach in optimization. In Cognitive Big Data Intelligence with a Metaheuristic Approach, pp. 71-99. Academic Press. https://doi.org/10.1016/B978-0-323-85117-6.00008-X

[12] Li, M., Chen, H., Wang, X., Zhong, N., Lu, S. (2019). An improved particle swarm optimization algorithm with adaptive inertia weights. International Journal of Information Technology & Decision Making, 18(3): 833-866. https://doi.org/14.10.1142/S0219622019500147

[13] Vinogradova, I. (2019). Multi-attribute decision-making methods as a part of mathematical optimization. Mathematics, 7(10): 915. https://doi.org/10.3390/MATH7100915

[14] Grillone, B., Danov, S., Sumper, A., Cipriano, J., Mor, G. (2020). A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings. Renewable and Sustainable Energy Reviews, 131: 110027. https://doi.org/10.1016/j.rser.2020.110027

[15] Eberhat, R., Kennedy, J. (1995, October). A new optimizer using particle swarm theory. In Sixth International Symposium on Micro Machine and Human Science, Piscataway, pp. 39-43. https://doi.org/10.1109/MHS.1995.494215

[16] Ogundoyin, S.O., Kamil, I.A. (2021). Optimization techniques and applications in fog computing: An exhaustive survey. Swarm and Evolutionary Computation, 66: 100937. https://doi.org/10.1016/j.swevo.2021.100937

[17] Xue, H., Bai, Y., Hu, H., Xu, T., Liang, H. (2019). A novel hybrid model based on TVIW-PSO-GSA algorithm and support vector machine for classification problems. IEEE Access, 7: 27789-27801. https://doi.org/10.1109/ACCESS.2019.2897644

[18] Conejo, A.N. (2021). Fundamentals of dimensional analysis: Theory and applications in metallurgy. Springer Nature. https://doi.org/10.1007/978-981-16-1602-0

[19] Pérez Domínguez, L., Luviano Cruz, D., Martinez Gomez, E.A., Villa Silva, A.J., Valles-Rosales, D.J. (2021). Dimensional analysis under linguistic pythagorean fuzzy set. Instituto de Ingeniería & Tecnología, 13(3): 440. https://doi.org/10.3390/sym13030440

[20] Lumbantoruan, G., Purba, E.N. (2022). Analisis nilai market jaminan pinjaman dengan metode moora. Methomika: Jurnal Manajemen Informatika & Komputerisasi Akuntansi, 6(2): 199-204. https://doi.org/10.46880/JMIKA.VOL6NO2.PP199-204

[21] Nainggolan, A., Siregar, A., Mesran, M. (2022). Sistem pendukung keputusan penilaian indeks kinerja sales marketing menerapkan metode moora. Hello World Jurnal Ilmu Komputer, 1(3): 121-129. https://doi.org/10.56211/HELLOWORLD.V1I3.125

[22] Bansal, J.C. (2019). Particle swarm optimization. In Evolutionary and Swarm Intelligence Algorithms, pp. 11-23. Springer, Cham. https://doi.org/10.1007/978-3-319-91341-4_2

NOMENCLATURE

gbest	Best optimal
pbest	Best position
t	Current number of iterations
CP	Current position of the particle
DA	Dimensional Analysis
MCDM	Multi Criteria decision making methods
MOORA	Multi-Objective Optimization Method Based on Proportions Analysis
PSO	Particle Swarm Optimization
IS	Similarity Index
T	Total iterations

Greek symbols

Ny	Contribution value
c_2	Cognitive coefficient
ωC	Degrees of preference for each criterion
Nx_i	Global evaluations of benefit criteria
Nx_j	Global evaluations of cost criteria
S_l^*	Ideal alternative
ω	Inertia weight
r_1, r_2	Learning influence
w_j	Normalized weight of criterion j
$f(x)$	Objective function / fitness function
v	Particle speed
η	Population size
c_1	Social coefficient
a	Solution value

Subscripts

i	Alternative
l, j	Criterion
ι	Particle