IJASRaR International Journal of Applied Sciences and Radiation Research
ISSN: 3062-2751 www.ijasrar.com ijasrar@gmail.com
Vol. 2-No.1 (2025) pp. 91-94
Research Article

Human Migration and Human Migration Algorithmic Perspective

Mitat Uysal[1]*, Aynur Uysal[2], Elif Erçelik[3]

[1]Doğuş University, Engineering Faculty, Dep. of Software Engineering, 34764, Istanbul-Türkiye
* **Corresponding Author Email:** muysal@dogus.edu.tr - **ORCID:** 0000-0001-9713-2525

[2]Doğuş University, Engineering Faculty, Dep. of Software Engineering, 34764, Istanbul-Türkiye
Email: auysal@dogus.edu.tr - **ORCID:** 0000-0002-2635-8903

[3]Doğuş University, Engineering Faculty, Dep. of Software Engineering, 34764, Istanbul-Türkiye
Email: eercelik@dogus.edu.tr - **ORCID:** 0000-0002-2008-8033

Article History:

DOI: 10.22399/ijasrar.29
Received: Mar. 11, 2025
Accepted: May. 03, 2025

Keywords:

Human migration,
Human Migration Optimization,
Metaheuristic algorithm,
Migration modelling ,
Algorithmic intelligence.

Abstract: Human migration is a complex phenomenon driven by socioeconomic, political, environmental, and demographic factors. Understanding and modeling migration patterns have become vital for planning, humanitarian response, and sustainable development. In parallel, nature-inspired optimization algorithms have gained attention for solving complex real-world problems. One emerging algorithm, Human Migration Optimization (HMO), draws inspiration from the collective behavior of migrating populations and models optimal solutions by simulating the movement of agents toward better "settlements" under survival pressure. This paper presents a comprehensive review of human migration theories and introduces a mathematical foundation for the Human Migration Optimization algorithm. The proposed HMO framework is defined with mathematical equations and compared with other metaheuristic methods. The effectiveness of HMO is highlighted through its unique migration logic, selection pressure, and memory-based movement.

1. Introduction

Human migration has historically shaped civilizations and continues to influence economies and environments worldwide [1]. Modern migration studies include demographic analysis, push-pull theory, network theory, and economic modelling [2,3]. At the same time, the field of optimisation seeks to solve high-dimensional, non-linear problems, often using heuristics inspired by natural or social phenomena [4]. Recently, the Human Migration Optimization (HMO) algorithm has been introduced to simulate the intelligent decision-making processes behind migration patterns for solving complex optimization problems [5]. This paper connects classical human migration theories with a mathematical model for the HMO algorithm.

2. Human Migration: Theoretical Background

Human migration refers to people moving from one place to another, intending to settle temporarily or permanently. [6]. Key drivers of migration include:

- **Push factors:** war, famine, unemployment.
- **Pull factors:** economic opportunities, safety, environmental quality.

Mathematically, the gravity model can be used to model the migration flow M_{ij} between region i and region j:

$$M_{ij} = G\frac{P_i^{\alpha}P_j^{\beta}}{D_{ij}^{\gamma}}$$

where,

- G is a constant
- P_i, P_j are the populations of regions i and j
- D_{ij} is the distance between them

- α, β, γ are empirical parameters [7].

The **agent-based model (ABM)** also simulates individual decisions based on local rules, such as economic utility or social networks [8].

3. Human Migration Optimization (HMO) Algorithm

Inspired by human migration, HMO simulates a population of agents (individuals or families) who move from low-fitness to high-fitness regions, mimicking real migration behaviours such as:

- Collective decision-making
- Information sharing and communication
- Resistance to harsh environments
- Memory of previously visited locations

3.1 Algorithm Structure

The HMO algorithm consists of the following components:

Step 1: Initialization

A population $X = \{x_1, x_2, \dots, x_N\}$ is randomly generated in the solution space.

$$x_i = [x_{i1}, x_{i2}, \dots, x_{id}], \quad i = 1, \dots, N$$

Each solution has a fitness value $f(x_i)$.

Step 2: Identify Pull Regions

Regions (solutions) with better fitness than the current location are identified as "attractors." Each agent evaluates possible destinations based on:

$$S_{ij} = \frac{f(x_j) - f(x_i)}{D_{ij} + \varepsilon}$$

where $D_{ij}$is the Euclidean distance between x_i and x_j, and ε is a small constant [9].

Step 3: Migration Decision

Each agent decides to migrate probabilistically based on social influence and survival needs:

$$P_{ij} = \frac{S_{ij}}{\sum_k S_{ik}}$$

Step 4: Movement Update

Agent i updates its position using:

$$x_i^{t+1} = x_i^t + \lambda \cdot \left(x_j^t - x_i^t\right) + \mu \cdot randn()$$

where:

- λ migration tendency
- μ noise factor (unpredictability)
- randn(): normally distributed random number

Step 5: Memory and Adaptation

A memory M_i of previously visited locations is stored to avoid poor regions:

$$M_i = \{x_i^k | f(x_i^k) < f(x_i^{k+1})\}$$

The agent avoids previously failed paths.

3.2 Convergence and Stopping Criteria

Convergence is checked via:

$$\Delta_f = \frac{1}{N}\sum_{i=1}^{N}\left|f(x_i^t) - f(x_i^{t-1})\right| < \delta$$

or maximum iteration count is reached.

Advantages of HMO

- **Social learning:** Combines multiple exploration strategies
- **Memory-based navigation:** Avoids repeated poor solutions
- **Diversity:** Noise and probabilistic decisions preserve exploration
- **Adaptability:** Suitable for dynamic environments

1. Comparison with Other Metaheuristics

Table 1 provides a comparison of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Migration Birds Optimization (MBO) and HMO.

Table 1. *Comparison of Metaheuristics*

Algorithm	Memory	Social Influence	Exploration	Mathematical Basis
PSO	No	Global Best	Medium	Velocity-Based
GA	No	Crossover/Mutation	High	Probabilistic
MBO	Partial	V-shaped Pattern	High	Role-based motion
HMO	Yes	Collective Migration	High	Utility-based motion

4. Conclusion

Human migration remains a rich domain for both social study and algorithmic modelling. The Human Migration Optimization algorithm brings together principles of social behaviour, adaptive learning, and spatial reasoning. Through mathematical modelling and social simulation, HMO demonstrates potential for solving real-world optimization problems involving resource allocation, logistics, and dynamic systems [10-25].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1]Castles, S., & Miller, M. J. (2009). The age of migration: International population movements in the modern world. *Palgrave Macmillan*.

[2]Massey, D. S. et al. (1993). Theories of international migration: a review and appraisal. *Population and Development Review*, 19(3), 431–466. https://doi.org/10.2307/2938462

[3]Skeldon, R. (2013). Global migration: Demographic aspects and its relevance for development. *United Nations Department of Economic and Social Affairs*.

[4]Yang, X. S. (2010). Nature-inspired metaheuristic algorithms. *Luniver Press*.

[5]Uysal, M. (2024). Human migration optimization: A novel metaheuristic algorithm. *Journal of Artificial Intelligence*, 45(2), 123–137.

[6]International Organization for Migration (IOM). (2020). *World Migration Report 2020*. https://publications.iom.int/system/files/pdf/wmr_2020.pdf

[7]Anderson, J. E. (2011). The gravity model. *Annual Review of Economics*, 3(1), 133–160.

[8]Epstein, J. M. (2006). Generative social science: Studies in agent-based computational modeling. *Princeton University Press.*

[9]Banerjee, A. et al. (2013). The diffusion of microfinance. *Science*, 341(6144). DOI: 10.1126/science.123649

[10]Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of the IEEE International Conference on Neural Networks* (Vol. 4, pp. 1942–1948). IEEE. https://doi.org/10.1109/ICNN.1995.488968

[11]Holland, J. H. (1992). Adaptation in natural and artificial systems. *MIT Press.*

[12]Bonyadi, M. R., & Michalewicz, Z. (2017). Particle swarm optimization for single objective continuous space problems: A review. *Swarm Intelligence*.

[13]Karaboga, D., & Basturk, B. (2007). Artificial bee colony (ABC) optimization algorithm. *Journal of Global Optimization*, 39(3), 459-471, https://doi.org/10.1007/s10898-007-9149-x

[14]Glover, F., & Kochenberger, G. A. (2003). Handbook of metaheuristics. *Springer*.

[15]Shi, Y., & Eberhart, R. C. (1998). Parameter selection in particle swarm optimization. In V. W. Porto, N. Saravanan, D. Waagen, & A. E. Eiben (Eds.), *Evolutionary programming VII* (pp. 591–600). *Lecture Notes in Computer Science, 1447*. Springer. https://doi.org/10.1007/BFb0040810.

[16]Kirkpatrick, S., Gelatt, C. D., Jr., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science, 220*(4598), 671–680. https://doi.org/10.1126/science.220.4598.671

[17]Mirjalili, S. (2016). Dragonfly Algorithm: A New Meta-heuristic Optimization Technique. *Neural Computing and Applications*, *27*(4), 1053–1073.

[18]Dorigo, M., & Stützle, T. (2004). *Ant colony optimization*. MIT Press.

[19]Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009). GSA: Gravitational search algorithm. *Information Sciences.*

[20]Deb, K. (2001). Multi-objective optimization using evolutionary algorithms. *Wiley.*

[21]Yang, X. S., & Deb, S. (2010). Engineering optimization by cuckoo search. *Int. Journal of Mathematical Modelling and Numerical Optimization,* 1(4), 330–343.

[22]Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Computing Surveys*, 35(3), 268–308. https://doi.org/10.1145/937503.93750

[23]Salcedo-Sanz, S. (2009). A survey of repair methods used as constraint handling techniques in evolutionary algorithms. *Computer Science Review*, *3*(3), 175–192. https://doi.org/10.1016/j.cosrev.2009.07.001

[24]Ghaidaa Saba Yousef, Hayder Dibs, & Ahmed Samir Naje. (2025). Environmental Assessment For Mapping Land Degradation and Lands Changes Using Remotely Sensed Data with Geospatial Analysis. *International Journal of Computational and Experimental Science and Engineering*, 11(1). https://doi.org/10.22399/ijcesen.1045

[25]Rahnamayan, S., Tizhoosh, H. R., & Salama, M. M. A. (2008). Opposition-based differential evolution. *IEEE Transactions on Evolutionary Computation,* 12(1), 64-79. doi: 10.1109/TEVC.2007.894200