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РОЗРОБКА ТА ВАЛІДАЦІЯ АГЕНТ-ОРІЄНТОВАНОЇ СИМУЛЯЦІЇ З ПРОСТИМ ШТУЧНИМ ІНТЕЛЕКТОМ ДЛЯ МОДЕЛЮВАННЯ ЕВОЛЮЦІЙНОЇ АДАПТАЦІЇ

Робота присвячена розробці агент-орієнтованої симуляції з агентами штучного інтелекту на основі правил для дослідження еволюційної адаптації в динамічному середовищі. Описано компоненти моделі (гени, сезони, клани) та представлено результати тестового запуску, що демонструють її функціональність.

Ключові слова: *Агент-орієнтоване моделювання (АОМ), еволюція, генетична конкуренція, адаптація, симуляція, змінні ресурси, сезонність, клани, штучне життя, стратегії виживання.*

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DEVELOPMENT AND VALIDATION OF AN AGENT-BASED SIMULATION WITH A SIMPLE ARTIFICIAL INTELLIGENCE FOR MODELING EVOLUTIONARY ADAPTATION

The paper is devoted to the development of an agent-based simulation with rule-based artificial intelligence agents to study evolutionary adaptation in a dynamic environment. The components of the model (genes, seasons, clans) are described and the results of a test run demonstrating its functionality are presented.

Key words**:** *Agent-based modeling (ABM), evolution, genetic competition, adaptation, simulation, variable resources, seasonality, clans, artificial life, survival strategies.*

Introduction and problem statement. The concept of "survival of the fittest" is a fundamental principle of natural selection; however, the evolutionary process is significantly more complex than direct competition for resources [1–3]. In reality, the success of populations depends not only on genetic advantages but also on the ability to adapt to dynamic environmental conditions. For example, the survival of various insect species during the dinosaur extinction era demonstrates that "less fit" organisms can dominate due to strategic flexibility [4,5]. This paradox finds theoretical grounding in the Parrondo effect, where combining two losing strategies leads to a winning outcome [6,7].

Research on the Parrondo effect in biology [8–12], ecology [9,10,26], and social systems [19,27–29] highlights its universality for modeling adaptations in changing conditions. However, it remains understudied how resource fluctuations (e.g., seasonal food changes) influence the dominance of specific genes within a population. Our work addresses this gap using an agent-based simulation, which allows for the real-time observation of evolutionary strategies.

Analysis of the latest research and publications. Classical theories of natural selection [1–3] do not fully explain species diversity. Research has shown that survival depends on: genetic variability – the ability of populations to generate new traits [2]; adaptability to change – examples include transitioning from nomadic to colonial lifestyles [23,24], and 'dormancy' mechanisms in plants [9,26]; social interactions – cell cooperation in multicellular organisms reduces cancer risk [11,12], and clan structures enhance survivability [20,21].

The paradox where combining two losing strategies results in a win manifests in various biological systems: at the molecular level: phase variation in bacteria [8,25], regulation of gene expression [13]; at the ecosystem level: dominance of populations with 'inefficient' traits due to resource fluctuations [10,22]; in social dynamics: accumulation of social wealth through strategy switching [19,28].

Modeling Evolutionary Strategies Current research utilizes:

- Agent-based models (ABMs) for analyzing resource competition [27–29].
- Stochastic simulations to test the Parrondo effect in various environments [7,14–16].
- Nonlinear dynamic systems for predicting ecosystem evolution [10,17–19].

There is insufficient research linking seasonal resource fluctuations (e.g., food) with the dominance of specific genes (speed, endurance) through the lens of the Parrondo effect. Our simulation offers a tool for such analysis. The agent-based model simulates resource fluctuations (seasons) and allows tracking of how a gene combination ('Endurance' + 'Vision') becomes a winning strategy even under conditions of temporary loss (e.g., winter). The clan mechanism reflects the social aspects of the Parrondo effect – cooperation enhances survivability, similar to models in [11,19,28]. Gene mutations allow investigating whether random changes lead to the emergence of new 'paradoxical' strategies, as in the works of [8,24].

The aim of the study. To investigate the competitive dynamics of different genetic strategies and the role of social structures (clans) in population adaptation to the environment with variable resource availability using agent-based modeling (ABM).

Experimental methodology. An agent-based model (ABM) was created to study the evolution of genetic traits in a population under the influence of the environment. Main stages:

1. Model development. Environment: A 256x256 grid with seasonal resource dynamics (food appears with different intensity by season). Agents: They have parameters (energy metabolism, movement, vision, decision), a genome with 10 slots (5 types of alleles: speed, endurance, etc.) and are subject to the rules of energy balance, reproduction (with mutations) and clan formation (based on genetic similarity).

2. Implementation and testing. The model is programmed in Python with visualization. Running a test scenario: initial population - 20 agents with random genomes, seasonal food parameters (spring: 4, summer: 5, fall: 3, winter: 2 units/sec).

3. Data collection and analysis. We tracked population dynamics, gene distribution, and clan formation. A qualitative analysis of agent behavior (feeding, social interactions) confirmed the model's performance for further experiments.

Presentation of the main research material. To investigate the impact of seasonal resource availability fluctuations on the competitive success of different genetic strategies and the role of social structures (clans) in population survival, an agent-based model (ABM) was developed and implemented. The ABM allows simulating the behavior and interaction of autonomous agents (individuals) in a virtual environment, observing the emergent properties of the system at the population level. The model was implemented using the Python programming language and relevant libraries.

The simulated environment is a two-dimensional discrete space of size 256x256 cells. The primary resource in the environment is food, units of which appear in random empty locations on the grid. The dynamics of food appearance depend on the cyclical change of four seasons: Spring, Summer, Autumn, and Winter. Each season lasts for 180 seconds of simulation time. The intensity of food appearance is: Spring: 4 units/second; Summer: 5 units/second; Autumn: 3 units/second; Winter: 2 units/second. Seasons also impose global modifiers on agents: Summer: Energy consumption of all agents increases by 10%. Winter: Movement speed of all agents decreases by 10%.

Agents represent individual organisms in the population. The simulation is initialized with 20 agents placed in random positions. Each agent is characterized by the following parameters:

Energy: Agents have a current energy level, which is consumed for vital functions and movement. The base consumption is 1 energy unit per second (resting energy). Additionally, 0.5 energy units are consumed for each cell traversed. Consuming one unit of food restores 50* energy units (* - default parameter). The initial energy level of each agent is 99 units. The base maximum energy capacity is 500 units (can be modified by genes). An agent dies if its energy level reaches zero.

Movement: The base movement speed of an agent is 2 cells/second (can be modified by genes and seasonal effects).

Perception: Agents have a field of vision that allows them to detect food and other agents. The base vision radius is 10 cells (can be modified by genes).

Each agent possesses a genome consisting of 10 gene slots. Each slot can contain one of five possible alleles (gene types), which determine the agent's phenotypic traits:

Type 0 (Empty): No phenotypic effect.

Type 1 (Speed): Increases base movement speed by 10% for each gene of this type present.

Type 2 (Endurance): Decreases total energy consumption (base and movement) by 10% for each gene of this type present.

Type 3 (Vision): Increases base vision radius by 2 cells for each gene of this type present.

Type 4 (Max. Energy): Increases maximum energy capacity by 100 units for each gene of this type present.

The phenotypic characteristics of an agent are calculated based on the combination of genes in its genome. For example, the actual speed of an agent is calculated as:

$$V = V_{base} \cdot (1 + 0.1 \cdot N_{speed}) \cdot (1 - 0.1 \cdot \text{Winter\_effect})$$

where V_{base} is the base speed, N_{speed} is the number of 'Speed' genes, and Winter_effect is 1 during Winter and 0 during other seasons. Other characteristics are calculated similarly.

Agent behavior is determined by a simple set of rules based on their state and perception of the environment, with the following action prioritization:

1. Food Search: If one or more food units are within the agent's field of vision, it moves toward the nearest one. If multiple agents move towards the same food unit simultaneously, the one arriving first obtains it.

2. Reproduction: If no food is in sight, but the agent has sufficient energy for reproduction (≥ 100 units), it searches for the nearest other agent also having ≥ 100 energy units, and moves towards it for mating.

3. Clan Assistance (if a clan member): If an agent is a clan member and receives a help signal from another member (with energy ≤ 5 units), and the agent itself has ≥ 150 energy units, it moves towards the agent needing help.

4. Calling for Help (if a clan member): If an agent's energy drops to ≤ 5 units, it ceases other actions, remains in place, and signals its clan members for help.

5. Waiting: If none of the above conditions are met, the agent remains stationary, minimizing energy expenditure.

Sexual reproduction occurs under the following conditions:

• Both potential parents are adjacent and have an energy level ≥ 100 units.

• Each parent expends 100 energy units for the reproduction attempt.

The probability of successful fertilization depends on the genetic similarity of the parents and is calculated using the formula:

$$P = ((S / N) \cdot (100 - P_{min})) + P_{min}$$

where: $N = 10$ – total number of gene slots; $P_{min} = 5\%$ – minimum probability of successful reproduction; S – a measure of genetic similarity, calculated as the sum of the minimum counts of each gene type (1-4) in both parents.

• Upon successful reproduction, a random number of offspring (from 1 to 4) are produced.

• The genome of each offspring is formed by inheriting genes randomly selected from both parents. Selection occurs slot by slot, with each parent having a 50% probability of transmitting their gene information for that slot.

• Each inherited gene slot has a 1% chance of mutation, meaning the allele changes to any other type (including 0) with equal probability.

After reproduction, the parents immediately disperse in random directions for 3 seconds (to reduce local competition) and enter a 30-second refractory period during which they cannot initiate new mating.

Agents can form social groups (clans) based on genetic similarity.

• Formation: An agent not belonging to a clan, possessing ≥ 7 genes of a single type (1, 2, 3, or 4), and having ≥ 200 energy units can attempt to create a new clan corresponding to that gene type. The attempt costs 50 energy units and has a 25% chance of success. Only one clan can exist for each gene type (1-4).

• Recruitment: The clan founder attempts to recruit new members (agents with ≥ 7 corresponding genes) every 35 seconds until the first success. Other clan members attempt recruitment every 30 seconds. If a clan member encounters a suitable candidate, recruitment occurs with an 80% probability.

• Intra-clan Assistance: Clan members can provide energy assistance (50 energy units) to other members of their clan who are near death (≤ 5 energy units), provided the donor has sufficient energy (≥ 150 units).

Result. This section presents the results of the simulation modeling for the baseline scenario, which is characterized by a balanced food value and distribution of food intensity by season. The results are visualized in Figure 1, which shows the dynamics of the total population size (top graph), the relative frequency (share) of each gene type (1-4) in the population gene pool (middle graph), and the dynamics of the number of members in clans for each gene type (bottom graph). Simulation parameters: food value - 50, intensity of emergence by season 4, 5, 3, 2 units per second.

In the conditions of moderate seasonal variability, the population of agents showed stable dynamics after the initial growth phase. The “Vision” gene (Gene 3) quickly established a dominant position, steadily maintaining a share of 40-50% of the total number of functional genes. The “Speed” (Gene 1) and “Endurance” (Gene 2) genes coexisted in the population, maintaining approximately the same, though lower, frequencies (about 20-30% each). The “Maximum Energy” gene (Gene 4) was the least competitive under these conditions, and its frequency rapidly decreased to minimal values. The simulations in this scenario were characterized by high stability (about 100% of successful launches). The clans were formed almost exclusively on the basis of the “Sight” gene, which correlates with its dominant position.

Conclusions. A software model of agent-based simulation for studying eco-evolutionary processes has been successfully developed and implemented. The model includes the genetic structure of agents, the impact of seasonal environmental changes, basic rule-based behavior (simple AI), and the mechanism for forming social groups (clans). The results of the test run confirmed the model's performance and its ability to simulate the competition of genetic strategies and basic population dynamics. The presented simulation is a validated tool for further research on the influence of various factors on evolutionary adaptation, which will be presented in the next paper.

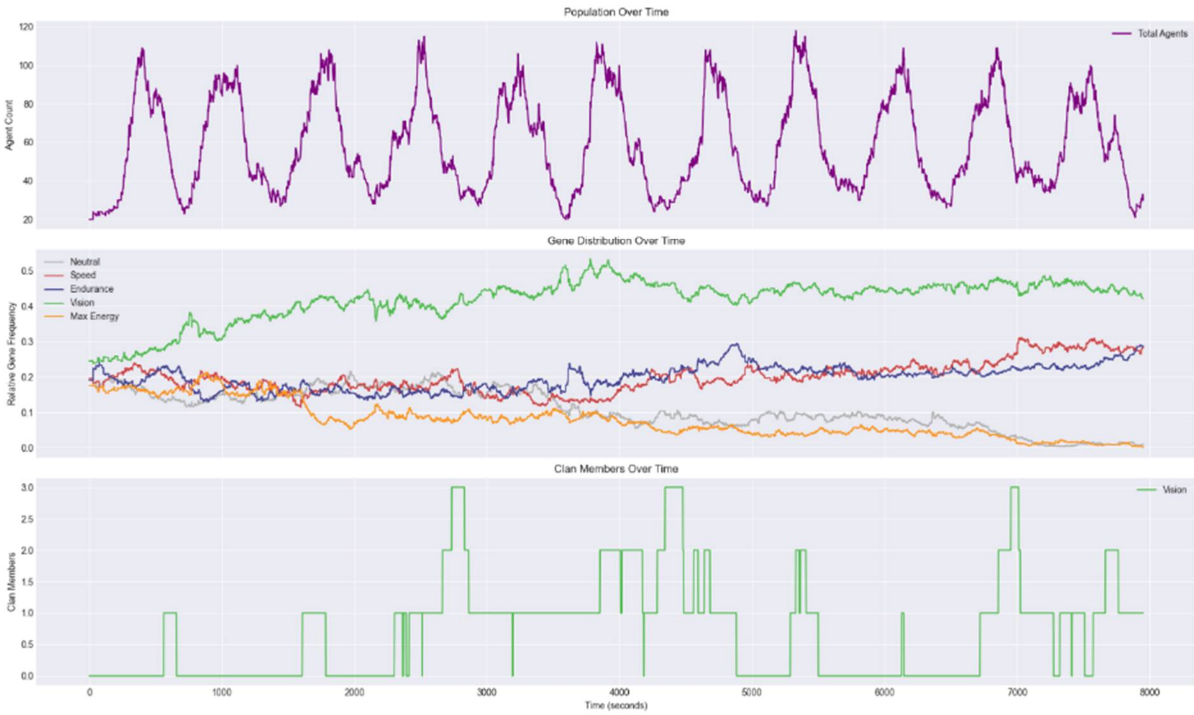

Figure 1. **Simulation results with parameters: food value 50, seasonal intensity - 4, 5, 3, 2**

List of references:

1. Spencer H. The principles of biology, vol. 1. Williams and Norgate; 1864.
2. Boyer S, Hérissant L, Sherlock G. Adaptation is influenced by the complexity of environmental change during evolution in a dynamic environment. PLoS Genet 2021;17(1):e1009314.
3. Lande R, Shannon S. The role of genetic variation in adaptation and population persistence in a changing environment. Evolution 1996:434–7.
4. Bateson P. Adaptability and evolution. Interface Focus 2017;7(5):20160126.
5. Badyaev AV. Role of stress in evolution: from individual adaptability to evolutionary adaptation. In: Variation. Elsevier; 2005. p. 277–302.
6. Harmer GP, Abbott D. Losing strategies can win by Parrondo's paradox. Nature 1999;402(6764):864.
7. Abbott D. Developments in Parrondo's paradox. In: Applications of nonlinear dynamics: model and design of complex systems. Springer; 2009. p. 307–21.
8. Wolf DM, Vazirani VV, Arkin AP. Diversity in times of adversity: probabilistic strategies in microbial survival games. J Theor Biol 2005;234(2):227–53.
9. Tan Z-X, Koh JM, Koonin EV, Cheong KH. Predator dormancy is a stable adaptive strategy due to Parrondo's paradox. Adv Sci 2020;7(3):1901559.
10. Cheong KH, Wen T, Benler S, Koh JM, Koonin EV. Alternating lysis and lysogeny is a winning strategy in bacteriophages due to Parrondo's paradox. Proc Natl Acad Sci 2022;119(13):e2115145119.
11. Wen T, Cheong KH, Lai JW, Koh JM, Koonin EV. Extending the lifespan of multicellular organisms via periodic and stochastic intercellular competition. Phys Rev Lett 2022;128(21):218101.
12. Liu D-M, Wu Z-X, Guan J-Y. Intercellular competitive growth dynamics with microenvironmental feedback. Phys Rev E 2023;108(5):054105.
13. Fotoohinasab A, Fatemizadeh E, Pezeshk H, Sadeghi M. Denoising of genetic switches based on Parrondo's paradox. Phys A, Stat Mech Appl 2018;493:410–20.
14. Rajendran J, Benjamin C. Playing a true Parrondo's game with a three-state coin on a quantum walk. Europhys Lett 2018;122(4):40004.
15. Lai JW, Cheong KH. Parrondo's paradox from classical to quantum: a review. Nonlinear Dyn 2020;100(1):849–61.

16. Rajendran J, Benjamin C. Implementing Parrondo's paradox with two-coin quantum walks. R Soc Open Sci 2018;5(2):171599.

17. Kocarev L, Tasev Z. Lyapunov exponents, noise-induced synchronization, and Parrondo's paradox. Phys Rev E 2002;65(4):046215.

18. Danca M-F, Chattopadhyay J. Chaos control of Hastings–Powell model by combining chaotic motions. Chaos, Interdiscip J Nonlinear Sci 2016;26(4).

19. Koh JM, Cheong KH. New doubly-anomalous Parrondo's games suggest emergent sustainability and inequality. Nonlinear Dyn 2019;96:257–66.

20. Capp J-P, Nedelcu AM, Dujon AM, Roche B, Catania F, Ujvari B, et al. Does cancer biology rely on Parrondo's principles? Cancers 2021;13(9):2197.

21. Mori L, Ben Amar M. Stochasticity and drug effects in dynamical model for cancer stem cells. Cancers 2023;15(3):677.

22. Posfai A, Taillefumier T, Wingreen NS. Metabolic trade-offs promote diversity in a model ecosystem. Phys Rev Lett 2017;118(2):028103.

23. Tan ZX, Cheong KH. Nomadic-colonial life strategies enable paradoxical survival and growth despite habitat destruction. eLife 2017;6:e21673.

24. Tan Z-X, Cheong KH. Periodic habitat destruction and migration can paradoxically enable sustainable territorial expansion. Nonlinear Dyn 2019;98:1–13.

25. Wolf DM, Vazirani VV, Arkin AP. A microbial modified prisoner's dilemma game: how frequency-dependent selection can lead to random phase variation. J Theor Biol 2005;234(2):255–62.

26. Gokhale CS, Sharma N. Optimizing crop rotations via Parrondo's paradox for sustainable agriculture. R Soc Open Sci 2023;10(5):221401.

27. Lai JW, Cheong KH. Social dynamics and Parrondo's paradox: a narrative review. Nonlinear Dyn 2020;101(1):1–20.

28. Wang L-G, Xie N-G, Xu G, Wang C, Chen Y, Ye Y. Game-model research on coopetition behavior of parrondo's paradox based on network. Fluct Noise Lett 2011;10(01):77–91.

29. Dinís L, Parrondo JM. Inefficiency of voting in Parrondo games. Phys A, Stat Mech Appl 2004;343:701–11.

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