Use of information society technologies

SWARM INTELLIGENCE IN MODELLING SOCIO-ECONOMIC PROCESSES

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Abstract

The goal is to model the behavior of primitive organisms and transfer the results to human life. A human choice process has been implemented, based on an ant algorithm that simulates the procedure for laying out an optimal, shorts route.

Keywords

swarm intelligence; bionics; biomimicry; ant algorithm; modeling of social behavior; choice

Introduction

«But what distinguishes the worst architect from the best of bees is this, that the architect raises his structure in imagination before he erects it in reality» [1, P. 185]. This famous observation by German philosopher and economist Karl Marx highlights the advantage of human strategic thinking over an animal. However, in 2010, a team of Japanese and British scientists have discovered that even a remarkably simple organism – a slime mold (Physarum Polycephalum) can design highly efficient transport networks, rivaling the work of highly qualified engineers and, in some cases, with even greater energy efficiency [2].

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This study builds on earlier research (2000), which explored a similar experiment but in a more theoretical and less applied form [3]. In both studies, T. Nakagaki (PhD in Biology, Japan), played a key role – work that earned him two Ig Nobel Prizes (2008 in cognitive science and 2010 for transport network planning).

It's worth noting that humans have long drawn inspiration from nature to solve practical and economic challenges, as explored in depth by T. Aguilar-Planets and E. Peralta (both – PhD in Engineering, Spain) [4]. While these bio-inspired solutions are not exact replicas of natural systems, being heuristic in nature, they often effectively address real-world problems with near-optimal results. This approach diminishes the need for rigid, deterministic logic characteristic of human reasoning [5], suggesting that in our ever-changing world, such precision may not be crucial for survival.

The collective behavior of social insects, including ants, termites, wasps, bees, bumblebees and locusts – is of particular practical interest due to its parallels with human societal organization. Remarkably, the engineering solutions developed by these insects often surpass human-designed systems in efficiency. In fact, many human innovations have been directly inspired by nature's own perfected designs.

Interestingly, while phylogenetically distant – such as ants and termites – these insect groups exhibit remarkably similar social structures. Even more striking is the convergence of their architectural solutions, with near-optimal designs emerging independently in their nest construction.

Insects of the order Hymenoptera exhibit a strong propensity for collective living. Notably, they display advanced eusocial behavior, marked by a rigid caste system and hierarchical structure. This social organization stems from both biological predispositions and command-driven regulation within the colony.

Each swarm develops its own sophisticated communication system within the hive, incorporating pheromones and intricate movement patterns. These colonies may even engage in human-like activities such as primitive agriculture (protecting aphids or cultivating fungus gardens), waging wars against other colonies and practicing a form of slavery. Within their societies, interactions between members sometimes include criminal behavior, while in other cases, acts of self-sacrifice can be observed, much like in human communities.

While the hive operates under strict hierarchical structures as previously noted, individual advancement within each insect's specialization remains possible based on demonstrated skills and experience. Moreover, colony members exhibit measurable personality differences rather than perfect uniformity. For further reading on social insect behavior, see the discussion between V.I. Alipov, B.S. Boyarshinov (PhD in Physics and Mathematics, Associate Professors) and E.B. Boyarshinova [6], or refer to works by V.E. Kipyatkov (DSc in Biology, Professor) [7-8].

The observations above suggest that insect societies, though simpler and more primitive than human ones, exhibit striking parallels to human communities. By modeling these simplified yet similar to complex systems, we can learn to control it or identify certain relationships and patterns that may be scalable to human contexts. This work aims to simulate the behavior of primitive organisms and translate the findings into practical applications for human society.

To achieve this, the research will focus on three key objectives:

- identifying problem space of swarm technology in everyday human life and practice;
- developing a technical implementation of a selected swarm algorithm;
- adapting this algorithm to model a relevant socio-economic process or phenomenon.

A noteworthy 2024 PNAS study by Israeli researchers explored a crucial question [9]: «What enables collective intelligence in biological systems?» Their findings revealed that swarm intelligence emerges most effectively from the simplicity of individual swarm members. More complex and cognitively advanced organisms tend to experience greater interpersonal conflict, which ultimately hinders collaborative efficiency.

This concept was explored in depth in «The Mythical Man-Month» by F.P. Brooks-Jr. (PhD in Informatics, USA) [10], where the scientist demonstrated how increased communication time reduces team productivity. This insight highlights that modeling role-based behavior works best for mass phenomena with predictable patterns, rather than unique or isolated cases.

1 Swarm Technology Origins

Stanisław Lem's «The Invincible» provides one of the most compelling literary explorations of swarm technology. The renowned Polish science fiction writer and futurist presents a visionary model where simple, primitive components self-organize into highly advanced, resilient systems through their interactions.

Swarm algorithms have found broad applications in human daily life, primarily serving as tools of bionics and biomimicry – a scientific discipline that adapts principles from biological systems to engineering solutions [4-5; 11]. Besides, these algorithms also incorporate organizational patterns from inanimate systems, drawing on concepts from chaos theory [12]. The diversity of these algorithms can be explored in the recent report by A.P. Karpenko (DSc in Physics and Mathematics, Professor) [13, 0:00-40:00] or his textbook called «Modern Search Optimization Algorithms» [14].

A comprehensive international review on this subject has been conducted by a team of Chinese researchers [15]. Further synthesis of swarm intelligence ideas and concepts is available in the work of L.V. Nguyen (PhD in Informatics, Vietnam) [16].

A closely related concept is collective decision-making – the process where multiple individuals refine and build upon each other's perspectives to arrive at optimal solutions for complex problems. This principle has been thoroughly examined in a joint study by V.I. Protasov (PhD in Physics and Mathematics, Associate Professor) and B.B. Slavin (DSc in Economics, PhD in Physics and Mathematics) [17].

A key advantage of swarm systems over single entities is their inherent resilience to failure or destruction. This robustness stems from element redundancy, the interchangeability of individual components. Notably, N.N. Taleb (PhD in Economics, USA) identifies redundancy as a fundamental defense against Black Swan events [18].

However, excessive resource allocation creates tradeoffs: higher agent density within the hive reduces energy efficiency and increases interference. This implies that swarm populations require careful optimization, not indefinite scaling, tailored to the specific operational requirements.

Advances in science have driven down technology costs while improving communication systems, enabling the development of affordable robotics designed for swarm-based interaction in the future. This trend is particularly prominent in military drone applications, as discussed by V.O. Kaskov and A.I. Masalovich (PhD in Physics and Mathematics) [19]. The principles of swarm intelligence are equally relevant to Internet of Things technologies [20], a connection substantiated by research from HSE specialists. Their work identifies three key application areas: autonomous control, smart energy distribution and robotics [21].

The key challenges in this domain involve establishing reliable and stable communication between devices and developing robust infection defense mechanisms. Specifically, swarm systems must be capable of both detecting malfunctioning components and rapidly isolating or eliminating them.

The interview reveals another notable advantage of particle swarm algorithm over gradient descent methods. As A.I. Masalovich notes, particle swarm algorithm typically converges to extrema faster [19, 14:00-16:00]. While we find this claim may not hold universally, particle swarm algorithm's greater flexibility and versatility often prove advantageous in practical implementations.

This discussion naturally extends to ABM (Agent-Based Modeling), where some agents form the core framework. In computational implementations, these agents effectively operate as a swarm, making swarm algorithms directly applicable. An example is the Sugarscape model developed by J.M. Epstein (PhD in Politics, USA) and R.L. Axtell (PhD in Informatics, USA), which simulates human society through insect-inspired interactions. Here, agents follow minimalist rules to search for sugar [22].

2 Ant Colony Optimization

2.1 Mathematical Basis

To illustrate the aforementioned concepts, let us examine in detail the well-known swarm algorithm called Ant Colony Optimization (ACO). Its development was motivated by the need to solve the Traveling Salesman Problem – essentially, the challenge of finding the shortest possible route that visits each vertex of a given graph (Fig. 1).

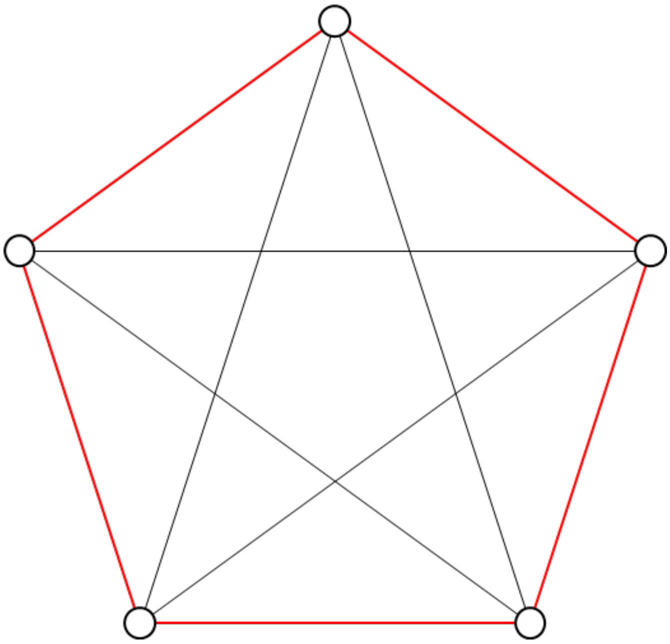

Fig. 1. Graph and movement along its vertices

○ – vertices of the graph;
– – possible routes of movement between the vertices of the graph;
– – the optimal, shortest route.

While this problem could theoretically be solved by exhaustively enumerating all possible paths, the computational complexity grows prohibitively large with even minor increases in graph size (in the most generalized case $n!$, where n is the number of graph vertices). This necessitates alternative approaches, such as the aforementioned ant colony algorithm, which efficiently generates approximate or near-optimal solution.

The algorithm was developed by scientists M. Dorigo (PhD in Informatics, Italy) and Th. Stützle (PhD in Informatics, Belgium), who comprehensively described their methodology in the joint work «Ant Colony Optimization» [23]. Their research was later introduced to the Russian-speaking academic community through the works of S.D. Shtovba (DSc in Technics, Professor, Ukraine) [24-25].

The ACO algorithm's core modeling parameters are: the distances l between network nodes and the pheromone τ concentrations along pathways. During route selection, each ant evaluates potential paths based on two key factors: the path's length and pheromone amount left by previous ants (with higher pheromone concentrations increasing the path's selection probability).

To better understand the computational procedures of the ACO algorithm, we recommend referring to the lecture by M.N. Kirsanov (DSc in Physics and Mathematics, Professor) [26]. The video tutorial by M. Tsarkov is also highly useful [27], as it clearly and concisely explains key calculation details involved in modeling insect colony behavior.

It is important to note that pheromone-based stigmergy is not the only approach for real-time route optimization. Honeybees, for instance, employ their «waggle dance» to communicate location information to hive mates. The intensity of these movements directly correlates with food source quality, prompting proportional colony response – stronger dances attract more foragers. For further reading, see works by A.N. Tsurikov (PhD in Technics, Associate Professor) [28] or the bee algorithm's creator, Professor Derviş Karaboğa [29].

The ant colony algorithm has several notable limitations [30, P. 108]:

- slow convergence with large-size problem (in the initial search phase, ants explore nearly all possible paths (including those that would clearly be non-optimal upon global inspection), significantly increasing number of calculations);
- getting stuck in local optima (this necessitates running multiple computational experiments with different parameters, though even this doesn't guarantee finding the global optimum).

Despite these drawbacks, the algorithm excels at mathematically formalizing selection processes. We find it particularly effective for modeling collective social behavior.

2.2 Technical Implementation of the ACO Algorithm

The aforementioned ACO algorithm was implemented by our team using the AnyLogic 8.9.1 Personal Learning Edition development environment. The implementation was based on the methodology described in the article «Run, Ant, Run» [31]. In our model, virtual insects are represented by airplane icons (Fig. 2-3).

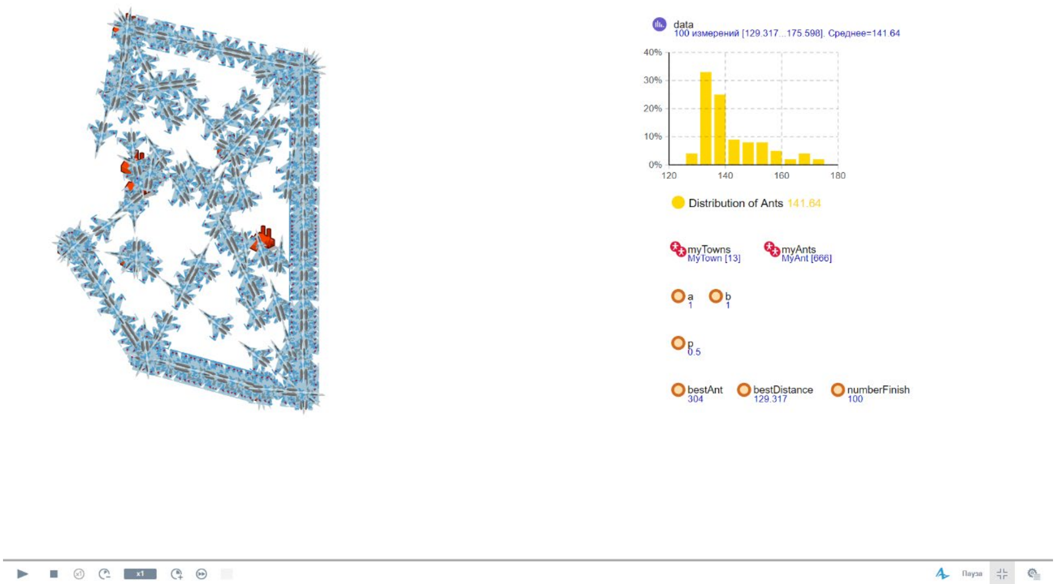

Fig. 2. Basic computer simulation of the ant algorithm:
Model state at time 278.19 s

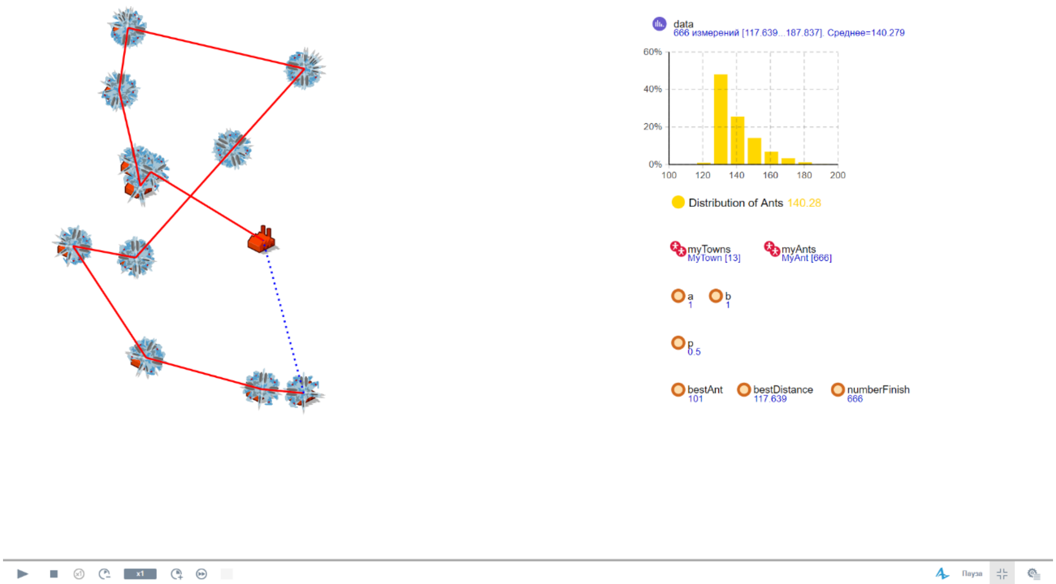

Fig. 3. Basic computer simulation of the ant algorithm:
Model state after all ants completed their routes (632.55 s)

myTown = 13 (pcs) – agents representing graph vertices;
myAnt = 666 (pcs) – ant agents moving at velocity υ = 1 m/s;
a, b = 1 – parameters controlling pheromone and path length importance;
p = 0.5 – pheromone evaporation rate;
bestAnt – identification number of the first ant to complete the optimal route;
bestDistance (m) – length of the shortest path found;
numberFinish (pcs) – number of ants that completed their routes;
– – shortest discovered route;
··· – closing edge of the shortest discovered route.

Among notable observations from our computer simulations, when parameters a, b and p emphasize pheromone trails, a larger portion of the ant population follows nearly identical paths close to the optimal route, thereby reducing the average path length (Fig. 4). A similar effect can be achieved by introducing elite ants into the population. Unlike their counterparts, these ants do not move probabilistically but instead follow the current best-known route, helping establish a clear trail for the rest of the colony [24, Pp. 73-74; 25, P. 8].

If the parameters are poorly configured, the distribution of ants will tend to follow a normal distribution (Fig. 5). However, this may sometimes yield better shortest-path results by amplifying probabilistic aspects in the model. Introducing randomness often significantly expands the modeling possibilities and can lead to unexpected yet insightful outcomes [32].

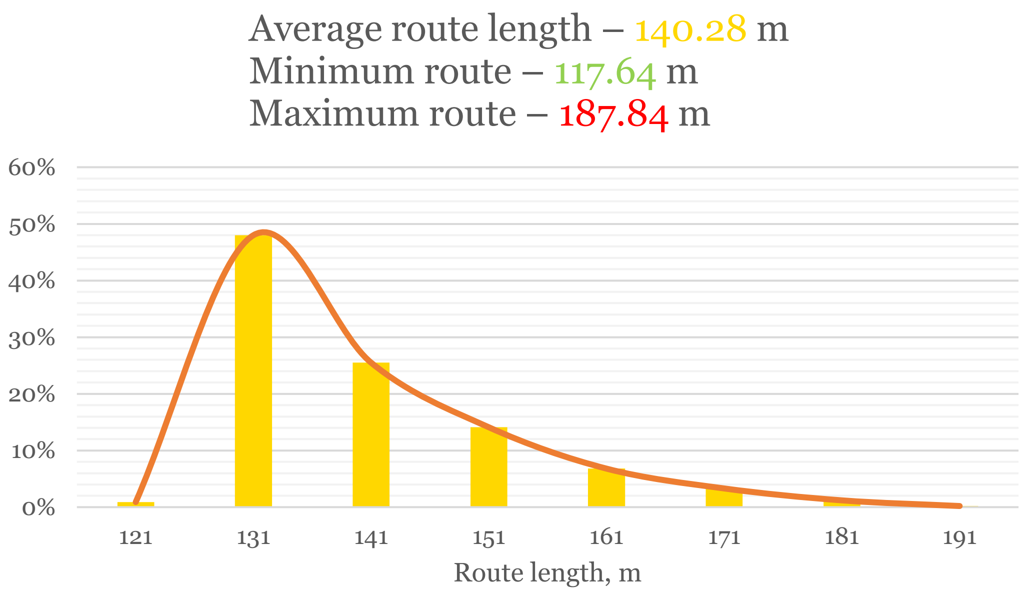

Fig. 4. Ant distribution by traveled route length:
With a = 1, b = 1 and p = 0.5

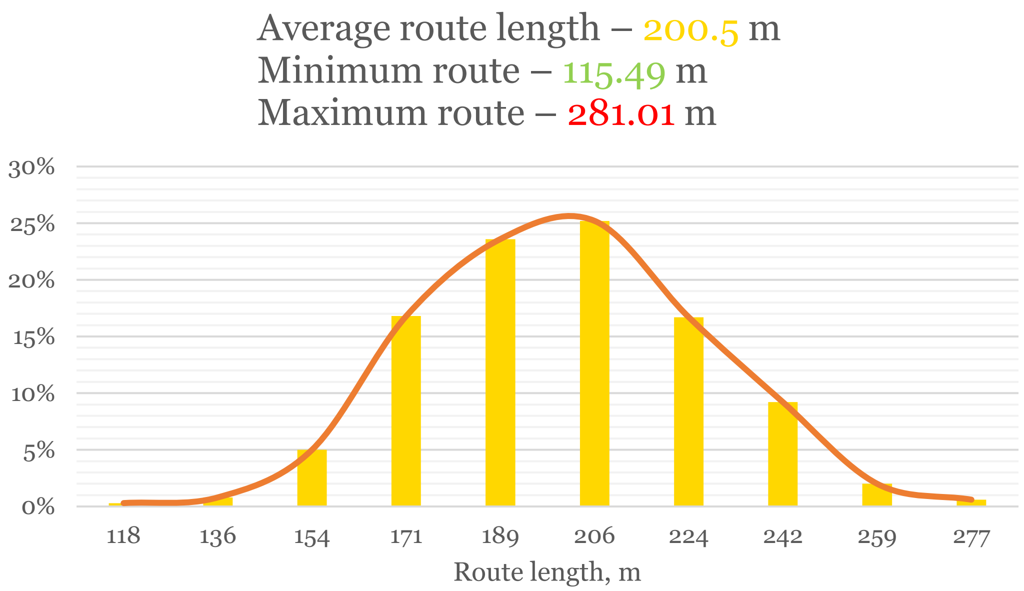

Fig. 5. Ant distribution by traveled route length:
With a = 0.15, b = 0.56 and p = 0.29

3 Practical Applications of ACO Algorithms

Let us begin by noting that many economic entities can be represented as networks of relationships – which are essentially mathematical graphs. For real-world implementations of this framework, we recommend the work by D.A. Alfer'ev (PhD in Economics) and K.A. Gulin (DSc in Economics, PhD in History, Associate Professor). Their study models a product value chain through graphs, enabling effective monitoring and real-time management of it [33].

Another noteworthy study in this context is the article by T.B. Melnikova (PhD in Economics, Associate Professor), which employs graph-based methods to analyze and evaluate scientific collaboration networks [34]. A recent, comprehensive and rigorous work on applying graph theory to practical human activities is the dissertation by V.A. Khitraya (PhD in Physics and Mathematics) [35]. Let us recall that the ants in the previously discussed algorithm navigate precisely across graphs.

Among humanity's most critical challenges are those in healthcare. The infrastructure of this sector can be modeled at various levels through different graph representations, which visualize flows of material, financial, human and other resources. In these systems, the role of virtual ants could be fulfilled by actual agents: patients, medical staff, transport units, etc.

Optimal route planning in healthcare can also be achieved through alternative methods, such as linear programming techniques [36]. This brief study focuses specifically on determining the optimal fleet size of ambulance vehicles required to efficiently serve communities within a given administrative district.

In a series of studies by researchers at PSI RAS, attempts were made to optimize patient-doctor visitation routes [37-39]. These papers thoroughly describe a class of so-called «myopic» algorithms that – analogous to dynamic programming principles – adjust routes based on real-time conditions. This approach offers the distinct advantage of relatively interpretable scenario modeling, unlike many other mathematical methods.

The ACO algorithm's implementation is notably intuitive and accessible even to non-technical specialists. Moreover, ant behavior closely mirrors simplified human social dynamics, making virtual ant-based results readily transferable to real-world economic systems. The approach also integrates seamlessly with Agent-Based Modeling – a cutting-edge method for simulating socio-economic processes (see [40] for details).

The ACO algorithm can model patient-hospital selection patterns, simulating resulting facility congestion or idle capacity. Travel distance to healthcare facilities serves as a key patient decision factor, while an aggregated hospital rating could function as the «pheromone» analog in this system.

In our view, the simplest metric would be location ratings from GIS platforms like Google or Yandex Maps. For more sophisticated implementations, composite scores could aggregate multiple heterogeneous indicators.

A research team from NIIOZMM has published a booklet addressing this specific measurement approach for healthcare facilities [41]. For broader applications across economic sectors, a SPbPU research group proposed a method for evaluating companies' digital profiles [42]. We have also published a detailed study on consolidating diverse statistical metrics into unified indicators – see [43, Pp. 10-11].

3.1 Maternity Hospital Selection

Let us demonstrate with a hypothetical case. The town of Sheksna lacks a maternity hospital, forcing expectant mothers to choose between two nearby cities: Vologda (79.7 km via road) or Cherepovets (34.6 km via road). Route distances were calculated automatically in AnyLogic using OpenStreetMap APIs.

The average ratings for maternity hospitals in these cities (based on Yandex Maps searches at the time of writing) were: «vologda maternity hospital» – 3.7/5 and «cherepovets maternity hospital» – 3.9/5. To properly integrate these into the ant algorithm, they need to be scaled using formula (1):

$$\tau^* = \frac{\tau\overline{\eta}}{\overline{\tau}}, \tag{1}$$

where τ – rating of the facility in question (in points);

$\overline{\tau}$ – average rating (in points) among all facilities of interest;

$\overline{\eta}$ – average inverse of the travel distance to the facilities of interest.

Thus, according to the available data and α and β set at 1, the estimated probability of expectant mothers from Sheksna choosing to give birth in Vologda is approximately 0.29, while for Cherepovets it is 0.71. Given data on road speeds, number of women and birth rates, the described scenario can be effectively implemented in the AnyLogic environment (Fig. 6).

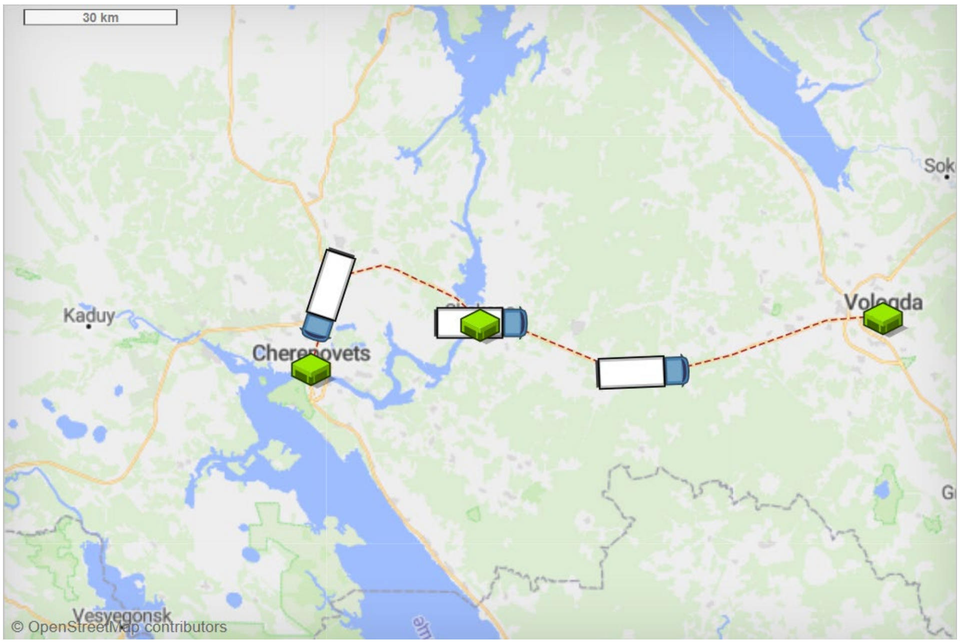

Fig. 6. Distribution of expectant mothers across maternity hospitals

– locations between which agents move (Cherepovets, Sheksna, Vologda);

– agents (women) moving between specified locations;

--- – roadway.

3.2 Dental Clinic Selection

Let us examine another example. Here, we will model the population's choice of standard dental services within these same municipalities – specifically, where people would prefer to receive dental care.

In addition to traveling to another town, patients may seek treatment locally. Therefore, to the existing route distance data, we will add intra-city travel distances, its value calculated as the square root of each location's area (Table 1).

Table 1. Distances to respective municipalities, km

	Vologda	Cherepovets	Sheksna
Vologda	10.8	114.3	79.7
Cherepovets	114.3	11	34.6
Sheksna	79.7	34.6	3.1

The average ratings of facilities for the search queries «vologda dentistry», «cherepovets dentistry» and «sheksna dentistry» in Yandex Maps, recorded at the time of writing this article, were approximately 4.2/5, 4.1/5 and 3.5/5 respectively. With α and β taken at the level of 1, the probable preference of the population of the respective settlements to receive dental treatment in one place or another was distributed as follows (Table 2):

Table 2. Distribution of population preference for receiving standard dental services in the respective settlement

	Vologda	Cherepovets	Sheksna
Population of Vologda	0.83	0.08	0.09
Population of Cherepovets	0.07	0.73	0.2
Population of Sheksna	0.04	0.09	0.87

Assuming that standard dental services are of roughly equal quality across all settlements, their cost may serve as the primary deciding factor. This phenomenon of seeking acceptable medical services (balancing quality and price) has become commonly known as «medical tourism».

According to the dental service aggregator 32top, the cost of caries treatment in Vologda in October 2024 ranged from 3.5 thousand RUB to 7 thousand RUB, while in Cherepovets it was between 3.5 thousand RUB and 4 thousand RUB. The healthcare portal 1vrach.ru reported prices for similar services in Sheksna during the same period at a fixed rate of 2 thousand RUB. If we use this pricing data instead of average facility ratings (taking the inverse values, since higher prices indicate worse accessibility), we obtain the following preference distribution (Table 3):

Table 3. Distribution of population preferences for receiving standard dental services in respective settlements when considering service costs

	Vologda	Cherepovets	Sheksna
Population of Vologda	0.68	0.09	0.23
Population of Cherepovets	0.04	0.61	0.35
Population of Sheksna	0.01	0.05	0.94

As can be observed, this distribution differs from the previous one (Table 2). When accounting for service costs, a significant portion of preferences has shifted toward Sheksna. This finding compels us as researchers, when modeling population behavior, to carefully determine the proper incentives that influence their choices.

Conclusions

In summary:

- Swarm intelligence is now being successfully applied to manage complex technical systems – particularly in robotics, drone networks and optimal energy distribution. As digital technologies advance, its potential for socio-economic applications appears highly promising.
- The Ant Colony Optimization algorithm serves as one of the visual and easily interpretable swarm intelligence methods. The decision-making processes of ant colonies show parallels to human societal behavior.

The ACO algorithm's core development focuses on pheromone updating and distribution mechanisms. Beyond the basic representation, we've previously discussed the Elitist Ant System (EAS) variant. Other common modifications include: pheromone deposition proportional to route rankings (RAS – Rank Ant System), Enforces upper/lower bounds on pheromone levels on the edges of the graph (MMAS – Max-Min Ant System).

Additional specialized enhancements to ACO algorithms can be found in the work by Yu.Yu. Dyulicheva (PhD in Physics and Mathematics, Associate Professor) [44, P. 39]. Significant contributions to this field have also been made by A.A. Kazharov (PhD in Technics) and V.M. Kureichik (DSc in Technics, Professor), particularly in their highly cited paper «Ant Algorithms for Solving Transport Problems» [45]. Additionally, we note that most current modifications to ant algorithms are not fundamentally qualitative in nature (their primary goal being to accelerate convergence without compromising solution quality). In this regard, future researchers should focus greater attention on developing extensions that incorporate novel aspects of insect behavior.

- The ACO algorithm was successfully applied in our modeling of population choices regarding certain medical services (reproductive health and dentistry). A crucial implementation aspect involved defining the incentive mechanism as the «pheromone» analog. The results obtained can be scaled to other regions and, consequently, to other domains of human economic activity.

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РОЕВЫЙ ИНТЕЛЛЕКТ В МОДЕЛИРОВАНИИ СОЦИАЛЬНО-ЭКОНОМИЧЕСКИХ ПРОЦЕССОВ

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Аннотация

Цель проделанной работы – моделирование поведения примитивных организмов и перенос полученных результатов в прикладную деятельность жизни людей. По итого этого был реализован процесс человеческого выбора, основой которого выступил муравьиный алгоритм, имитирующий процедуру прокладывания колонией насекомых оптимального, наименьшего маршрута до источника пищи.

Ключевые слова

роевый интеллект; бионика; биомимикрия; муравьиный алгоритм; моделирование поведения социума; выбор

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