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GEOCITY—A NEW DYNAMIC-SPATIAL MODEL OF URBAN ECOSYSTEM

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Abstract: In this paper the initialization of the city is considered, which consists of several steps, including the creation of city objects with their locations, creation of residents with their attributes and own daily schedules, etc. A description of the model is provided as a tuple of attributes. The adequacy of the simulation model is checked based on the statistical data from the city of Lviv, Ukraine. Generated locations of city ecosystem objects are presented. The daily schedule of residents is simulated. A possible work schedule for each specialty is given, and separate schedules are created for working days and holidays. A unique schedule is predicted for the resident, which depends on their age and work specialty. The dynamics of visits to facilities by residents on weekdays and at weekends are analyzed. Based on the conducted experiments, the adequacy of the model and its realistic reflection of the functioning of the city's ecosystem during the day are proven. It means that by using this model, researchers can assess the impact of different behavioral scenarios on the residents within the city ecosystem more reliably. This enables a better understanding of how certain actions or changes in behavior can affect the spread and control of diseases in a specific geographic area. This model has the potential to serve as a foundation for future modeling of systems at the medium and macro scales.

Keywords: simulation model; resident; geo-object; GeoCity; urban ecosystem

1. Introduction

Models dynamic in time are extremely powerful and convenient for calculating processes in the city ecosystem. Such models demonstrate the principle that local interaction contributes to the creation of a global pattern. And for this, methods of parallel data processing are appropriate (Batty & Jiang, 1999; Campbell et al., 2005; Smeureanu et al., 2012). Therefore, it is clear that the models should be able to simulate from micro to macro levels, based on discrete moving residents, imitating people's behavior in the GeoCity (Anderson, 2001; Cotfas et al., 2010; Pinto et al., 2016).

In particular, two approaches to modeling spatial processes are known. The first approach is based on statistical data about the modeled object. Accordingly, the data are

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obtained using various statistical methods and artificial intelligence techniques, resulting in the prediction of time dependencies. Models cannot forecast processes that have not yet occurred; therefore the results of this approach cannot be displayed on a global map.

Another approach to modeling spatial processes is modeling simple objects and studying their behavior and properties. This approach can be divided into micro and macro levels. Accordingly, the interaction of one object with another or with a group of people is modeled at the micro level, while collaboration within the city or country is at the macro level (Lemos et al., 2015; Rodriguez-Mier et al., 2016; Yu et al., 2009). City models can be autonomous because they contain information about the interaction of all objects in a large area over a certain time. Such models can be parallelized. After all, having information about several cities, it is possible to parallelize processes in a day. According to the meaning of the term, data from different cities are aggregated. Consequently, the statistical dependence of the behavior of objects becomes known, or the common features of model objects are determined (Bellifemine et al., 2007; Cavedon et al., 2004; Smeureanu et al., 2012).

Comparing these two approaches, it can be highlighted that models based on statistical data are well-studied and often used for modeling a group of objects. However, models that describe the city as an object of modeling are rarely used. Such models are not extensively studied, but they are used in research (Chen et al., 2004; Dioşteanu et al., 2009; Fox et al., 2000).

Ultimately, this paper is dedicated to developing an adequate and accurate model-simulator of everyday life, behavior, and interaction of people at the city level. Using models that study the behavior of one object or a group makes it quite challenging to project the behavior of each object at the city level. Forecasting for this amount of data is a time-consuming and costly process. The research focuses on the city model. From the city model, we can quickly reach the indicators for a country or the world. There are very few such models, and they are divided into three types (Batty & Jiang, 1999; Klügl et al., 2006; Smeureanu et al., 2012): (1) Cellular automata models—where objects are superimposed with a grid on a geographical map of the area whose data were projected, (2) model based on molecular dynamics—where residents can move around city areas, and (3) multi-agent systems (MAS).

The first type of models allows simulating the spatial distribution of processes. The complexity of these models is an adequate comparison of a static cell map with real moving objects such as people. Such models have proven themselves well in the work of Valjarević et al. (2018). This research focused on examining how health facilities are distributed across Belgrade, the capital of Serbia, and their relationship with the city's public transport system. Taking into account the movement of citizens and patients around the city, Teixeira et al. (2018), calculated the accessibility of medical centers based on the characteristics of public transport. The second type of models is suitable for modeling human behavior in micro-level systems such as buildings or transport (McIlraith et al., 2001; Xiao et al., 2022). The third type of model is considered in this study. MAS is a computational framework with multiple autonomous residents that interact, make decisions, and act based on their goals and surroundings. MAS is used to model and simulate complex systems and study emergency behaviors. As a basis for this model, we have chosen a real city that has its own shape, location, and internal structure. This city consists of houses and workplaces (schools, offices, shops, factories, etc.). Residents live as families in houses. This model will use the simplest workday schedule to consider only the main factors of interaction between residents.

Accordingly, knowing the residents' place of residence and their place of stay during the day makes it possible to model the resident's spatial schedule. The use of such models allows us to visualize the location of residents on the map during the day and throughout the simulation period. This approach makes it possible to simulate the life and interaction of people over a long period of time as realistically as possible. And this is the basis of the most realistic simulation of space-time processes.

To model the behavior of objects in the ecosystem, it is necessary to build an adequate Multi-agent geospatial model—GeoCity. It is the paper of discrete mobile residents that makes it possible to model human behavior in a certain ecosystem (Chen et al., 2003; Kravari et al., 2010; Taillandier et al., 2010). It is relevant today to create a mathematical model and develop a simulation program based on it for the geospatial functioning of a city and the interaction of its inhabitants throughout the day (Bodea et al., 2007; Braubach et al., 2006; Klügl et al., 2006). Generally, the following requirements can be outlined for this mathematical model-simulator:

- It should be adequate and relatively simple to implement;
- Able to account for various factors such as categories of people, age characteristics, and different types of objects where people live, work, or spend their leisure time;
- Consider personal parameters of individuals in relation to the processes being modeled, such as immunity;
- Simulate people's lives and contacts as realistically as possible by: (1) taking into account personal parameters of individuals, (2) considering the peculiarities of daily schedules and locations of residents, (3) simulating contacts between people based on schedules and circles of communication (family);
- Display results on a geographic map;
- Be fast in computation to enable a large number of computer experiments for training a neural network with reinforcement, optimizing the simulated processes; and
- Capable of parallelization, allowing the use of computer clusters for calculation and simulation at the macro level of states and the world.

2. Data and methods

This paper proposes the GeoCity multi-agent geospatial model, based on discrete moving residents simulating human behavior. These residents allow for the simulation of their location changes and interactions with other residents as realistically as possible. One advantage of this model is its ability to account for a large number of residents, closely representing the actual population of a city. This, in turn, enables the modeling of stochastic processes involving a small number of "special residents", such as those infected with tuberculosis, with 44 cases per 100,000 residents. This is a necessary condition for further modeling of various stochastic processes characterized by small numbers, particularly bacterial pandemics, information spread, advertising, and other processes in real time. Another advantage of this model is its capability to display information on a geographic map and analyze it. Furthermore, the model meets all the requirements specified for it at the beginning of the article.

2.1. Conceptual description of the model

This model is based on a real city, which has its own geographical shape, location and internal structure. This city consists of workplace buildings (kindergartens, schools, universities, offices, shops, etc.) and public facilities (shops, supermarkets, etc.). Kindergartens are considered a workplace for both children and educators. The model also takes into account that for residents, the same object can be both a public place and a workplace. For instance, a supermarket: for sellers, it is a workplace, while for visitors, it is public. That is, a supermarket salesperson can sell goods and act as a visitor to the same store in their daily schedule (Greenwood et al., 2004; Klusch et al., 2006; Lord et al., 2005; Yu, 2009).

Each city is populated by multiple residents. Each resident has their own unique attributes, such as age, gender, and unique properties that are used in modeling various processes, like immunity parameters. Residents form families, taking into account the age characteristics of a person, and settle in houses (apartments). A unique daily schedule is separately formed for each resident with a breakdown of 1 hour. In the daily schedule, the identifier of the object where the resident is located during the hour is indicated. Using this identifier, it is possible to identify a set of residents that interact with each other at a certain point in time and simulate the necessary processes of propagation (for example, a virus or bacteria).

The resident spends the night at home with their family. From eight to nine in the morning, the resident travels to work by their own car, bus, or on foot. At lunch, the resident visits a store or restaurant. Afterward, they return to their workplace. The resident goes back home using the same mode of transport that they used to get to work. Additionally, it is considered that the resident may visit the supermarket closest to their place of residence. Depending on the age and workplace of the resident, their schedules can vary significantly. For instance, children's daily schedules are not as saturated as those of adults. Typically, children travel to kindergarten or school on foot or by car with their parents, as schools and kindergartens are often chosen based on the proximity to the residence. However, individual schedules can be created for children attending schools located far from their homes. Children spend their daytime hours at school or kindergarten and spend evenings at home with their parents. As mentioned, this schedule can be adjusted based on the child's characteristics and preferences. It is also necessary to create separate schedules for weekdays and weekends or holidays, as this significantly affects the circle of people and, consequently, the distribution process of the simulated systems. On a day off, an adult person can travel by public transport, on foot, or in their own car to various supermarkets and shops. Generally, one of the supermarkets visited should be the one closest to the person's place of residence. As mentioned earlier, each resident has their own unique schedule, which can be generated depending on the city, state, age structure, and other factors.

In general, the application of this model for simulating the spread of a pandemic can be described as follows. Residents visit various objects that comprise the city according to their schedule. In each of these facilities, residents interact with one another and spread the infection for one hour. The infection can also be spread through public transport. To simulate the spread of an infection from an infected person to a healthy person, separate models are employed, which are beyond the scope of this article. According to the proposed model, it is sufficient to apply the infection spread model only to objects where infected residents are present. In cases with few infected individuals, the number of such objects is also small. This significantly speeds up the calculation time, allowing the construction of models with a large number of residents without a substantial increase in computation time. Generating the city and schedule takes the longest time (Martin et al., 2004; Shen et al., 2007). Once the schedule is formed, city simulation does not take much time, provided that the schedule remains unchanged.

2.2. Formalization of the model

The GeoCity model comprises a set of geo-objects (*G*), transport (*T*), a list of residents (*A*) residing in the city, daily schedule rules (*R*) for residents, and a set of data describing interaction processes, such as the health status of a resident (*H*) and the rules for the spread of infection upon a contact with infected and healthy residents (*V*). This model can be described as a tuple with the following attributes (Equation 1):

$$GeoCity = \{G, T, A, R, H, V\}_{city} \tag{1}$$

2.2.1. Geo-objects

As described above, the proposed GeoCity model consists of sets of geo-objects (Equation 2) such as city street maps (C_t), houses (H_m), workplaces (W_p), and public places (P_p):

$$G = \{C_t, H_m, W_p, P_p\} \tag{2}$$

Each attribute of this model is a separate complex object, having its own structure and consisting of distinct attributes, as detailed in Equations 3–6:

$$C_t = \{pol_p\}_{p=\underline{1,M}} \tag{3}$$

where pol_p is the polygon of the city district, and M is the number of all districts that make up the city map. Therefore, the location of residential buildings is formed hm_h randomly within the city $(l_{h=\underline{1,N_h}} \subset C_t)$. This number can be obtained from official sources or calculated from the average number of residents ($\widetilde{P_h}$), which is also taken from official statistics (State Statistics Service of Ukraine [SSSU], 2022).

$$H_m = \{hm_h\}_{h=\underline{1,N_h}} = \{l_h, r_h\}_{h=\underline{1,N_h}} \tag{4}$$

where l_h stands for coordinates (longitude and latitude) of the location of the house h, r_h is the number of residents of the house, and N_h is the number of houses.

$$W_p = \{wp_w\}_{w=\underline{1,N_w}} = \{l_w, r_w\}_{w=\underline{1,N_w}} \tag{5}$$

where l_w, r_w are the location and number of employees (w) at the workplace, N_w is the number of workplaces.

$$P_p = \{pp_p\}_{p=\underline{1,N_p}} = \{l_p, r_p, c_p\}_{p=\underline{1,N_p}} \tag{6}$$

where l_w, r_w are the location and maximum permissible number of visitors to a public place (p), c_p is a type of public place (supermarket, shop, park, etc.), N_p is the number of public places.

2.2.2. Transportation

Also, the GeoCity model consists of the attribute transport (T_p) represented by the Equation 7:

$$T_p = \{r_t\}_{t=1,N_t} \tag{7}$$

where r_t is the maximum number of passengers in public transport t, N_t the number of public transports.

As can be seen from Equation 1–6, houses, workplaces, and public places consist of the geographical coordinates of the location of these objects and the number of people who live, work, or spend time there. In this model, it is assumed that residents do not change homes and jobs during the simulation. The situation with transport and public places is different. During the simulation, any resident can change public transport and visit any public place. In addition, transport and public spaces have different sizes and can fill up differently during the day. Therefore, the maximum allowable number of residents that can be located in this object during an hour at the same time is indicated. This number can be obtained either from technical specification of transport or from Open Street Map (OSM) data (Gunasekera et al., 2010; Kopecký et al., 2008; Pedrinaci et al., 2014). When simulating the transmission of infection, it is absolutely unimportant which route the transport takes; the main thing is how many and which residents are in it at the same time during a certain period of time, so the location of the transport is not necessary in this approximation. The location of public places is also not important, because the resident can choose an arbitrary place. However, according to the approach, residents usually visit the supermarket closest to their place of residence to buy products. Therefore, to determine the nearest supermarket, it is necessary to store the location of these objects.

2.2.3. Residents

As mentioned above, the city is filled with residents (Equation 8):

$$A = \{a_i\}_{i=1,P} = \left\{\left\langle x_{1i},\dots,x_{mi}\right\rangle\right\}_{i=1,P} \tag{8}$$

where a_i is personal data of the resident, such as: age, gender, etc., P is population of the city. Each resident has $x_{1i},\dots,x_{mi}$ rules of behavior and health signs of virus spread.

2.2.4. Daily schedule

Under the rules in this model, the residents' behavior during the working day is determined. To form such a behavior (schedule) one needs to know the list of objects that each resident will visit during the day and the transport they use. Thus, the rules represent a set of tuples for each resident a_i. The tuple is an hourly list of objects in which the resident will be located during the day. Each resident will have a workday schedule (*Sw*) and a weekend schedule (*Sh*) represented by the Equation 9:

$$Sw(Sh) = \{r(a_i)\}_{i=\underline{1,P}} = \{\langle(o,id)_{06:00},\dots,(o,id)_{21:00},(hm_h)_{22:00}\rangle_i\}_{i=\underline{1,P}} \tag{9}$$

where (*o*, *id*) is object type and its identifier. For example, a house and house number, or transport, transport identifier. It is believed that from 10 p.m. to 6 a.m., the resident is at home with their family.

In this way, it is indicated hourly where and in which facility the resident will be located. This makes it possible to select a set of objects where infected residents are located, and therefore to simulate the infection process in these objects. With small numbers of infected people, this significantly speeds up the process of simulating the spread of infection.

2.2.5. Health status (H) and interaction rules (V) of residents

Health status and interaction rules of residents depend on the type of infection (or other situations) being simulated, which is beyond the scope of this study.

2.3. City generation

The process of setting up the virtual model of the city involves multiple steps, which encompass creating objects within the city, determining their locations, and assigning a population to each of them:

- Urbanization of the territory—both public open resources and OSM databases can be used to determine the spatial structure of a city (C_t);
- Initialization of residential buildings (H_m)—official sources can be used to determine the location of buildings. Quite often, this information is not available. In the model, the trajectory of people's movement is not taken into account. Only objects in which people stay for a long time are important (Canito et al., 2019; Ferreira Filho & Ferreira, 2009; Klusch et al., 2016);
- Initialize people—first of all, the list of people is initialized with the number *P*. According to the statistics of the World Health Organization (WHO, 2022), all people are divided into age groups (age_g_i): child (0–4), pupil (4–14), student (15–24), adult (25–64), elderly (≥65). Each person's age (age_i) within the group is randomly generated within the age range. A person's gender is also randomly determined. This data is necessary for further planning of the daily schedule and is stored in the resident's attributes (Huhns, 2002; Pinto, 2015; SSSU, 2022);
- Settlement of people—People are randomly assigned to houses according to the maximum number of residents (r_h). The main condition for the settlement of people is that children under the age of 14 cannot live in the house alone without adults;
- Defining occupations—Depending on a person's age, every inhabitant can occupy various professions (p_{pi}), in particular: children aged to 4 can either be at home or go to kindergarten. One of the adult females living with a minor child is assigned the profession of "mother". Children aged 4 to 14 are considered 100% as schoolchildren. People aged 15 to 24 can be either university students or workers. Individuals over the age of 65 are considered pensioners. All other people aged 25 to 64, as well as young people of student age who are not students, can work in professions such as office worker, shop assistant, salesperson, or public transport driver. Residents without a profession are labeled as unemployed. Vacancy statistics for the number of employees by profession are determined from the known statistical data (SSSU, 2022). Occupation is stored as a resident attribute in Equation 8;
- Determination of the location of workplaces—at this stage, the locations of offices, shops, universities, schools, and kindergartens are randomly determined within the city limits ($w \subset C_t$). Depending on a person's profession, it is randomly determined at which of the locations ($wp_w \subset w_p$) they will work. It is considered that schoolchildren and children attending kindergarten go to the facility located closest to their place of residence. All other places of work do not depend on a person's place of residence;
- Determination of the nearest supermarket—in the simulation, it is assumed that people returning from work, with a certain probability, can visit the supermarket closest to their place of residence ($sup_p \subset P_p$). Therefore, to speed up calculations for each individual, the nearest supermarket is indicated as an attribute of each resident; and

- Determination of the transport by which a person moves (r_t)—At this stage, the means of transport a person uses to commute to work is determined. Furthermore, it is assumed that small children and schoolchildren travel to school or kindergarten by their own transport or on foot. The availability of a personal car is randomly determined based on the statistics of car ownership (SSSU, 2022).

2.4. Generation of a daily schedule

At this stage, the objects in which a person is located during each hour, and their identifiers are determined (SSSU, 2022). The algorithm for creating an hourly schedule is as follows:

- Determination of working hours—at this stage, the hourly presence at work for each individual is determined based on their specialty;
- Definition of transport—after determining the hours when the resident must be at the workplace, the means of transport used to reach the workplace are identified;
- Determination of the nearest supermarket—it is assumed that after work the resident with probability p_{sup} can visit the nearest supermarket with an identifier sup_p;
- Visiting other shops and facilities—when creating the schedule, it is assumed that a person who was at their workplace during the day does not visit any other stores or supermarkets, except for the nearest one. A person who has not worked during the day may visit two to three supermarkets and two to three stores randomly throughout the day. Furthermore, one of the supermarkets must be the one closest to their place of residence sup_p;
- Staying with family—as stated in Equation 9, at the end of the working day, each person is in their own house with their family. For this, the daily schedule of the resident is supplemented with the attribute $(hm_{hi})_{22:00}$.

So, the result is a multitude of people A (Equation 8). Every individual a_i is described by a tuple of the following attributes (Equation 10):

$$A = \langle age\_g_i, age_i, hm_{hi}, p_{ji}, wp_{wi}, sup_{pi}, r_{ti}, Sw_{ji}, Sh_{ji} \rangle_{i=\underline{1,P}} \quad (10)$$

In the case of applying this model to the spread of infection and other processes, appropriate parameters describing these processes are added to the attributes of an individual (Kravari et al., 2012; Santos et al., 2016).

2.5. Simulation of the day and interaction of residents

At this stage, according to the schedule (taking into account workdays and weekend days), it is determined hourly in which object a resident is located. In the case of simulating the spread of infection, objects are determined hourly $v \subset (H_m \cup W_p \cup P_p \cup T_p)$ in which there is an infected person. For each of these objects, a set of infected people who are present there is determined (N_{inf}^{in}). For every healthy individual located near an infected person, the probability of infection is determined according to the corresponding infection spread model. This approach allows for a significant increase in computational capacity, as only those objects containing infected individuals will be considered (Carneiro et al., 2019; Santos et al., 2016; Teixeira et al., 2017). The simulation continues until no infected individuals remain, or the simulation is forcibly stopped.

3. Results and discussion

3.1. Model hyperparameters

Verification of the adequacy of modeling was carried out on the simulation of the city of Lviv, Ukraine (49°50′33″N, 24°01′56″E). The real population of the city of Lviv is about 700,000 inhabitants (SSSU, 2022). The city center has a spherical shape. The outskirts of the city have branches and a complex geometric structure (Figure 1).

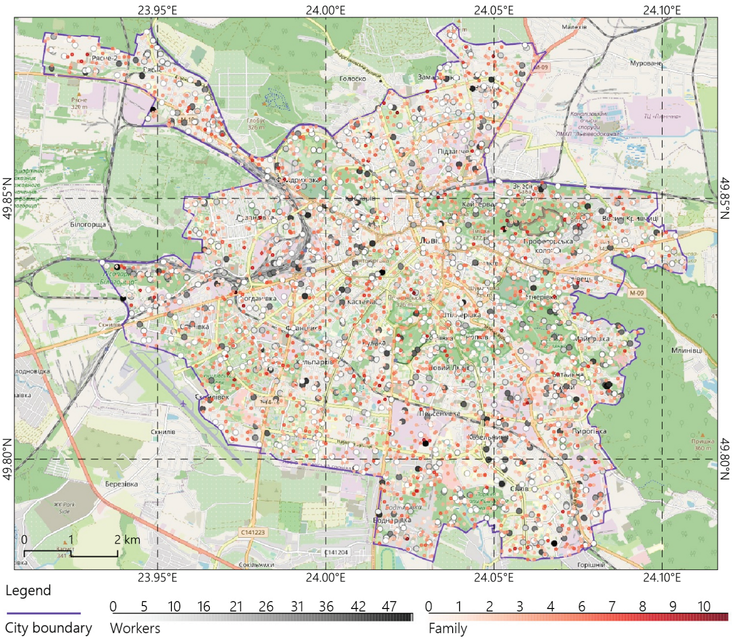

Figure 1. Spatial structure of the generated city of Lviv.

To construct the city model, we opted for a multi-agent system comprising 100,000 agents, which is approximately one seventh of the actual city's population. Consequently, all other statistical attributes of the city, obtained from official statistics (SSSU, 2022), were adjusted by dividing them by a factor of 7.0: number of houses (apartments)—30,000, grocery stores and supermarkets—1,000, kindergartens—30, schools—70, universities—2, large hospitals—2, shops—500, public transport—100, and enterprises—50. According to statistical data (SSSU, 2022), only 20% of Ukrainians have their own transport. This means that 80% of the population either walks or uses public transport. In the simulation, it was assumed that 50% travel by public transport and 30% on foot. According to statistical data (SSSU, 2022), 60% of children attend kindergarten. The number of students is 80% of the student age category and 6% of people are unemployed. It is assumed that one of the family members visits a supermarket near their place of residence after work. People who do not work (mothers, unemployed) and are at home visit an average of two to three supermarkets and one clothing store during the day.

Figure 1 displays the generated locations of the aforementioned objects. As can be observed from the figure, they are evenly distributed across the city's territory and do not extend beyond its borders. Additionally, it is evident that all branches of the city on the outskirts are uniformly filled with objects. To analyze the adequacy of modeling, a study of statistical indicators of modeled objects was conducted.

3.2. Statistics of the generated city

3.2.1. Residential buildings

To check the adequacy of the composition of families and their number, a statistical analysis of the formed houses and the age composition of the families living in them was carried out. Figure 2A illustrates the relationship between the number of houses and the number of residents living in them. As observed in Figure 2A, the largest number of houses is occupied by families with three members. This is followed by families consisting of two and four members. It can also be seen that there is a small number of large families, specifically: five families have 12 residents, two families have 13 residents, and there is one family consisting of 14 residents. The statistical distribution of the number of families with at least one child is presented in Figure 2A. As shown in the figure, the most numerous families consist of three and four members. The number of families comprising a mother and one child is also quite large. Figure 2A further displays the distribution of the number of families with minor children. As seen, the largest number of families consists of those with one child, followed by families with two, three, or more children. Additionally, there are three families with nine minor children and seven families with eight minor children.

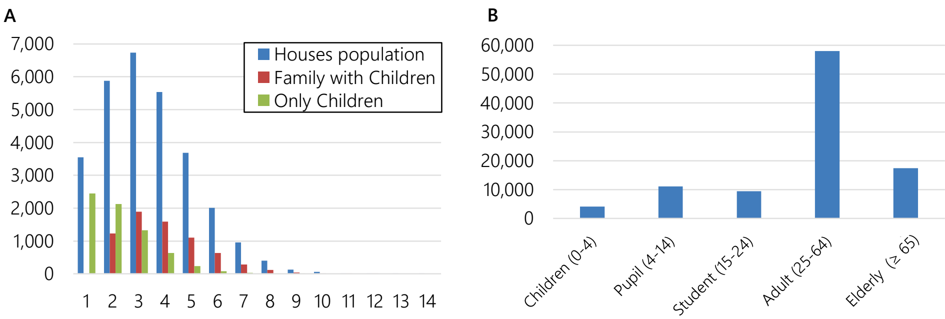

Figure 2. The number of families based on the number of residents and the number of children (A) and age distribution of the city's residents (B).

3.2.2. Age groups

Figure 2B presents the resulting distribution of the number of people depending on the age group. As can be seen from Figure 2B, this distribution aligns well with the data provided by WHO (2022).

3.2.3. Distribution of office workers

In the proposed model, the number of workers is randomly selected from a normal distribution. Figure 3A shows the distribution of the number of enterprises by the number of employees. The study showed that most enterprises have up to 5 employees. It is also evident that the number of enterprises employing a large number of people is quite small. The largest enterprises accommodate up to fifty people.

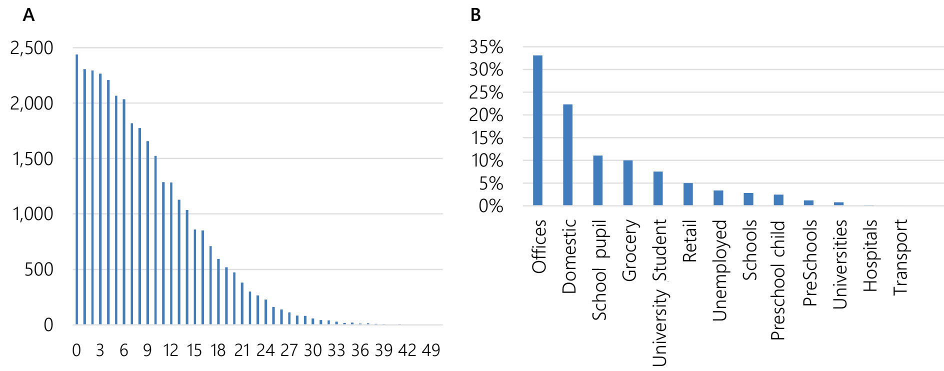

Figure 3. Distribution of the number of enterprises based on the number of employees (A) and relative distribution of population by employment (B).

3.2.4. Distribution by professions

Figure 3B displays the distribution of people by profession. As can be seen from the figure, the largest population consists of individuals who work in offices. Offices should be understood as any profession that is located in the premises or at the enterprise. The second largest group comprises the unemployed (domestic). It should also be noted that children, students, teachers, and educators are divided into separate groups, despite being in the same room. The groups of people who work in supermarkets and transport are also listed separately. It is worth noting that individuals who work in supermarkets may visit other supermarkets, as well as those in which they work, as customers. Similarly, transport drivers can use other means of transport to reach the transport depot.

Table 1. Relative distribution (%) of population employment by age groups

Age	Domestic	Grocery	Hospitals	Offices	Preschools	Preschool child	Retail	School pupil	Schools	Transport	Unemployed	Universities	University student
Adult (25–64)	3.3	9.6	0.2	32.1	1.2		4.8		2.7	0.1	3.3	0.8	
Elderly (≥65)	17.4												
Children (0–4)	1.7					2.4							
Pupil (4–14)								11.1					
Student (15–24)		0.4		1.1			0.2		0.1		0.1		7.5

Note. Results of simulations.

More detailed information on the distribution of professions depending on age groups is provided in Table 1. In particular, the table shows that people in the age group from 25 to 64 years occupy almost all professions. The most popular profession for them is an office worker. The next most popular is a supermarket and store worker. A similar situation exists among people aged 15–24. The most popular profession among them is a student. However, people who are not students work in shops, offices, schools, and are partially unemployed. Schoolchildren are fully engaged in learning at school. Furthermore, all older people are unemployed. It should also be noted that not all children attend kindergarten, as evident from the table.

Figure 4A displays the distribution of people who do not work and are considered unemployed. According to the obtained data, 68% of such individuals are pensioners. The next two categories, roughly equal in size (13% each), are adults. Category 1 comprises the unemployed, that is, those who cannot find a job. Another category includes mothers who take care of their children. Seven percent are children who do not attend kindergarten and stay at home with their mothers. Less than 1% are unemployed students.

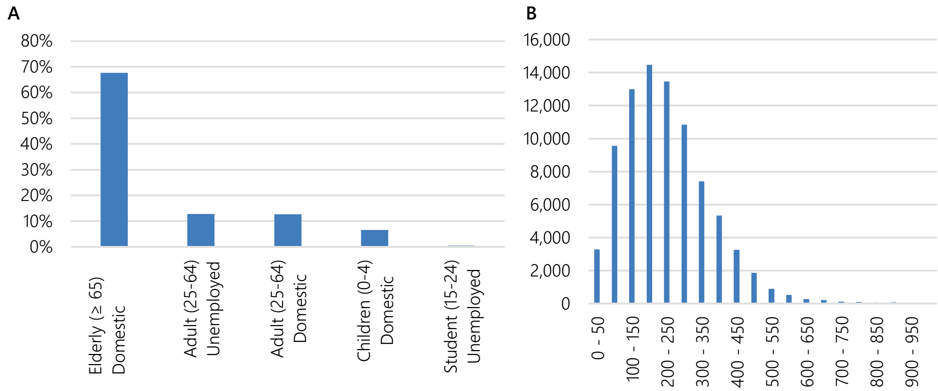

Figure 4. Relative distribution of the unemployed population (A) and the average distance (in meters) that people cover to the nearest supermarket (B).

3.2.5. Distance to the nearest supermarket

Figure 4B illustrates the average distance people travel to the nearest supermarket. As can be seen from the graph, the most common distance is 150–250 m. Only about a hundred people cover more than 900 m to the nearest grocery store. Therefore, such a distance can be covered on foot without using public transport. This finding is in good agreement with the conditions of the model.

3.2.6. Distance to workplaces

Similar calculations of the distance to workplaces from the place of residence are shown in Figure 5. As indicated in the model, children usually attend the school or kindergarten closest to their place of residence. As shown in the figures, schoolchildren cover a shorter distance than children attending kindergartens, averaging 900 m and 1.5 km, respectively. This can be explained by a larger number of schools, and therefore a greater choice of the nearest school. It can also be observed that a significant number of people travel a long distance to a kindergarten or school. This tail is due to adults who work in kindergartens or schools.

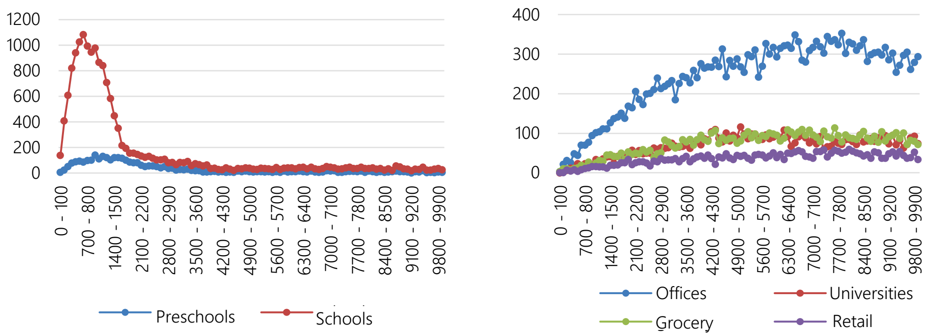

Figure 5. The average distance (in meters) that people cover to their workplace.

An interesting situation is observed among people who work in universities, offices, shops, etc. As stated in the model, the choice of workplace does not depend on the distance. The graphs clearly show that on average, people travel to work at distances ranging from 3 to 10 km. The number of people who work near their place of residence is insignificant. This could be due to the fact that there is a limit on the number of job vacancies. A similar situation is observed for drivers and hospital workers. However, their number is small, and the statistics are not as clearly observed as in other types of professions.

3.3. Simulation of the resident's daily schedule

First of all, a possible work schedule for each specialty is generated. Moreover, separate schedules are made for weekdays ($Sw_j = \langle w_j^h \rangle_{h=\underline{7,21}}$) and weekends ($Sh_j = \langle w_j^h \rangle_{h=\underline{7,21}}$). It is considered that the working day lasts from 7:00 in the morning to 21:00 in the evening. After 22:00 and before 07:00 a.m., a person is at home. Only supermarkets, shops, and transport operate at weekends. It is also assumed that each person commutes to and from work by public transport or their own car, as determined in the previous step. After work, with a certain probability, a person visits the supermarket closest to their place of residence. At weekends, people visit more supermarkets and shops. The same applies to the schedule for mothers and unemployed people. Children and school children do not visit shops and supermarkets. Each resident has their own unique schedule that depends on their age and work specialty.

Figure 6 presents the dependency of the number of people on the facilities where they are during the day in the case of the working week and weekends. As seen from the dynamics of working days, most people work in offices. Only at lunchtime does the number of employees in offices decrease significantly due to people's going to lunch. Traffic congestion is the greatest in the morning and evening when people commute to and from work. The load on supermarkets increases in the evening when people return from work. Regular stores are visited by a small number of people who do not have a job.

A completely different situation is observed at weekends. As can be seen, the number of people working is insignificant. These are mainly people who work in the service sector. Transport is also most actively used in the morning and evening, particularly by people returning from and going to work. However, the number of people who use transport is significantly smaller. The popularity of supermarkets and shops is consistently the same throughout the weekend.

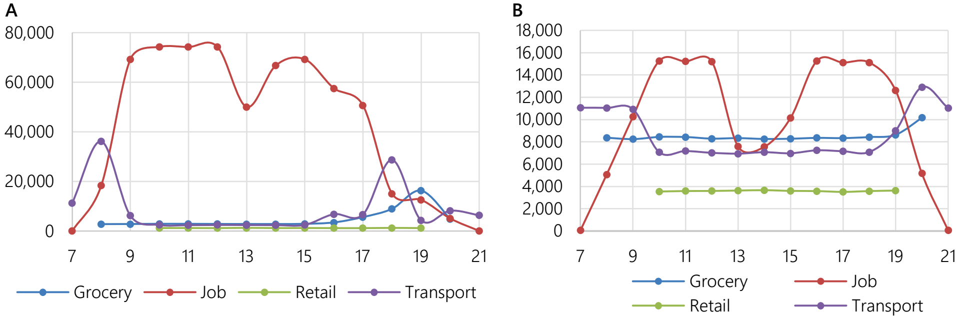

Figure 6. Dependencies of the number of people on the type of facility where they are during the working week (A) and weekends (B).

Taking into account all the information presented in Figure 6, it can be concluded that the model sufficiently and accurately reflects the functioning of the city's ecosystem during the day, both on working days and at weekends.

4. Conclusions

As already mentioned above, modeling the spatial spread of viral infections at the city level is important for several reasons:

- Predicting spread—models help understand how a viral infection can spread within a city. This can help identify potential hotspots or risk zones where the infection may spread more rapidly or intensively. It allows for better resource planning, including hospitals, healthcare personnel, and public health measures;
- Assessing control measures—modeling can help evaluate the effectiveness of different control strategies and interventions to limit the spread of the virus. It allows for assessing the potential impact of vaccination, quarantine, social distancing, and other interventions on the infection spread;
- Epidemic response planning—models can assist in developing strategies for epidemic response at the local level. They can be used to calculate the optimal allocation of resources such as vaccines, medications, medical equipment, and personnel to ensure an effective and timely response to the infection spread; and
- Understanding the impact of human behavior—modeling allows for considering the behavior and mobility of the population in the context of viral infection spread. This includes factors such as travel, social connections, and contact between individuals. Understanding these aspects helps identify key factors influencing the infection spread and can be used to develop effective control strategies.

All of these factors highlight the importance of modeling the spatial spread of viral infections at the city level to better understand the infection process and develop effective strategies for control and management. The result of the study was the development of a multi-agent model, which was implemented in the city ecosystem. The structure for modeling, simulation, and verification of the simulation model of city residents' collaboration is presented in detail.

The article analyzed the adequacy and accuracy of modeling the functioning of the city and its components. The obtained results showed a high adequacy of the simulated model to the real city. Therefore, the outcome of the study is to demonstrate a multi-agent modelling process to support operational decision-making for urban ecosystem management for preventing different crisis of spread processes like epidemic. The relevance is clearly confirmed by the increased interest in this topic in articles, as well as in the conduct of research and the conclusions drawn. The results indicate that the validated multi-agent model is applied to assess the impact of different behavioral scenarios on the residents of the city ecosystem. The proposed model can be the basis for further modeling of systems at the medium and macro level.

Despite all the advantages of the model, one of the main limitations is the computational time required for simulation. When modeling large systems and utilizing neural networks with reinforcement learning for optimal spatial prevention strategies, it becomes necessary to involve large computer clusters. In future plans, we intend to use this model to validate the spatial spread simulation of various viral and bacterial infections. Confirming the adequacy of these models will allow us to move toward modeling macro-level systems such as countries and the world as a whole, using reinforcement learning neural networks.

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