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Agent-based modelling of interactions between air pollutants and greenery using a case study of Yerevan, Armenia

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ABSTRACT

Urban greenery such as trees can effectively reduce air pollution in a natural and eco-friendly way. However, how to spatially locate and arrange greenery in an optimal way remains as a challenging task. We developed an agent-based model of air pollution dynamics to support the optimal allocation and configuration of tree clusters in a city. The Pareto optimal solutions for greenery in the city were computed using the suggested heuristic optimisation algorithm, considering the complex absorptive-diffusive interactions between agent-trees (tree clusters) and air pollutants produced by agent-enterprises (factories) and agent-vehicles (car clusters) located in the city. We applied and tested the model with empirical data in Yerevan, Armenia, and successfully found the optimal strategy under the budget constraint: planting various types of trees around kindergartens and emission sources.

1. Introduction

As is known, many countries and cities currently face the problem of increasing air pollution caused by industrial activities and the increasing number of vehicles. Previous research (e.g., Brunekreef and Holgate, 2002) has proven the strictly negative influence of air pollutants (organic and inorganic dust, carbon monoxide (CO), sulphur dioxide (SO2), nitrogen oxides (NOx), volatile organic compounds (VOCs), heavy metals, etc.) on human health. Air pollution mainly affects respiratory diseases such as asthma, allergy, chronical obstructive pulmonary diseases, lung cancer, cardiovascular diseases and skin diseases. In addition, infants and children are especially vulnerable to the influence of air pollution.

There are known approaches to reducing air pollution using natural-based solutions (NSB); in particular, urban greenery (e.g., Nesshöver et al., 2017). Among research concerning this topic can be highlighted a work (Fuiii et al., 2005) which investigated air pollutant removal by plant absorption and adsorption in Japan. This research yielded the important conclusion that the efficiency of plant absorption depends on the photosynthesis actively performed in the spring and summer. Thus, the contribution of NBS to air pollution removal can be significantly improved in countries having better climate characteristics—e.g., a higher number of sunny days during the year, as in the Republic of Armenia (having approximately 300 sunny days per year in the city of Yerevan).

Thus, the internal chemical processes of absorption and adsorption of different kinds of air pollutants by different kinds of plants have been very well investigated on the micro level (e.g., Fuiii et al., 2005; Omasa et al., 2002; Bell and Treshow, 2002). The results raise the flowing questions: what is the positive impact of urban greenery in reducing air pollution; how should the best kinds of trees be chosen and allocated in a city to protect the human population; and which greenery strategies are better, taking into account limited urban budgets?

Solving such problems are impossible without modelling air pollution dynamics and forecasting the movement of air pollutants in the urban atmosphere. There are three main groups of models that can be used to model air pollution dynamics.

The first is based on a statistical approach (e.g., Bolzern et al., 1982; Harnandez et al., 1992) and intended mostly for analysis of historical data on pollutant concentrations and short-term forecasting. The second group consists of deterministic and deterministic-statistical models (e.g., Lamb and Seinfeld, 1973; Genikhovich, 2004). Pure statistical approaches to the investigation of air pollution dynamics are mainly simplified, and their applications are limited. The main reason for the limitation is that they ignore many factors with important influences on the dynamics of air pollution concentration, such as plants located on paths of pollutant masses. Such plants are natural barriers implementing absorption effects. Some environmental factors, e.g., changing wind directions and collusions between trees and landscape

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objects, cannot be taken into account using statistical methods.

The last group of methods is based on modelling the dynamics of emission plumes using Gaussian dispersion models (e.g., Turner, 1994; Beychok, 2005) and are intended for the investigation of air diffusion processes, taking into account different climate factors. Such models are the most realistic, but they are characterised by significant computation complexity.

However, such models are not always capable of representing the roles of different sources and sinks of air pollution, such as cars, factories and trees, along with the multiple interactions between them. Specifically, agent-based models can provide a better understanding of the role of trees as sinks of air pollution than provided by diffusion reaction models and, thus, support the implementation of informed public policies to reduce pollution effects.

There are other well-known and simpler models of air pollution dynamics such as Lagrangian models, Eulerian models, chemically reactive compound models and analytical models (e.g., Seinfeld, 1975; Zak, 1983; Seinfeld, 1986; Barbulescu and Barbes, 2017; Ridley, 2017; Corani and Scanagatta, 2016). Such models focus on forecasting trajectories of moving air pollutants without taking into account the impact of interaction with other landscape objects (e.g., trees, buildings). Nevertheless, some studies have been devoted to researching air pollution dynamics taking into account some elements of the urban landscape (e.g., Turner, 1964; Finzi and Tebaldi, 1982; Santiago et al., 2017).

In contrast, the agent-based simulation approach suggested here for modelling air pollution dynamics involving interaction with landscape objects, particularly with tree clusters, allows the dimensionality of the considered problem to be reduced significantly. This ensures that the advantages of deterministic models are maintained.

The idea of combining computational air fluid dynamics (Abbot and Basco, 1989) and agent-based modelling has already been suggested elsewhere (Epstein et al., 2011). However, the agent-based model of air pollution dynamics using interactions with tree clusters having individual characteristics, such as the geometry of planting (e.g., simple circle, arithmetic spiral, double circle), the type of tree (e.g., popular, oak, maple), and the distance between the nearest tree clusters is suggested herein for the first time. This method aims to reduce the air pollution concentration in cities.

Many studies have confirmed the positive impact of greenery in reducing air pollution in urban areas (e.g., Jim and Chen, 2008; Wong et al., 2009). However, there are not any systems that determine the optimal number of tree clusters, their location coordinates and planting geometry, the best kind of trees and other parameters that could be computed to minimise the average daily concentration of air pollution if the urban greenery budget is limited. This omission has been due to the overly high computational complexity needed for such tasks, which involve large-scale multi-objective optimisation problems.

To achieve this goal, we have combined computational air pollution dynamics with simulations of the ecological behaviour of different urban agents, such as agent-enterprises (factories), agent-vehicles (car clusters) and agent-trees (tree clusters). Moreover, we have used a special multi-objective genetic algorithm (Akopov and Hevencev, 2013) aggregated with the developed simulation through objective functions to determine the Pareto optimal solutions for greenery in a city.

There is a line of research to develop agent-based models and multi-objective systems to enhance the management of complex environmental systems (Hadka and Reed, 2015; Sun et al., 2016; Tesfatsion et al., 2017; West et al., 2018).

In the suggested model, trees and air pollutants are considered interactional agents with individual characteristics. This means that different tree clusters interacting with heterogeneous air pollutants have dissimilar absorptive-diffusive characteristics and different influences on the daily air pollution concentration.

Agent-based modelling approaches in combination with other simulation methods have been described elsewhere (Papaleonidas and Iliadis, 2012; Letcher et al., 2013; Zenonos et al., 2015; Vallejo et al., 2015; Ridley, 2017; Akopov et al., 2017). These studies have identified certain associated advantages for ecological modelling, the most important of which is the possibility of modelling the dynamics of agent interactions without the need to develop complex analytical models.

This study is focused on designing an agent-based model to determine the best ecological trade-offs for urban greenery. The case study of the city of Yerevan, Armenia will be presented. The main purpose behind the development of the original decision-making system was to analyse effective scenarios for greenery allocation under the budget constraint in the city of Yerevan, Armenia to reduce the average daily pollution concentration.

The suggested system can be applied to identify optimal greenery strategies to reduce air pollution concentrations in other urban areas and regions if appropriate data are available. In addition, the developed approach improves the precision of the model by including additional characteristics, such as the prevailing wind direction, wind velocity, air pollution intensities generated by agent-enterprises and agent-vehicles.

2. Data and method

2.1. Study area

The city of Yerevan, Armenia has many features that should be taken into account for simulation development. Yerevan has an average height of 990 m (3248.03 ft), with a minimum of 865 m (2837.93 ft) and a maximum of 1390 m (4560.37 ft) above sea level. It is located on to the edge of the Hrazdan River, in the northeast of the Ararat plain (Ararat Valley).

The important aspect of the location of Yerevan is that the city is surrounded by the Caucasian Mountains. The mountains significantly restrict the possibility of simple relocation of enterprises that are the main stationary sources of air pollution outside the city. Another problem is the hard restriction of the budget that can be used for environmental activities, caused by the difficult economic state of Armenia. These factors require the use of natural-based solutions and relatively low-cost methods for reducing the air pollution concentration, such as the greenery allocation in the city.

The following types of agents are used in the model:

- agent-enterprises and agent-vehicles (car clusters), which are sources of emissions in the
- city;
- agent-trees, which consist of small groups of homogeneous closely located trees; and
- agent-emissions, which are air pollutants produced by agent-enterprises and agent-vehicles.

In addition, concepts of the personal space of an agent-tree and the personal space of an agent-emission are suggested.

The personal space of an agent-tree is defined by the crones of plants forming the group (Fig. 1). The personal space of agent-trees consists of closely located, separate, homogenous trees. Several closely located agent-trees with a specific planting geometry are considered a tree cluster (one agent-tree consists of 10 trees). The crown of a plant refers to the totality of an individual plant's aboveground parts, including stems, leaves, and reproductive structures. A plant community canopy consists of one or more plant crowns growing in a given area. Therefore, it can be considered as a tree cluster.

The personal space of an agent-emission is defined by its radius length. In the model, all agent-emissions are formed by masses of homogenous air pollutants, and radiuses of agent-emissions define areas having persistent concentrations of homogenous air pollutants. To simplify, the concentration of air pollutants belonging to any agent-emission are assumed to be proportional to the agent-emission radius length. The radius length of the agent-emission is reduced when the agent-emission is touched by some agent-tree (Fig. 2).

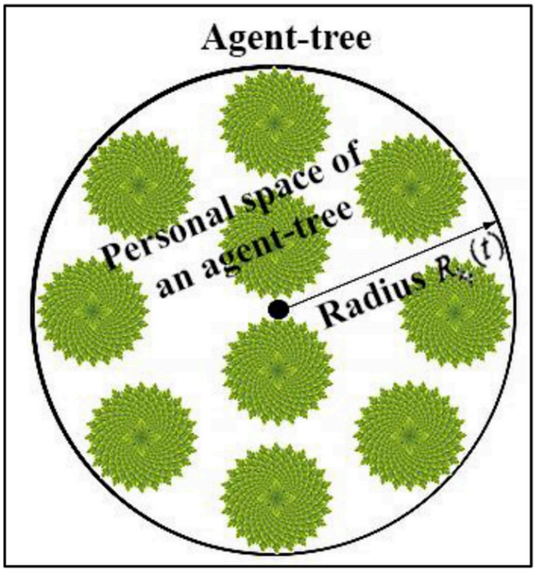

Fig. 1. Illustration of an agent-tree as a tree cluster with the associated personal space.

Thus, the ‘absorption effect’ is implemented. Nevertheless, agent-emissions with radiuses significantly less than the radiuses of agent-trees will pass through. Thus, the ‘diffusion effect’ is implemented. The behaviour of such agents is based on natural observations taken in the city Yerevan, Armenia. All experiments were conducted in selected urban areas with agent-trees consisting of separate trees with fixed distances between each other. Further, emissions of different volumes of dust occurred, and a special dust detector was used for estimation of the associated air pollution concentration in protected urban areas. The ratio between the emitted dust volume (which defines the initial radius of the agent-emission) and the size of the tree cluster (which defines the radius of the agent-tree) when the agent-trees do not protect from air pollutants was successfully identified. Such measurements were taken for different kinds of pollutants using different kinds of trees. Depending on the number of agent-trees, their radiuses, the kinds of trees and other characteristics, the rate of change in the air pollution concentration from the point of the emission source to the point of the protected urban area was found. Such absorption and diffusion effects have other known justifications (e.g., Fuiii et al., 2005; Omasa et al., 2002).

There are following agent-emissions are considered in the model: organic dust, inorganic dust, heavy metals, carbon monoxide (CO), sulphur dioxide (SO2), nitrogen oxides (NOx), carbonates (without volatile organic compounds), volatile organic compounds (VOCs) and other emissions.

The finite state of agent-emissions caused by their life span is dissipation when the agent-emission do not have a radius. In the model, the radiuses of undissipated agent-emissions are summarised at the monitoring station or in protected urban areas and are used for estimating the average daily air pollution concentration.

The intersection of different agent-emissions in air space is simulated without mixing their pollutants (Fig. 2). This assumption allows for the modelling of the daily pollution concentrations of different air pollutants in the areas of appropriate agent-emissions. These areas are reduced quickly in the presence of multiple contacts with agent-trees, as well as slowly as a consequence of natural dissipation over time.

The important characteristic of the described model is the daily concentration of air pollution, which can be estimated as the sum of the areas of the circles of all $j_{i,v}^{ths}$ agent-emissions located at the fixed zone of ecological monitoring (the monitoring station) with known coordinates $\{\widehat{x}, \widehat{y}\}$, and $\widehat{R}$ is the radius of observation. Here, $j_{i,v} \in \tilde{J}_{i,v}$ is the set of indexes of agent-emissions produced by the i^{th} emission source that contains the v^{th} air pollutant (a homogenous mass).

The main justification for using such a simplified approach for estimation of the daily air pollution concentration is that the initial radiuses of agent-emissions were chosen proportionately to appropriate volumes of pollutants produced by each agent-enterprise and agent-vehicle. The current values of the radiuses of agent-emissions located in the monitoring zone depend on many factors, in particular, all agent-trees that they have previously touched. Thus, the sum of the areas of the circles of agent-emissions can be used for model estimation of air pollution as the most representative metric in this model.

The air pollution concentration of the $j_{i,v}^{th}$ agent-emission consisting of the v^{th} pollutant in the zone of the monitoring station with the radius $\widehat{R}$ at the time t ($t \in \tilde{T}$) is:

$$g_{j_{i,v}}(t) = \begin{cases} \pi r_{j_{i,v}}^2(t), \text{ if } \sqrt{-\widehat{x}\Big)(\tilde{x}_{j_{i,v}}(t)^2 + -\widehat{y}\Big)\Big(\tilde{y}_{j_{i,v}}(t)^2} \\ \quad \le \widehat{R} \text{ and } st_{j_{i,v}}(t) = 1, \\ 0, \text{ if } \sqrt{-\widehat{x}\Big)(\tilde{x}_{j_{i,v}}(t)^2 + -\widehat{y}\Big)\Big(\tilde{y}_{j_{i,v}}(t)^2} > \widehat{R}, \end{cases} \tag{1}$$

$i \in \tilde{I}$, $v \in \tilde{V}$, $j_{i,v} \in \tilde{J}_{i,v}$,where.

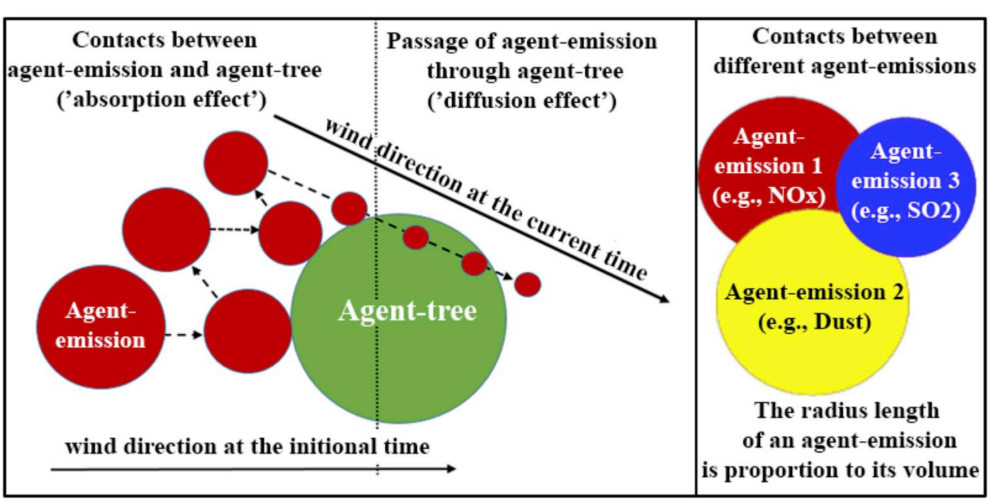

Fig. 2. Illustration of contact between an agent-emission and an agent-tree.

Table 1
Absorption coefficients of different kinds of trees.

Emission types	Kind of tree				
	Poplar	Oak	Maple	Pine	ULMUS
carbon dioxide CO2	0.22	0.21	0.2	0.2	0.21
organic dust	0.15	0.15	0.15	0.15	0.9
inorganic dust	0.15	0.15	0.15	0.15	0.9
total heavy metals	0.005	0.005	0.005	0.005	0.005
sulphur dioxide (SO2)	0.02	0.02	0.02	0.02	0.02
carbon monoxide	0.01	0.01	0.01	0.01	0.01
nitrogen oxides (NOx)	0.035	0.035	0.035	0.035	0.035
carbonates (without volatile organic compounds)	0.01	0.01	0.01	0.01	0.01
volatile organic compounds (VOCs)	0.009	0.009	0.009	0.03	0.009

- $\tilde{T} = \{t_0, t_1, ..., t_T\}$ is the set of temporal intervals, and the set is in days of a one-year period, T is 365 days;
- $\tilde{I} = \{i_1, i_2, ..., i_I\}$ is the set of indexes of emission sources that produce air pollutants (agent-enterprises and agent-vehicles) located in the city, I is the number of emission sources;
- $\tilde{V} = \{v_1, v_2, ..., v_V\}$ is the set of indexes of air pollutants (e.g., CO2, organic dust, inorganic dust, heavy metals, SO2, NOx), V is the number of air pollutants;
- $\tilde{J}_{i,v} = \left\{j_{1,i,v}, j_{2,i,v}, ..., j_{J_{i,v}(t)}\right\}$ is the set of indexes of agent-emissions produced by the i^{th} emission source that contains the v^{th} air pollutant (a homogenous mass), $\tilde{J}_{i,v}$ is the number of agent-emissions at the moment $t \in \tilde{T}$;
- $\left\{\tilde{x}_{j_{i,v}}(t), \tilde{y}_{j_{i,v}}(t)\right\}$ are coordinates of agent-emissions in the WGS 84 (the World Geodetic System) coordinate system at the moment $t \in \tilde{T}$;
- $r_{j_{i,v}}(t)$ is the radius of the $j^{th}_{i,v}$ agent-emission at the moment $t \in \tilde{T}$, which changes as a result of interaction of the agent-emission with any k^{th}_{ς} agent-tree, reflected in Fig. 2, and $r_{j_{i,v}}(\tau_{j_{i,v}}) \in [1, 10]$ is the known initial radius of the $j^{th}_{i,v}$ agent-emission defined at the moments of air pollution production by different sources of emissions;
- $\{\widehat{x}, \widehat{y}\}$ are known coordinates of the monitoring station in the city;
- $\widehat{R}$ is the radius of observation of the monitoring station;
- $\tilde{H}_{j_{i,v}} = \left\{t_0 + u_i, t_0 + 2u_i, ..., \lfloor \frac{t}{u_i} \rfloor u_i\right\}$ is the set of regular time moments of producing the $j^{th}_{i,v}$-agent-emission, u_i is the emissions intensity of the i^{th}-source ($u_i = 7$ for all agent-enterprises and $u_i = 2$ for all agent-vehicles); and
- $st_{j_{i,v}}(t) \in \{1, 0\}$ is the state of the $j^{th}_{i,v}$ agent-emission, wherein $st_{j_{i,v}}(t) = 1$ if the $j^{th}_{i,v}$ agent-emission is active, $st_{j_{i,v}}(t) = 0$ if the $j^{th}_{i,v}$ agent-emission is dissipated, and $\tilde{t}_{j_{i,v}}$ is the life time of the $j^{th}_{i,v}$ agent-emission:

$$st_{j_{i,v}}(t) = \begin{cases} 1, & \text{if } t - \tau_{j_{i,v}} \le \tilde{t}_{j_{i,v}}, \\ 0, & \text{if } t - \tau_{j_{i,v}} > \tilde{t}_{j_{i,v}}, \end{cases} \tag{2}$$

$\tau_{j_{i,v}} \in \tilde{H}_{j_{i,v}}, i \in \tilde{I}, v \in \tilde{V}, j_{i,v} \in \tilde{J}_{i,v}$.

The daily air pollution concentration summarised for all agent-emissions and averaged for all associated pollutants that have reached the monitoring zone is:

$$DC(t) = \frac{1}{V}\sum_{i=1}^{I}\sum_{v=1}^{V}\left(\varkappa_v \sum_{j_{i,v}=1}^{J_{i,v}(t)} g_{j_{i,v}}(t)\right) \tag{3}$$

$i \in \tilde{I}, v \in \tilde{V}, j_{i,v} \in \tilde{J}_{i,v}, t \in \tilde{T},$

Here, ϖ_v is the weight coefficient reflecting the importance of the v^{th} pollutant for a decision maker: $\sum_{v=1}^{V} \varkappa_v = 1, 0 \le \varkappa_v$. Using the weight coefficients ($\varkappa_v, v \in \tilde{V}$) takes into account the importance (for a decision maker) of different air pollutants in the problem of air pollution minimisation.

The daily air pollution concentration should not exceed the maximum permissible concentration, which is fixed individually for each air pollutant, including dust, heavy metals, sulphur dioxide (SO2), nitrogen oxides (NOx), carbonates, and volatile organic compounds (VOCs). The maximum permissible concentration is aggregated and denoted as $\overline{DC}$ in the model:

$$DC(t) \le \overline{DC}$$

The average daily air pollution concentration is:

$$ADC = \frac{1}{T}\sum_{t=t_0}^{T} DC(t) \tag{4}$$

2.2. Data

Detailed data including datasets of agent-enterprises, agent-vehicles and agent-trees, as well as locations of emission sources and protected kindergartens are presented in the data in brief paper (Akopov et al., 2019).

The number of agent-emissions and their initial radiuses are directly proportional to the total air pollution produced by agent-enterprises.

The main characteristics of agent-trees are presented in Tables 1 and 2. The value of the absorption coefficient is calculated by considering the estimated value of the maximum volume of absorption by one tree and the total number of trees included in one tree cluster.

The main characteristics of agent-vehicles (car clusters) are presented in Table 3 and in *Data in brief*. There are approximately 300000 cars in Yerevan, which form 1000 car clusters.

The total emissions produced per day by one agent-vehicle (consisting of 300 cars) is approximately 3.8 tonnes. One agent-emission has an initial radius of 10 m deposits and 1.9 tonnes of total pollutants (mainly CO2). Thus, for one event occurring with a fixed intensity of 2 (one time for two days, taking into account parking), a total of $(3.8 * 2)/1.9 = 4$ agent-emissions are produced for one event by one agent-vehicle (Table 3). The initial radius of agent-emissions produced by an agent-vehicle was obtained from the results of air pollution measurements near roads, and the measurement reflects areas with maximum concentrations of pollutants.

Wind characteristics such as the prevailing wind direction and wind speed variation by month have an important influence on air pollution dynamics (Table 4). Here, an 8-wind compass rose is used, with the four ordinal directions forming the bisecting angle of the cardinal winds: north (N), west (W), northeast (NE), south (S), southeast (SE), southwest (SW), northwest (NW). All data were obtained from the main weather station of Yerevan, Armenia.

Here, the prevailing wind direction is used for correction of the movement directions of agent-emissions when there are not any agent-trees along the movement paths or there is a ‘diffusion effect’. In the presence of obstacles, such as agent-trees, the prevailing wind direction disappears, and the movement directions of agent-emissions are defined by interactions between agent-emissions and agent-trees.

There are different methods available for collecting air quality monitoring data, as described in previous works (Papaleonidas and

Table 2
Main characteristics of agent-trees in Yerevan, Armenia.

Trees	Cost of planting a tree, USD	Radius of agent-tree, metres
Poplar	900	35
Oak	700	30
Maple	600	25
Pine	1000	21
Ulmus	1000	25

Table 3
Main characteristics of agent-vehicles in Yerevan, Armenia.

Characteristics	Values
Number of agent-vehicles (car clusters)	1000
Number of cars in one agent-vehicle	300
Number of agent-emissions produced for one event by one agent-vehicle	4
Initial radius of agent-emissions, metres	10
Emissions intensity	2
Distribution type of vehicles by roads of the city	According to the known density of cars in urban areas (Akopov et al., 2019)

Table 4
Main characteristics of wind in Yerevan, Armenia.

Month no.	Prevailing wind direction	Average wind speed, m/s	Maximum wind speed, m/s
1	SW	0.60	34
2	NE	1.00	28
3	SW	1.00	24
4	SW	1.70	20
5	NE	1.70	20
6	N	2.20	24
7	NE	2.70	24
8	NE	2.20	20
9	NE	1.40	20
10	W	0.80	20
11	SW	0.70	20
12	W	0.50	20

Iliadis, 2012; Zenonos et al., 2015). In this research, the standard approach was applied based on reading real data using equipment such as gas analysers, dust analysers, sensors, and spectroscopes and comparing the real data against the simulation results.

Samples were collected and treated at the Central Analytic Laboratory of the Centre of Ecological Noosphere Studies of the National Academy of Sciences of Armenia – CENS, accredited by ISO/IEC 17025. The laboratory has modern equipment, including a Serinus 30 carbon monoxide analyser, Serinus 40 analyser, Serinus 40 nitrogen oxides analyser, Serinus 51 sulphur dioxide analyser, VOC72 M Gas Chromatography Volatile Organic Compounds (BTEX) analyser, and dust analyser OPASTOP GP4000HD. The collected samples were treated and analysed for air pollutant contents (dust, CO, NOx, SO2, heavy metals, VOCs) through the atomic absorption method (AAnalyst 800, Perkin Elmer, US) (ISO 8573 and ISO 12500, air quality).

2.3. Method

The developed simulation model employs the earlier-developed agent-based approach of modelling ecological-economic systems suggested in a previous study (Akopov et al., 2017). In this work, agents are agent-enterprises that produce air pollution, and a method to find the best trade-offs for ecological modernisation of enterprises towards pure ecological manufacturing is developed. However, such an approach assumes reduction of the production capacity of enterprises and appropriate outputs together with emissions in the atmosphere. Furthermore, ecological modernisation requires significant expenditures. In contrast, developing urban greenery is an alternative and relatively inexpensive approach to reducing the air pollution concentration.

First, the idea of using agent-emissions instead of a more natural emissions plume should be explained. As is known, modelling the dynamics of an emissions plume requires more complex models based on differential equations with partial derivatives that describe appropriate chemical processes on the molecular level (Beychok, 2005; Turner, 1994). The explicit advantage of such models is the possibility of investigating internal air dispersion and diffusion processes that depend on many factors, such as wind direction, temperature and air humidity. Therefore, these models are the most realistic and accurate. However, such models are characterised by significant computation complexity. Therefore, their application is justified for local and limited systems without taking into account complex interactions between trees and air pollutants on the scale of a whole city employing different strategies of urban greenery. On the other hand, emission plumes can be considered ensembles consisting of separate agent-emissions controlled by external factors on the individual level, e.g., the prevailing wind direction and interactions with plants, if the resulting precision will be enough to model the air pollution dynamics. Because modelling atmospheric dispersion is not critical for investigating the influence of greenery on pollution removal, using agent-emissions instead of emission plumes is justified.

There is a known concept of agent states in agent-based modelling. Each agent can have a set of individual characteristics that are called agent states, e.g., the agent-emission can be active or dissipated, the agent-enterprise can be non-ecological and not surrounded by trees or ecological. There are transitions between such states that can be controlled by special rules or can be under natural (temporal) control. The scheme of possible states of the considered agents is presented in Fig. 3.

The model starts with the initial states of agents, which are highlighted in grey in Fig. 3. The initial conditions of the model are defined by the locations of the agent-enterprises and agent-vehicles in the city according to known coordinates for enterprises and stochastic coordinates of roads for vehicles. The next step is the distribution of new agent-trees with maximum initial radiuses of personal space and absorption characteristics within the city according to the defined optimal tree cluster configurations.

Some states of agent-trees, agent-vehicles and agent-emissions are interconnected. In particular, new agent-emissions with maximum initial radiuses are generated by agent-enterprises and agent-vehicles when they are in their second and third states of producing air pollution. The production cycles of air pollution by agent-enterprises and agent-vehicles are defined by the emission intensities, usually equal to seven days for agent-enterprises and two days for agent-vehicles.

Further, the abstract mathematical description of the suggested model is considered, as well as multi-criteria optimisation problems for rational greenery allocation in the city to minimise the air pollution concentration, where:

- $\tilde{Z} = \{\zeta_1, \ \zeta_2, \ ..., \ \zeta_Z\}$ is the set of indexes of tree clusters where agent-trees are located;
- $\tilde{K}_\zeta = \{k_{1,\zeta}, \ k_{2,\zeta}, \ ..., \ k_{K_\zeta}\}$ is the set of indexes of agent-trees that absorb air pollutants belonging to the ζ^{th} tree cluster;
- $s_{j_{i,v}}(t)$ is the speed of movement of the $j_{i,v}^{th}$ agent-emission, which equals the average wind speed at the moment $t \in \tilde{T}$;
- $\alpha_{j_{i,v}}(t)$ is the angle of movement of the $j_{i,v}^{th}$- agent-emission $j_{i,v} \in \tilde{J}_{i,v}$ when there are not any agent-tree on its path or if the 'diffusion effect' takes place at the moment $t \in \tilde{T}$. This angle takes into account the influence of the prevailing wind direction (Table 5):

- $\beta_{j_{i,v}k_\xi}(t)$ is the angle of bypass of the $j_{i,v}^{th}$ agent-emission $j_{i,v} \in \tilde{J}_{i,v}$ around the k_ζ^{th} agent-tree $k_\zeta \in \tilde{K}_\zeta$ at the moment $t \in \tilde{T}$;
- $\gamma_{j_{i,v}k}(t)$ is the angle of the rebound of the $j_{i,v}^{th}$ agent-emission $j_{i,v} \in \tilde{J}_{i,v}$ from the k_ζ^{th} agent-tree $k_\zeta \in \tilde{K}_\zeta$ at the moment $t \in \tilde{T}$;
- $\mathrm{c}_{j_{i,v}}(t)$ is the rebounding coefficient of the $j_{i,v}^{th}$ agent-emission from the k_ζ^{th} agent-tree ($\mathrm{c}_{j_{i,v}}(t) = 10$ for all $j_{i,v} \in \tilde{J}_{i,v}$);
- $R_{k_\xi}(t)$ is the radius of the k_ζ^{th} agent-tree depending on tree kind (e.g., poplar, oak, maple);
- $dist_{j_{i,v}k_\xi}(t)$ is the Euclidean distance between the $j_{i,v}^{th}$ agent-emission and the k_ζ^{th} agent-tree;
- $\xi_{j_{i,v}k_\zeta}(t)$ is the event when the $j_{i,v}^{th}$ agent-emission touches the k_ζ^{th} agent-tree.

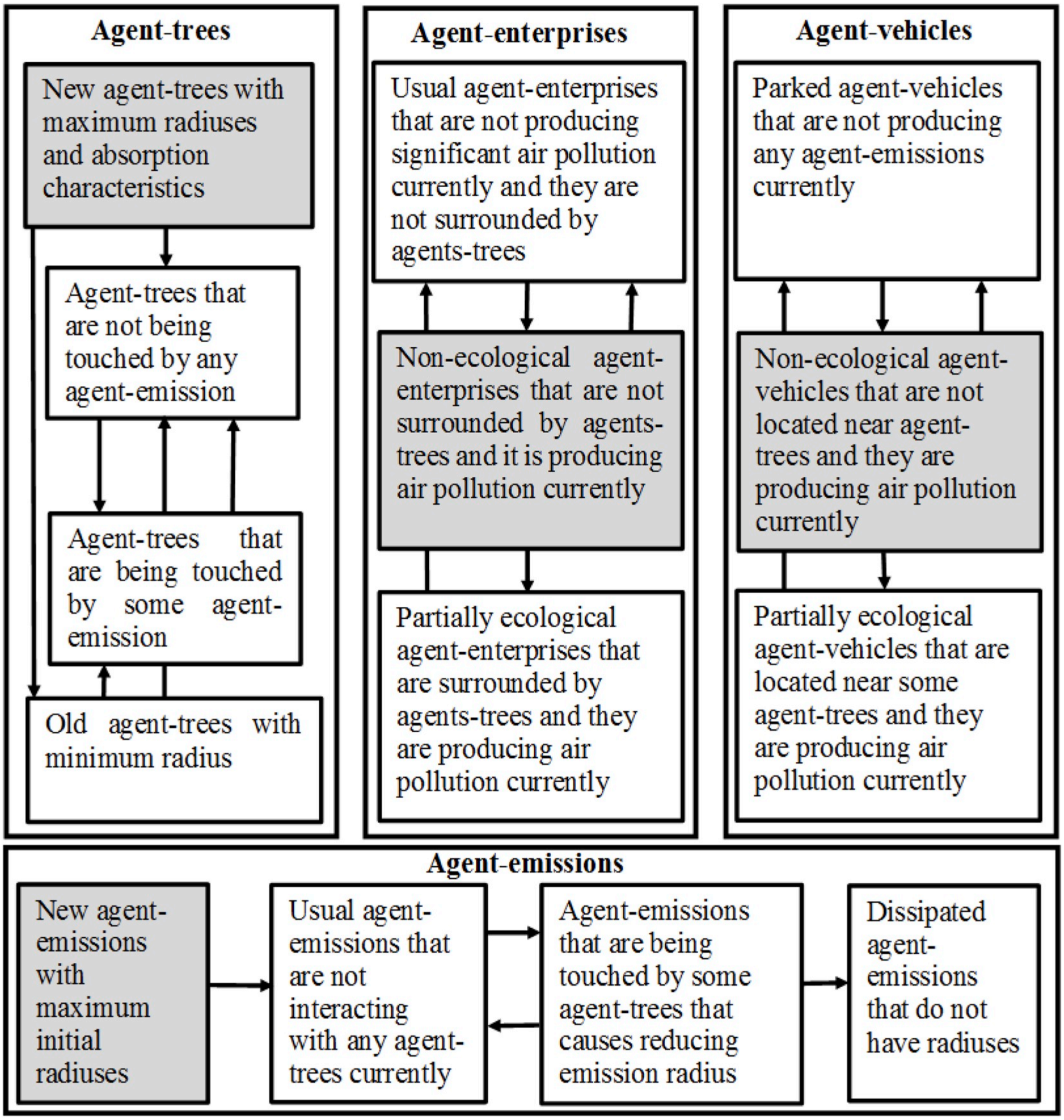

Fig. 3. The scheme of possible states of the considered agents.

Table 5
Prevailing wind direction in Yerevan, Armenia.

north	northeast	east	southeast	south	southwest	west	northwest
0^0	45^0	90^0	135^0	180^0	225^0	270^0	315^0

$$\xi_{j_{i,v}k_\zeta}(t) \in \begin{cases}1, & \text{if } dist_{j_{i,v}k_\zeta}(t) \le r_{j_{i,v}}(t) + R_{k_\zeta}(t),\\ 0, & \text{if } dist_{j_{i,v}k_\zeta}(t) > r_{j_{i,v}}(t) + R_{k_\zeta}(t),\end{cases} \quad (5)$$

$i \in \tilde{I}$, $v \in \tilde{V}$, $j_{i,v} \in \tilde{J}_{i,v}$, $\zeta \in \tilde{Z}$, $k_\zeta \in \tilde{K}_\zeta$.

In the absence of a connection between the $j_{i,v}^{th}$ agent-emission ($j_{i,v} \in \tilde{J}_{i,v}$, $i \in \tilde{I}$, $v \in \tilde{V}$) and the k_ζ^{th} agent-tree ($k_\zeta \in \tilde{K}_\zeta$, $\zeta \in \tilde{Z}$), the radius of the former will not be changed (Fig. 4). An appropriate interaction can take place if any agent-tree is located on the track of any agent-emission and the radius of the latter is not much smaller than the radius of the agent-tree that has been touched. This case can be considered the 'absorption effect'. After an event in which an agent-emission has been touched by some agent-tree, the radius of the former will be significantly reduced. In this case, the agent-emission can pass through any agent-tree. This case can be considered the 'diffusion effect'.

Thus, the radius of the $j_{i,v}^{th}$ agent-emission at moment t ($t \in \tilde{T}$) is defined by the same recursive procedure:

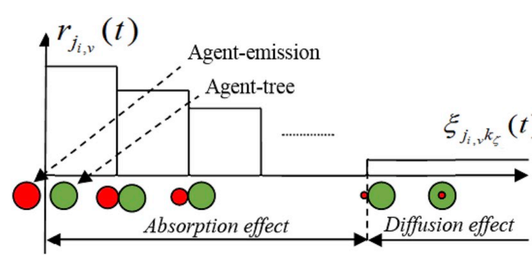

Fig. 4. The radius of the agent-emission depending on interaction with any agent-tree.

$$r_{j_{i,v}}(t) = \begin{cases} r_{j_{i,v}}(\tau_{j_i}), \text{ if I is true,}\\ r_{j_{i,v}}(t-1)\exp\left(-\eta_{j_{i,v}}\right), \text{ if II is true,}\\ r_{j_{i,v}}(t-1)\exp\left(-\eta_{j_{i,v}}\right)\mu_{k_\zeta j_{i,v}}, \text{ if III is true,}\\ 0, \text{ if IV is true,}\end{cases} \quad (6)$$

where:

I. $t = \tau_{j_{i,v}}, \tau_{j_{i,v}} \in \tilde{H}_{j_{i,v}}$,
II. $\left(\xi_{j_{i,v}k}(t) = 0 \text{ or } r_{j_{i,v}}(t) < R_{k_\zeta}(t)/\varpi\right)$ and $st_{j_{i,v}}(t) = 1$
III. $\left(\xi_{j_{i,v}k}(t) \neq 0 \text{ and } r_{j_{i,v}}(t) \geq R_{k_\zeta}(t)/\varpi\right)$ and $st_{j_{i,v}}(t) = 1$,
IV. $st_{j_{i,v}}(t) = 0$,

$i \in \tilde{I},\ v \in \tilde{V},\ j_{i,v} \in \tilde{J}_{i,v},\ \zeta \in \tilde{Z},\ k_\zeta \in \tilde{K}_\zeta$, where:

- $\mu_{k_\zeta j_{i,v}}$ is the fixed coefficient reflecting the 'absorption effect' of the k_ζ^{th} agent-tree regarding the $j_{i,v}^{th}$ agent-emission containing the v^{th} pollutant ($\mu_{k_\zeta j_{i,v}} < 1$);
- $\eta_{j_{i,v}}$ is the fixed coefficient reflecting the exponential fading of the $j_{i,v}^{th}$ agent-emission $\left(\eta_{j_{i,v}} = 0.01\right)$; and
- ϖ is the fixed coefficient reflecting the 'diffusion effect' ($\varpi = 10$).

Agent-emissions move towards different directions under the influence of applied forces caused by the wind velocity and interactions with different landscape objects, in particular, agent-trees. Such movement of masses of air pollutant types can be described by well-known differential equations with variable structures.

Thus, the dynamics of the $j_{i,v}^{th}$ agent-emission for the time period of $t_r \leq \psi \leq t_{r+1}$ are described by the following system of differential equations at time:

$$\frac{d\tilde{x}_{j_{i,v}}(\psi)}{d\psi} = \begin{cases} s_{j_{i,v}}(\psi)\cos\alpha_{j_{i,v}}(\psi), \text{ if V is true,} \\ s_{j_{i,v}}(\psi)\cos\left(\pm\beta_{j_{i,v}k_\zeta}(\psi)\right) + \frac{c_{j_{i,v}}}{dist_{j_{i,v}k_\zeta}}\cos\gamma_{j_{i,v}}(\psi), \text{ if VI is true,} \\ 0, \text{ if VII is true,} \end{cases} \tag{7}$$

$$\frac{d\tilde{y}_{j_{i,v}}(\psi)}{d\psi} = \begin{cases} s_{j_{i,v}}(\psi)\sin\alpha_{j_{i,v}}(\psi), \text{ if V is true,} \\ s_{j_{i,v}}(\psi)\sin\left(\pm\beta_{j_{i,v}k_\zeta}(\psi)\right) + \frac{c_{j_{i,v}}}{dist_{j_{i,v}k_\zeta}}\sin\gamma_{j_{i,v}}(\psi), \text{ if VI is true,} \\ 0, \text{ if VII is true,} \end{cases} \tag{8}$$

$i \in \tilde{I},\ v \in \tilde{V},\ j_{i,v} \in \tilde{J}_{i,v},\ \zeta \in \tilde{Z},\ k_\zeta \in \tilde{K}_\zeta$, where:

V. $(dist_{j_{i,v}k_\zeta}(\psi) > r_{j_{i,v}}(\psi) + R_{k_\zeta}(\psi)$ for all $k_\zeta \in \tilde{K}_\zeta)$ or $r_{j_{i,v}}(\psi) < R_{k_\zeta}(\psi)/\varpi$ for the nearest $k_\zeta \in \tilde{K}_\zeta$ and $st_{j_{i,v}}(\psi) = 1$,
VI. $(dist_{j_{i,v}k_\zeta}(\psi) \leq r_{j_{i,v}}(\psi) + R_{k_\zeta}(\psi)$ for the nearest $k_\zeta \in \tilde{K}_\zeta)$ and $r_{j_{i,v}}(\psi) \geq R_{k_\zeta}(\psi)/\varpi$ for the nearest $k_\zeta \in \tilde{K}_\zeta$ and $st_{j_{i,v}}(\psi) = 1$,
VII. $(dist_{j_{i,v}k_\zeta}(\psi) \leq r_{j_{i,v}}(\psi) + R_{k_\zeta}(\psi)$ and $r_{j_{i,v}}(\psi) \geq R_{k_\zeta}(\psi)/\varpi$ for all $k_\zeta \in \tilde{K}_\zeta)$ or $st_{j_{i,v}}(\psi) = 0$.

The system of Eqs. (7) and (8) is similar in some elements to the model of crowd behaviour described in previous works (Akopov and Beklaryan, 2015; Beklaryan and Akopov, 2016). This is due to agent-emissions colliding with agent-trees and taking on some characteristics of crowds, such as chaotic movement and targeting to bypass landscape obstacles.

The main approach to minimisation of the air pollution concentration is the control of parameters related to tree cluster configurations on the individual level.

The control parameters for each ζ^{th} tree cluster ($\zeta \in \tilde{Z}$) consisting of the k_ζ^{ths} agent-trees ($k_\zeta \in \tilde{K}_\zeta$) are defined at the initial moment $t_0 \in \tilde{T}$ as:

- $\{\hat{x}_\zeta(t_0),\ \hat{y}_\zeta(t_0)\}$ are the coordinates of the ζ^{th} tree cluster centre (for simplification, these coordinates are equal to the coordinates of agent-enterprises and protected urban areas);
- $\tilde{C}_\zeta = \{0,\ 1, ..., 4\}$ is the set of possible configurations of the ζ^{th} tree cluster, and $cnf_\zeta(t_0) \in \tilde{C}_\zeta$ is the selected configuration: $cnf_\zeta(t_0) = 0$ – without agent-trees, $cnf_\zeta(t_0) = 1$ –simple circle, $cnf_\zeta(t_0) = 2$ – arithmetic spiral (with the fixed step), $cnf_\zeta(t_0) = 3$ – double circle, $cnf_\zeta(t_0) = 4$ – double circle with variable distances between the nearest agent-trees, considering the ζ^{th} tree cluster and $cnf_\zeta(t_0) \in \tilde{C}_\zeta$;
- $\tilde{S}_\zeta = \{1,\ 2, ..., 5\}$ is the set of possible kinds of agent-trees located in the tree cluster, and $tp_\zeta(t_0) \in \tilde{S}_\zeta$ is the selected kind of agent-trees: $tp_\zeta(t_0) = 1$ – poplar tree cluster, $tp_\zeta(t_0) = 2$ – oak tree cluster, $tp_\zeta(t_0) = 3$ – maple tree cluster, $tp_\zeta(t_0) = 4$ – pine tree cluster, $tp_\zeta(t_0) = 5$ – ulmus tree cluster;
- $\delta_\zeta(t_0)$ is the distance between the nearest agent-trees and the ζ^{th} tree cluster: $\underset{\sim}{\delta} \leq \delta_\zeta(t) \leq \bar{\delta},\ \zeta \in \tilde{Z}$, where $\underset{\sim}{\delta},\ \bar{\delta}$ are the lower and upper boundaries of the distance range; and
- $\tilde{R}_\zeta(t_0)$ is the radius of the ζ^{th} tree cluster that defines the planting area: $\tilde{R} \leq \tilde{R}_\zeta(t_0) \leq \bar{R}\zeta \in \tilde{Z}\}$, where $\tilde{R},\ \bar{R}$ are the lower and upper boundaries of the radius range.

The target number of agent-trees to be planted around agent-enterprises for reducing the air pollution concentration can be found by solving the bi-objective optimisation problem, which will be considered later:

$$K_\zeta(t_0) = f\left(cnf_\zeta(t_0),\ tp_\zeta(t_0), \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\right) \tag{9}$$

$\zeta \in \tilde{Z},\ t_0 \in \tilde{T}$.

The needed greenery budget is:

$$GB = \sum_{\zeta=1}^{Z}\sum_{k_\zeta}^{K_\zeta} c_{k_\zeta} n_\zeta \tag{10}$$

$\zeta \in \tilde{Z},\ k_\zeta \in \tilde{K}_\zeta$

where c_{k_ζ} is the known cost of planting one tree of the k_ζ^{th} agent-tree of the ζ^{th} tree cluster, and n_ζ is the number of closely located trees to one agent-tree of the ζ^{th} tree cluster ($n = 10$ for all $\zeta \in \tilde{Z}$).

Here, the cost of planting depends on the tree kind (e.g., 900 USD for a poplar, 700 USD for an oak), and it includes all expenses related to the support of the tree life cycle during a year (e.g., irrigation, digging the soil).

The number of planted agent-trees in all ζ^{ths} tree clusters ($\zeta \in \tilde{Z}$) is:

$$N = \sum_{\zeta=1}^{Z} K_\zeta \tag{11}$$

Problem A. *The need to minimise the average daily pollution concentration and greenery budget through the set of control parameters* $\{cnf_\zeta(t_0),\ tp_\zeta(t_0), \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\}$:

$$\begin{cases} \min\limits_{\left\{cnf_\zeta(t_0),\ tp_\zeta\left(t_0\right), \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\right\}} [ADC], \\ \min\limits_{\left\{cnf_\zeta(t_0),\ tp_\zeta\left(t_0\right), \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\right\}} [GB], \end{cases} \tag{12}$$

where:

$$ADC = \frac{1}{T}\sum_{t=t_0}^{T} DC(t)$$

$$GB = \sum_{\zeta=1}^{Z}\sum_{k_\zeta}^{K_\zeta} c_{k_\zeta} n_\zeta$$

$$DC(t) = \frac{1}{V}\sum_{i=1}^{I}\sum_{v=1}^{V}\left(\kappa_v \sum_{j_{i,v}=1}^{J_{i,v}(t)} g_{j_{i,v}}(t)\right)$$

$$DC(t) \leq \overline{DC}$$

$$\sum_{v=1}^{V(t)} \kappa_v = 1$$

$$0 \le \kappa_v$$

$$\underset{\sim}{\delta} \le \delta_\zeta(t_0) \le \bar{\delta}$$

$$\tilde{R} \le \tilde{R}_\zeta(t_0) \le \bar{R}$$

$$cnf_\zeta(t_0) \in \tilde{C}_\zeta$$

$$tp_\zeta(t_0) \in \tilde{S}_\zeta$$

$\zeta \in \tilde{Z},\ k_\zeta \in \tilde{K}_\zeta,\ i \in \tilde{I},\ v \in \tilde{V},\ j_{i,v} \in \tilde{J}_{i,v},\ t_0 \in \tilde{T}$.
under different other constraints.

Further, some modifications of the problem of minimising the average daily pollution concentration will be considered.

There is an important problem of protecting selected urban areas with a significant social relevance, e.g., kindergartens and hospitals, from harmful emissions produced by agent-enterprises and agent-vehicles. A strategy considering this issues can be useful in conditions of greenery budget deficit and a lack of free areas acceptable for planting. Each kindergarten has its own personal space that should be protected from air pollutants.

The problem will be considered for the protection of kindergartens of the city Yerevan, Armenia as an example.

Here.

- $\tilde{P} = \{p_1,\ p_2,\ ...,\ p_P\}$ is the set of indexes of kindergartens located in the city that should be protected, and P is the total number of kindergartens;
- $\{x_p,\ y_p\}$ are the coordinates of the p^{th} kindergarten; and
- $\hat{R}_p$ is the known radius of the p^{th} kindergarten, defined by the personal space where the average daily pollution concentration should be minimized.

The air pollution concentration of the $j_{i,v}^{th}$ agent-emission consisting of the v^{th} pollutant in the p^{th} kindergarten with radius $\hat{R}_{\tilde{p}}$ at time t ($t \in \tilde{T}$) is:

$$g^*_{j_{i,v,p}}(t) = \begin{cases} \pi r^2_{j_{i,v}}(t),\ \text{if } \sqrt{(\tilde{x}_{j_{i,v}}(t) - x_p)^2 + \left(\tilde{y}_{j_{i,v}}(t) - y_p\right)^2} \\ \quad \le \hat{R}_p \text{ and } st_{j_i}(t) = 1, \\ 0,\ \text{if } \sqrt{(\tilde{x}_{j_{i,v}}(t) - x_p)^2 + \left(\tilde{y}_{j_{i,v}}(t) - y_p\right)^2} > \hat{R}_p, \end{cases} \tag{13}$$

$i \in \tilde{I},\ v \in \tilde{V},\ j_{i,v} \in \tilde{J}_{i,v},\ p \in \tilde{P}$.

The daily air pollution concentration summarised by all agent-emissions and averaged by protected urban areas (kindergartens) is:

$$DC*(t) = \frac{1}{P \cdot V} \sum_{p=1}^{P} \sum_{i=1}^{I} \sum_{v=1}^{V} \left(\kappa_v \sum_{j_{i,v}=1}^{J_{i,v}(t)} g^*_{j_i,v,p}(t) \right) \tag{14}$$

The daily air pollution concentration should not exceed the maximum permissible concentration, which is fixed individually for each air pollutant, including dust, heavy metals, sulphur dioxide (SO2), nitrogen oxides (NOx), carbonates, and volatile organic compounds (VOC). The maximum permissible concentration will be aggregated and denoted as $\overline{DC}$ in the model: $DC(\tilde{t}) \le \overline{DC}$.

The average daily air pollution concentration in protected kindergartens is:

$$ADC* = \frac{1}{T} \sum_{t=t_0}^{T} DC*(t) \tag{15}$$

The number of planted agent-trees needed for protection of the kindergartens is:

$$N* = \sum_{\zeta=1}^{Z} K^*_\zeta \tag{16}$$

$$\zeta \in \tilde{Z}$$

where K^*_ζ is the target number of agent-trees to be planted around kindergartens.

The number of tree clusters planted around protected kindergartens (K^*_ζ) can significantly differ from the number of tree clusters planted around agent-enterprises (K_ζ) due to differences in location, the sizes of their areas, remoteness from emissions sources and the accumulations of air pollutants produced by many agent-enterprises and agent-vehicles.

Problem B. *The need to minimise the average daily pollution concentration and the greenery budget in protected urban areas (kindergartens) through the set of decision variables* $\{cnf_\zeta(t_0),\ tp_\zeta(t_0), \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\}$:

$$\begin{cases} \min\limits_{\left\{cnf_\zeta(t_0),\ tp_\zeta(t_0),\ \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\right\}} [ADC*], \\ \min\limits_{\left\{cnf_\zeta(t_0),\ tp_\zeta(t_0),\ \delta_\zeta(t_0),\ \tilde{R}_\zeta(t_0)\right\}} [GB*], \end{cases} \tag{17}$$

where

$$ADC* = \frac{1}{T} \sum_{t=t_0}^{T} DC*(t)$$

$$GB^* = \sum_{\zeta=1}^{Z} \sum_{k_\zeta}^{K^*_\zeta} c_{k_\zeta} n_\zeta$$

$$DC*(t) = \frac{1}{P \cdot V} \sum_{p=1}^{P} \sum_{i=1}^{I} \sum_{v=1}^{V} \left(\kappa_v \sum_{j_{i,v}=1}^{J_{i,v}(t)} g^*_{j_i,v,p}(t) \right)$$

$$DC*(t) \le \overline{DC}$$

$$\textstyle\sum_{v=1}^{V} \kappa_v = 1$$

$$0 \le \kappa_v$$

$$\underset{\sim}{\delta} \le \delta_\zeta(t_0) \le \bar{\delta}$$

$$\tilde{R} \le \tilde{R}_\zeta(t_0) \le \bar{R}$$

$$cnf_\zeta(t_0) \in \tilde{C}_\zeta, \quad tp_\zeta(t_0) \in \tilde{S}_\zeta$$

$\zeta \in \tilde{Z},\ k_\zeta \in \tilde{K}_\zeta,\ i \in \tilde{I},\ v \in \tilde{V},\ j_{i,v} \in \tilde{J}_{i,v},\ p \in \tilde{P},\ t_0 \in \tilde{T}$.

The model (Eqs. (1-17)) was implemented in the well-known *AnyLogic* simulation tool that supports agent-based modelling methods with GIS integration. Original *Java* classes were developed for implementation of the individual behaviour rules of all agents, including agent-trees, and agent-emissions. As a result, over 12 000 replicated agents can be simulated in the system to calculate values of the objective functions (Eq. (12), (17)). Further, the simulation was aggregated with suggested genetic algorithms through these objective functions to seek the Pareto optimal solutions.

A line of the heuristic optimisation algorithms can be applied for the considered bi-objective optimisation problem (e.g., Zitzler and Thiele, 1999; Kim et al., 2004; Zhong et al., 2004). Among them, the SPEA (Strength Pareto Evolutionary Algorithms) class proposed by Zetzler (Zitzler and Thiele, 1999) and developed in previous works (Akopov and Hevencev, 2013; Kim et. al, 2004; E. Zaenudin and Kistijantoro, 2016) can be highlighted. Using heuristic optimisation algorithms is effective for solving large-scale optimisation problems of ecological-economic systems (e.g., Akopov et al., 2017; Vallejo et al., 2015).

The MAGAMO (multi-agent genetic algorithm for multi-objective optimisation) algorithm, based on some aspects of previous work (Zhong et al., 2004) and suggested in a previous study (Akopov and Hevencev, 2013), was used for solving the considered problem (17). The MAGAMO paralleling of evolutionary processes has some advantages when objective functions are the result of agent-based simulations.

The important feature of MAGAMO is the possibility to organise the heuristic optimisation in the parallel mode, where each process is responsible for the evolution of previously selected decision variables. The decision variables in the set are separated into subsets associated with the corresponding genetic algorithms (GA). GAs are exchanged by the best values of the decision variables within the evolutionary search. For the considered optimisation problem, this means that each evolving tree cluster consisting of agent-trees and with its own characteristics will be associated with one independent genetic algorithm. This approach allows reduction of the population size of each GA and improvement of the time efficiency and rate of convergence of the global heuristic search.

There are two optimisation functions for solving Problem A and Problem B:

- The average daily pollution concentration: *ADC* and *ADC*∗ and
- The greenery budget: *GB* and *GB*∗.

These criteria were chosen because they reflect the interests of potential decision makers aiming to seek appropriate trade-offs. In addition, these objective functions are the most important for the city of Yerevan, having limited financial resources and problems with air quality.

In the developed model, there are multiple interactions between agent-emissions and agent-trees that are complicating factors. However, using ordinary differential equations with a variable structure (Eq. (7), (8)) for modelling the dynamics of air pollutants interconnected with agent-trees allows significant simplification of the computation procedure and estimation of the objective functions (Eq. (12), (17)). When using emission plumes instead of agent-emissions, the model can be more realistic, but the computation process could be complicated because there is a need to solve more complex systems of differential equations describing appropriate dispersion processes for each tree cluster connected with air pollution over continuous time.

Within the considered problem, the computed configurations of tree clusters are described by the following set of decision variables: $\{cnf_\varsigma(t_0),\ tp_\varsigma(t_0), \delta_\varsigma(t_0),\ \tilde{R}_\varsigma(t_0)\}$, where the pair $\{cnf_\varsigma(t_0),\ tp_\varsigma(t_0)\}$ are discrete variables and the pair $\{\delta_\varsigma(t_0),\ \tilde{R}_\varsigma(t_0)\}$ are continuous variables. The genetic algorithm (MAGAMO) is responsible for control of the tree cluster configurations on the individual level. Configuration samples of the suggested decision variables are presented in Fig. 5.

The optimisation of tree cluster configurations (e.g., the geometry of planting) is based on the control of agent-tree locations and their characteristics, instead of separate trees, to simplify the problem.

The values of the main parameters of the genetic optimisation algorithm are presented in Table 6. In the model, 83 tree clusters were created around the main sources of emissions (agent-enterprises located in Yerevan) to solve Problem A.

Solving the considered optimisation problems involves significant computational complexity due to the calculation time of the objective functions being significant (over 10 min for each simulation run). This is caused by the complex interaction mechanism between agent-trees and agent-emissions described by the system of differential equations with variable structures.

The main steps of the heuristic optimisation of tree cluster configurations are the following:

- **Step 0.** Code chromosomes to represent the decision variable values with following distribution between all agent-processes of the GA responsible for the evolution of personal tree clusters.

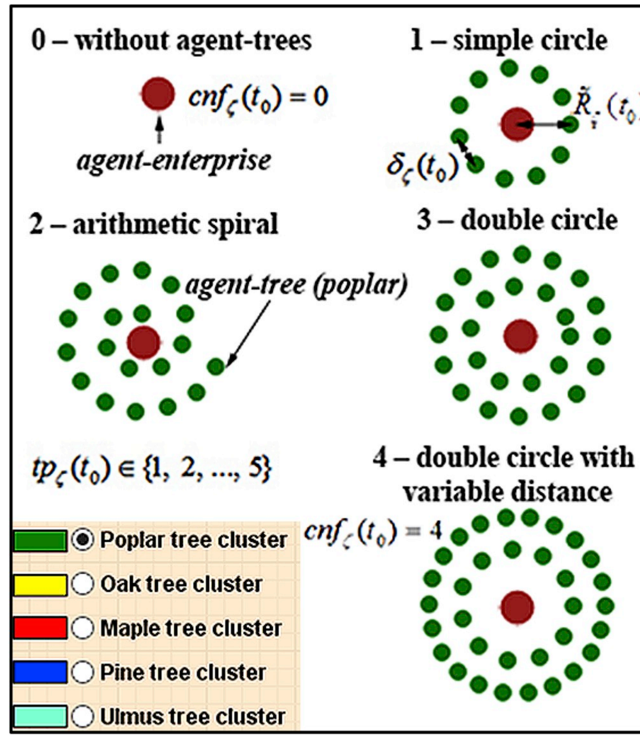

Fig. 5. Configurations of tree clusters.

Table 6
Main parameters of the heuristic optimisation algorithm.

Parameters	Values
Number of objectives	2
Number of decision variables	4 × 83
Number of user agent-processes in the parallel GA	83
Operator of crossover	two-point crossover
Number of parents	3
Number of offspring	15
Probability of mutation	0.0001
Minimum convergence	10^{-5}
Maximum generations (per process)	1000
Minimum number of Pareto optimal solutions that should be obtained	20

- **Step 1.** Form the initial population of solutions with estimations of fitness functions, which are the results of the simulation (Eqs. (1-17)). Create the initial global archive of non-dominated solutions for all tree clusters.

For each agent-process, the following evolutionary steps should be completed:

- **Step 2.** Select parents from the archive of non-dominated solutions with the highest Pareto ranking and located sufficiently remote from each other to avoid inbreeding.
- **Step 3.** Perform the crossover and mutation to generate offspring.
- **Step 4.** Run the simulation (Eqs. (1-17)) to obtain values of fitness functions, taking into account all constraints. Reject the solution without waiting for the end of the simulation process if any constraint has been exceeded.
- **Step 5.** Send the best decisions for personal tree clusters from the local population to the global archive of non-dominated solutions with an estimation of the Pareto ranking. Retrieve the best decisions for other tree clusters from the global archive of non-dominated solutions.

- **Step 6.** If the minimum convergence of GA and the minimum needed number of Pareto optimal solutions in the global archive are not reached, repeat **Steps 2–5.**

2.4. Software

The simulation model was developed using the AnyLogic tool aggregated with other components, such as the database and genetic algorithm. At the current time, the software has not been shared for global users, and it is implemented as the regional decision-making system for Yerevan, Armenia.

The model is available online at: http://www.runmycode.org/companion/view/3420.

The software allows conduction of multiple optimisation experiments using real data for different scenarios of urban greenery for reducing the daily concentration of air pollution. The model consists of two levels. The first is the top-level dashboard used for the setup of control parameters (Fig. 6).

As shown in Fig. 6, a decision maker can set up values of the control parameters, such as the configuration of tree clusters both in a united configuration for all agent-enterprises that should be surrounded by agent-trees and in individual configurations of tree clusters previously computed using the genetic optimisation algorithm (the MAGAMO) with selection of optimal scenarios on the Pareto front.

An illustration of the air pollution dynamics in the city of Yerevan during the first seven days after emissions is shown in Fig. 7 in more detail. Here, agent-emissions are denoted by black points and agent-trees are denoted by yellow, red and green circles, depending on agent-tree kind. As can been seen from Fig. 7, tree clusters are natural barriers for agent-emissions.

At least 13 546 agents are simulated in the system, which include agent-emissions, agent-trees, agent-enterprises and agent-vehicles.

3. Results and model validation

3.1. Results

Simulation experiments consisted of two parts. The first block is related to solving Problem A, i.e., the minimisation of the average daily pollution concentration and the greenery budget through planting tree clusters around agent-enterprises that are the main stationary sources of air pollutants.

The results of the simulation for the first problem are presented in Figs. 8–13.

The Pareto front computed with MAGAMO for the considered optimisation Problem A is shown in Fig. 8.

At least 500 simulation runs with a thousand internal iterations of the MAGAMO were completed to form the sustainable Pareto front shown in Fig. 8. The quality of the Pareto optimal decisions was estimated using different known methods, such as the hypervolume metric and the space between decisions. The area of the best decision was selected, with which the decision maker can obtain acceptable reduction of the average daily pollution concentration in the range of 0.05–0.07 me/m^3 with the minimum greenery budget (2.95–6.32 mUSD).

Equal values of weight coefficients reflecting the importance of each air pollutant for a decision maker were used.

The results obtained for Problem A using the genetic algorithm show that over 20 Pareto optimal solutions were obtained, and 3 scenarios were selected as the final decisions.

- **Scenario 1.** *Expensive complex greenery.* This scenario assumed forming tree clusters planting around agent-enterprises using mainly complex configurations such as regular circles, double circles and double circles with variable distances between agent-trees, which require many trees and a significant greenery budget. The

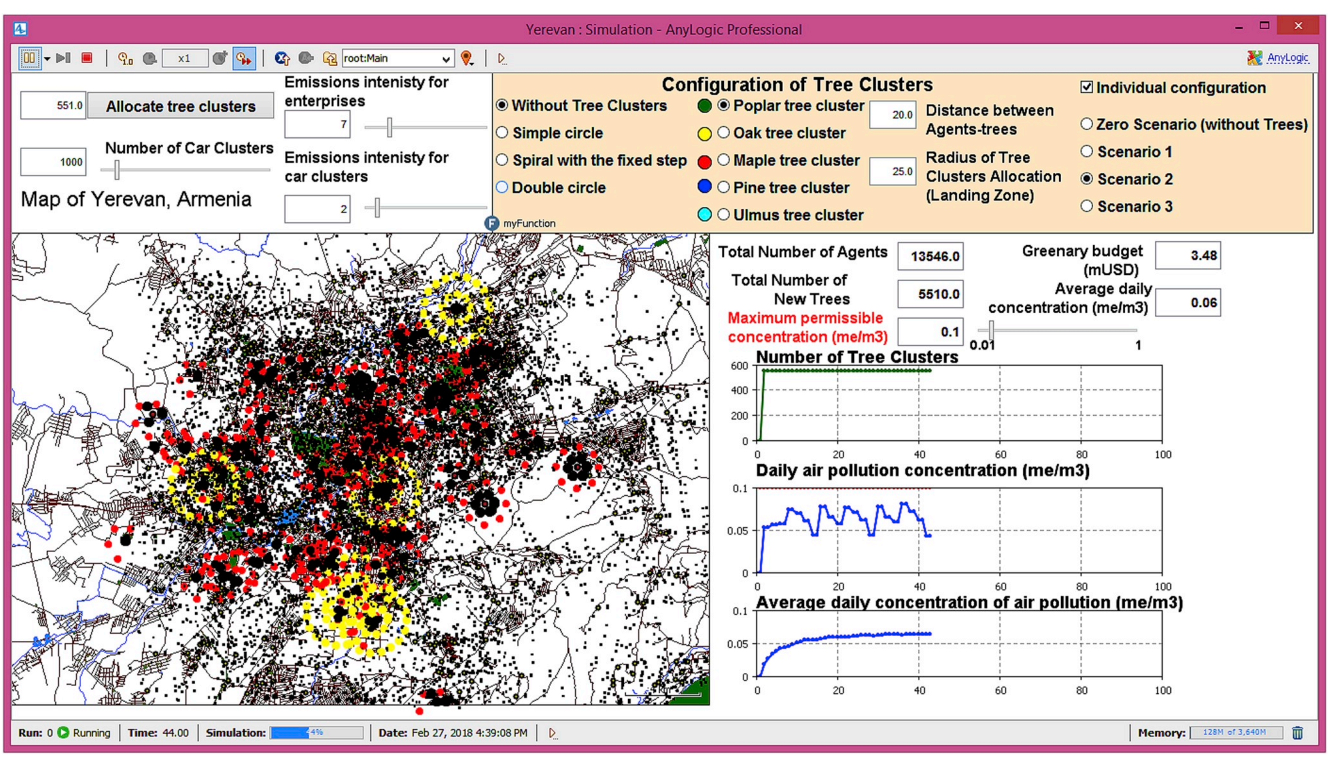

Fig. 6. The dashboard of the developed simulation in the AnyLogic tool.

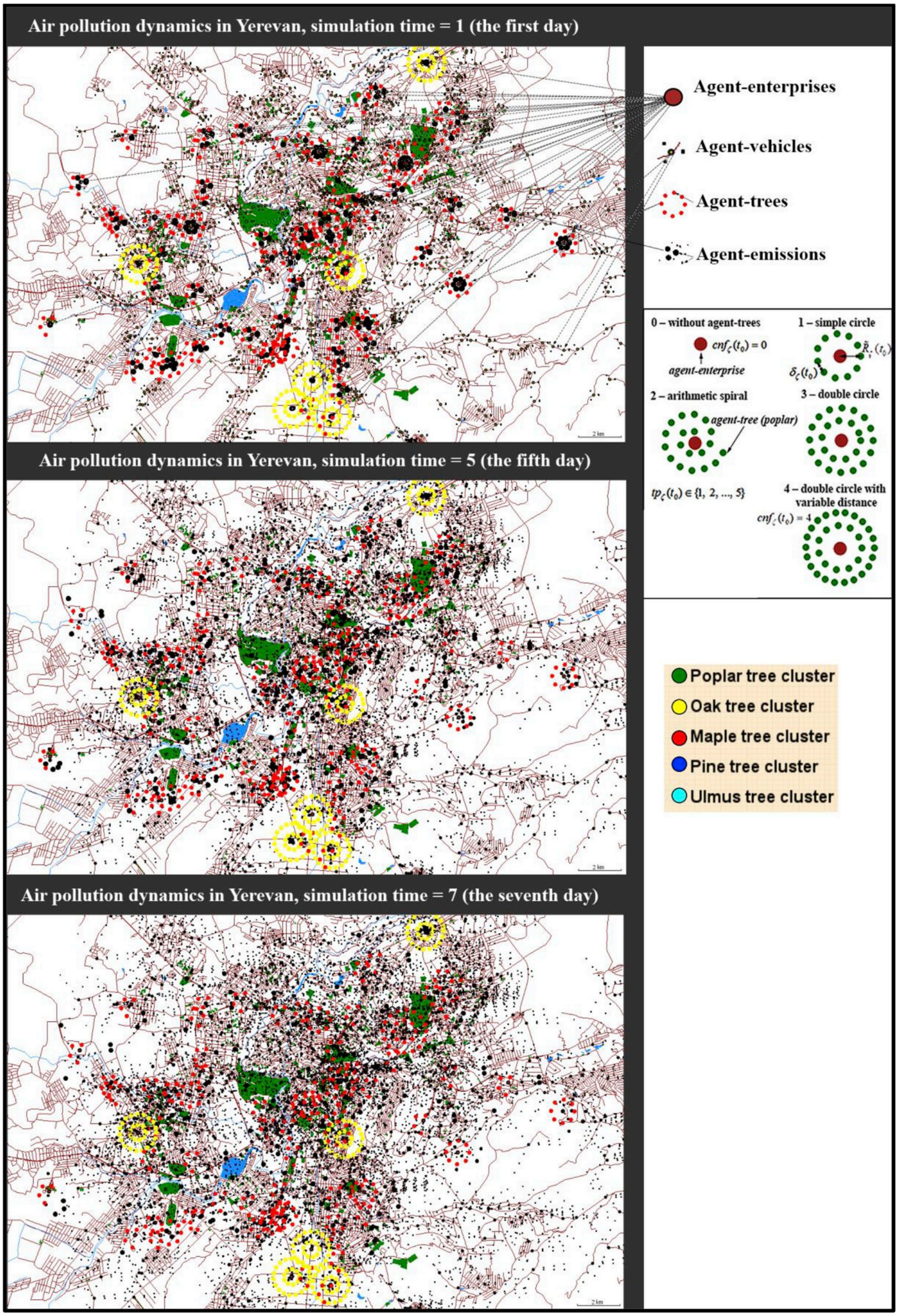

Fig. 7. Illustration of the air pollution dynamics in the city of Yerevan.

considered trees are mainly poplar and oak. Additionally, the configurations of tree clusters are different for each agent-enterprise. The maximum effect on reducing the daily pollution concentration is expected.

- **Scenario 2.** *Compromise greenery.* This scenario assumed using mainly individual configurations of tree clusters such as simple circles and arithmetic spirals, which require an average number of agent-trees and a more preferable size of the greenery budget. The considered trees are mainly maple and oak for each agent-enterprise (Appendix A). An acceptable and sustainable reduction of the daily pollution concentration is expected.
- **Scenario 3.** *Inexpensive greenery.* This scenario assumed using mainly individual configurations of tree clusters such as arithmetic spirals, which require the fewest number of agent-trees and the

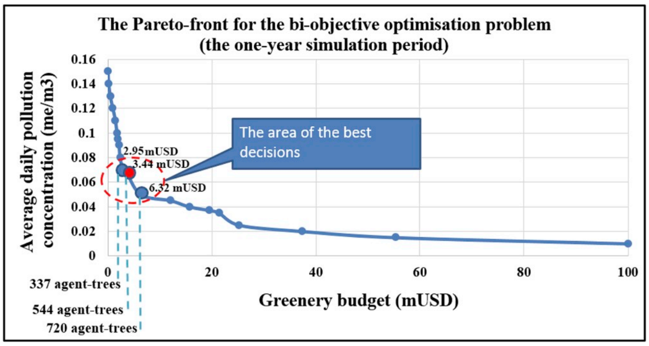

Fig. 8. The Pareto front for the considered bi-objective optimisation problem for the minimisation of the average daily pollution concentration.

minimum possible size of the greenery budget. The considered trees are mainly poplar for each agent-enterprise. An unsustainable reduction of the daily pollution concentration to less than the maximum permissible level of the air pollution concentration is expected.

Table 7 shows the numbers of agent-trees and separate trees and the amount of greenery budget (*GB*) defined by solving Problem A using the suggested GA. Here, the distance between the nearest agent-trees (consisting of 10 closely located trees) is 200 m and the radius of planting zones is 250 m for all tree cluster configurations (e.g., simple circle, double circle).

Table 8 shows the simulation results obtained using different configurations of tree clusters consisting of different tree kinds for Problem A.

As seen in Table 8, the individual configurations of tree clusters obtained for Scenario 2 are the most preferable in conditions of greenery budget deficit.

The configurations of tree cluster planting around agent-enterprises obtained for these scenarios are illustrated in Figs. 9–11 using a map of Yerevan, Armenia.

Here, poplar tree clusters are denoted by green circles, oak tree clusters are denoted by yellow circles, maple tree clusters are denoted by red circles, pine tree clusters are denoted by blue circles, ulmus tree clusters are denoted by aquamarine circles and agent-emissions are denoted by black points.

For the scenarios considered, the dynamics of the daily air pollution concentration were computed and are shown in Fig. 12. As shown in Fig. 12, Scenario 1 gives the greatest reduction in the daily air pollution concentration while maintaining a significant reserve compared to the maximum permissible concentration (0.1 me/m^3). Scenario 2 is characterised by a smaller reduction of the daily air pollution concentration, though the daily air pollution is less than the maximum permissible concentration on any day. Scenario 3 is flawed because sometimes the daily air pollution concentration reaches the maximum permissible concentration; however, it can be considered if there is only a small budget available for greenery.

The dynamics of the average daily air pollution concentration (*ADC*) are presented in Fig. 13.

As shown in Fig. 13, the average daily air pollution concentration exceeds the maximum permissible concentration if there are not any tree clusters. Using the Pareto optimal solutions (scenarios) allows significant reduction of the average daily air pollution concentration.

The main reason why tree clusters allow for the reduction of the air pollution concentration is the interaction of agent-trees with agent-emissions to cause the ‘absorptive-diffusive’ effect. In addition, tree clusters separate streams of air pollutants, change their directions and block them in locations with emission sources.

The second block of simulation experiments is related to solving Problem B, i.e., minimisation of the average daily pollution concentration and the greenery budget through planting tree clusters around selected urban areas that should be protected from air pollutants using a case study of kindergartens in the city Yerevan, Armenia.

There were 2 scenarios obtained for Problem B:

- **Scenario 4.** This scenario assumed planting agent-trees around kindergartens without greenery near emissions sources. Additionally, individual configurations of tree clusters would be implemented for each kindergarten as regular circles, double circles and double circles with variable distances. Such tree clusters mainly consist of poplar, oak and ulmus.
- **Scenario 5.** This scenario assumed planting agent-trees around kindergartens and agent-enterprises at the same time. Thus, the greenery budget would be separated between planting around emissions sources and protected urban areas. Individual configurations of tree clusters would be implemented for each kindergarten. Such tree clusters consist trees of different kinds of trees, dominated by maple and oak.

In Fig. 14 is presented the first optimisation scenario (Scenario 4), where agent-trees are planted around protected urban areas (kindergartens) without greenery near emission sources. Here, mainly simple

Table 7
Optimal numbers of agent-trees and greenery budget values for Problem A(planting around agent-enterprises).

Scenarios	Number of agent-trees	Number of trees	Greenery budget (mUSD)
Scenario 1. *Expensive complex greenery*	720	7200	6.32
Scenario 2. *Compromise greenery*	544	5440	3.44
Scenario 3. *Inexpensive greenery*	337	3370	2.95

Table 8
Average daily pollution concentration and greenery budget for Problem A(planting around agent-enterprises).

Configurations of tree clusters	Kind of trees	Average daily pollution concentration (me/m^3)	Greenery budget (mUSD)
Without tree clusters		0.153	0.00
Simple circle (for all tree clusters)	Poplar	0.052	5.98
	Oak	0.058	4.65
	Maple	0.064	3.98
	Pine	0.063	6.64
	Ulmus	0.051	6.64
Arithmetic spiral (for all tree clusters)	Poplar	0.076	2.99
	Oak	0.088	2.32
	Maple	0.098	1.99
	Pine	0.089	3.32
	Ulmus	0.079	3.32
Double circle (for all tree clusters)	Poplar	0.023	11.95
	Oak	0.030	9.30
	Maple	0.040	7.97
	Pine	0.041	13.28
	Ulmus	0.028	13.28
Double circle with variable distances between agent-trees (for all tree clusters)	Poplar	0.019	17.93
	Oak	0.025	13.94
	Maple	0.024	11.95
	Pine	0.024	19.92
	Ulmus	0.021	19.92
Scenario 1	different trees	0.048	6.32
Scenario 2	different trees	0.064	3.44
Scenario 3	different trees	0.069	2.95

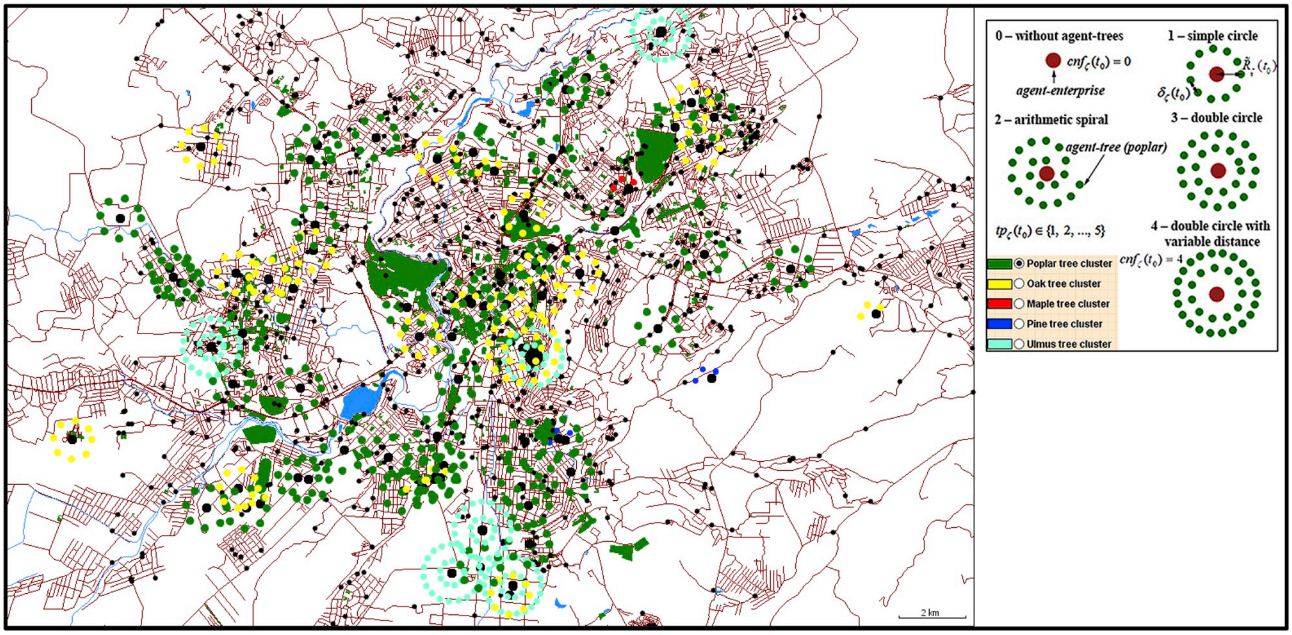

Fig. 9. Configurations of tree clusters obtained for the first scenario, '*Expensive complex greenery*'.

circles and arithmetic spirals are used. Additionally, poplar, oak and ulmus tree clusters dominate. The considered scenario provides significant reduction of the average daily pollution concentration to a value comparable to that achieved by planting around agent-enterprises. The other approach includes planting agent-trees around kindergartens and agent-enterprises simultaneously. This is the balanced and more preferable optimisation scenario.

Table 9 shows the numbers of agent-trees, tree kinds and the greenery budget ($GB*$) defined by solving Problem B using the suggested GA.

Table 10 shows the simulation results obtained using different configurations of tree clusters consisting of different tree kinds for Problem B. Here, the base distance between the nearest agent-trees (consisting of closely located trees) is 60 m and the radius of planting zones is 120 m for all tree cluster configurations (e.g., simple circle, double circle).

In comparison with planting agent-trees around agent-enterprises only (Scenarios 1–3), a much greater number of trees and a higher greenery budget are needed to minimise the average daily pollution concentration (Scenario 4). The main reason that the protection of kindergartens from air pollutants requires more agent-trees is that in the absence of agent-trees around agent-enterprises, appropriate pollutants reach areas of kindergartens faster without absorption. Additionally, unlike the central monitoring station, many kindergartens are located near sources of emissions. Thus, the best strategy is planting agent-trees around kindergartens and agent-enterprises at the same

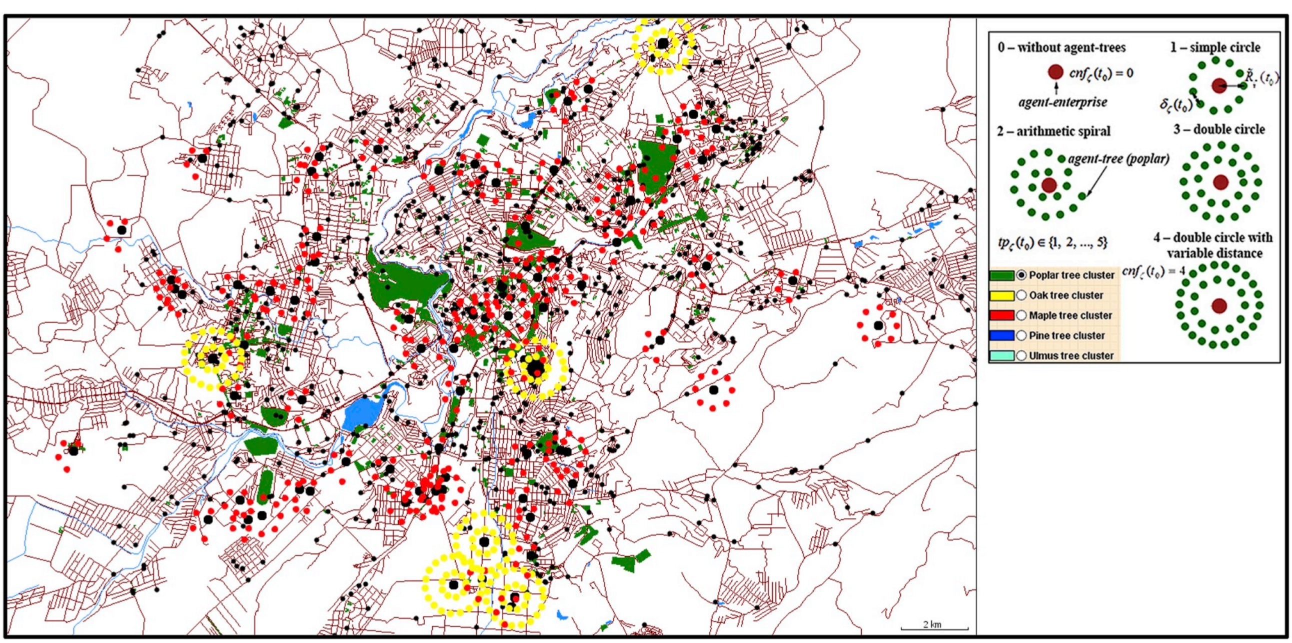

Fig. 10. Configurations of tree clusters obtained for the second scenario, '*Compromise greenery*'.

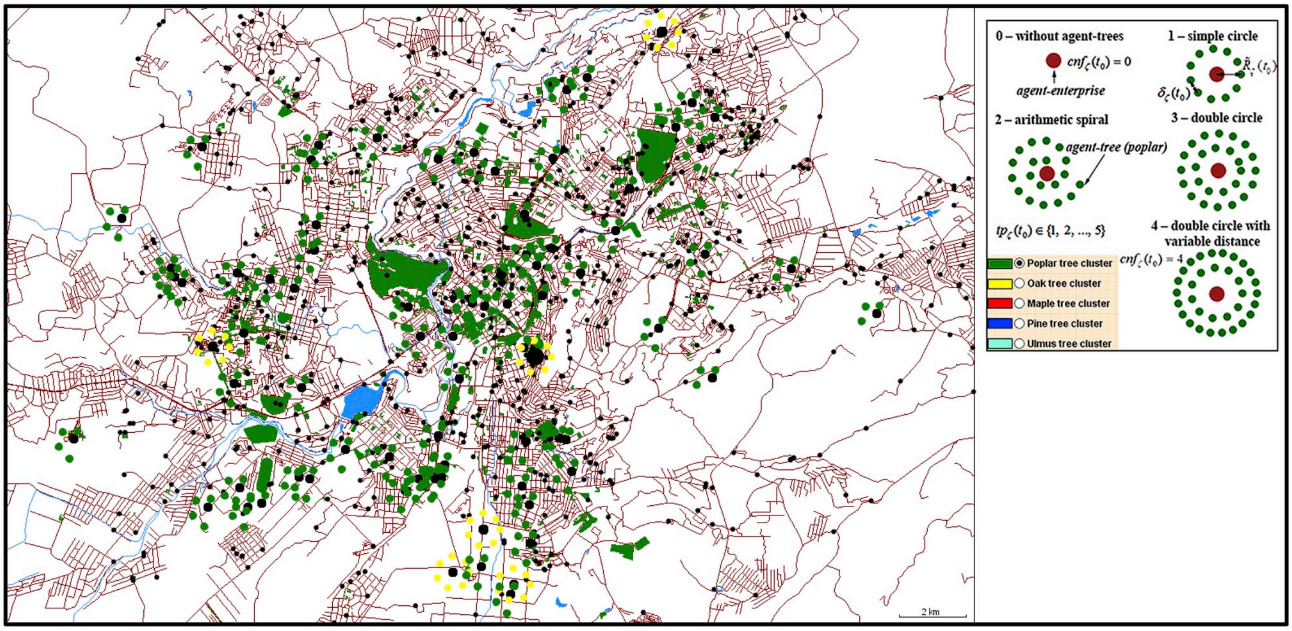

Fig. 11. Configurations of tree clusters obtained for the third scenario, '*Inexpensive greenery*'.

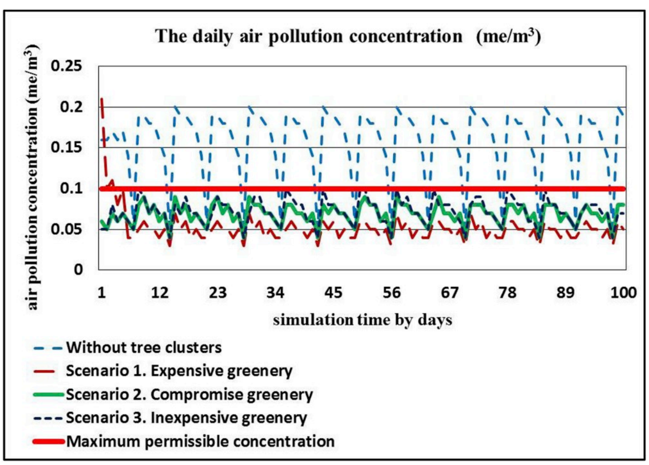

Fig. 12. The daily air pollution concentration.

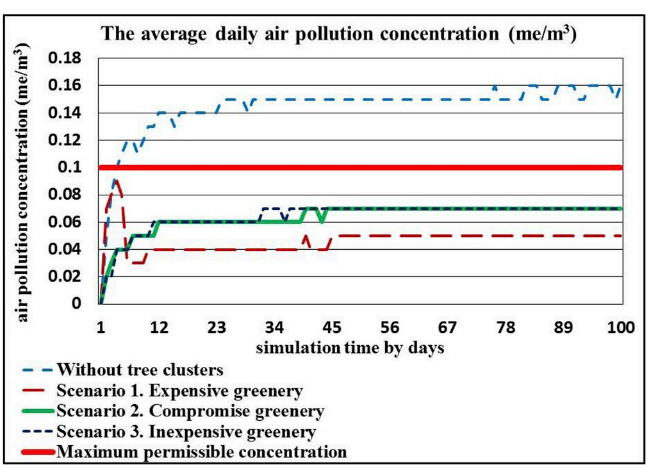

Fig. 13. The average daily air pollution concentration.

time (Scenario 5). In comparison with the strategy of planting around sources of emissions only discussed earlier, Scenario 5 is a more expensive but better approach for protection of the human population from air pollution.

The comparison of all considered scenarios is represented in Table 11.

As it can be seen as from Table 11, the scenario 5 is more preferable than scenarios 2–3 because it provides the lower level of the average daily pollution concentration (0.045 me/m3) with keeping the acceptable greenery budget (7.41 mUSD). In addition, the scenario 5 is better than scenario 4 because it needs the less greenery budget. It seems the effect of scenario 5 is similar with the results of the scenario 1 (expensive complex greenery). However, the average daily air pollution concentration is minimized in the observation zone of the monitoring station only in scenarios 1–3. In contrast, the daily air pollution concentration is minimized in multiple protected urban areas (near kindergartens) in scenarios 4–5. Hence, the last two scenarios can be considered as the more live safer and the reliability.

The model was validated using real data. The validation procedure was based on comparative analysis of the average daily air pollution concentration obtained through the developed simulation with real data collected in the selected monitoring station in Yerevan which records daily air quality readings.

3.2. Model validation

The developed simulation was validated using historical data recorded both in the zone of the monitoring station located in the centre of Yerevan, Armenia (scenario 2) and in protected kindergartens (scenario 5).

The forecasted errors are based on the following estimation using the known method of ordinary least squares.

The model error estimated in the area of the motoring station is:

$$\sqrt{\left(\frac{ADC-\widehat{ADC}}{\widehat{ADC}}\right)^2+\left(\frac{N-\widehat{N}}{\widehat{N}}\right)^2}\le\bar{\chi}_1, \tag{18}$$

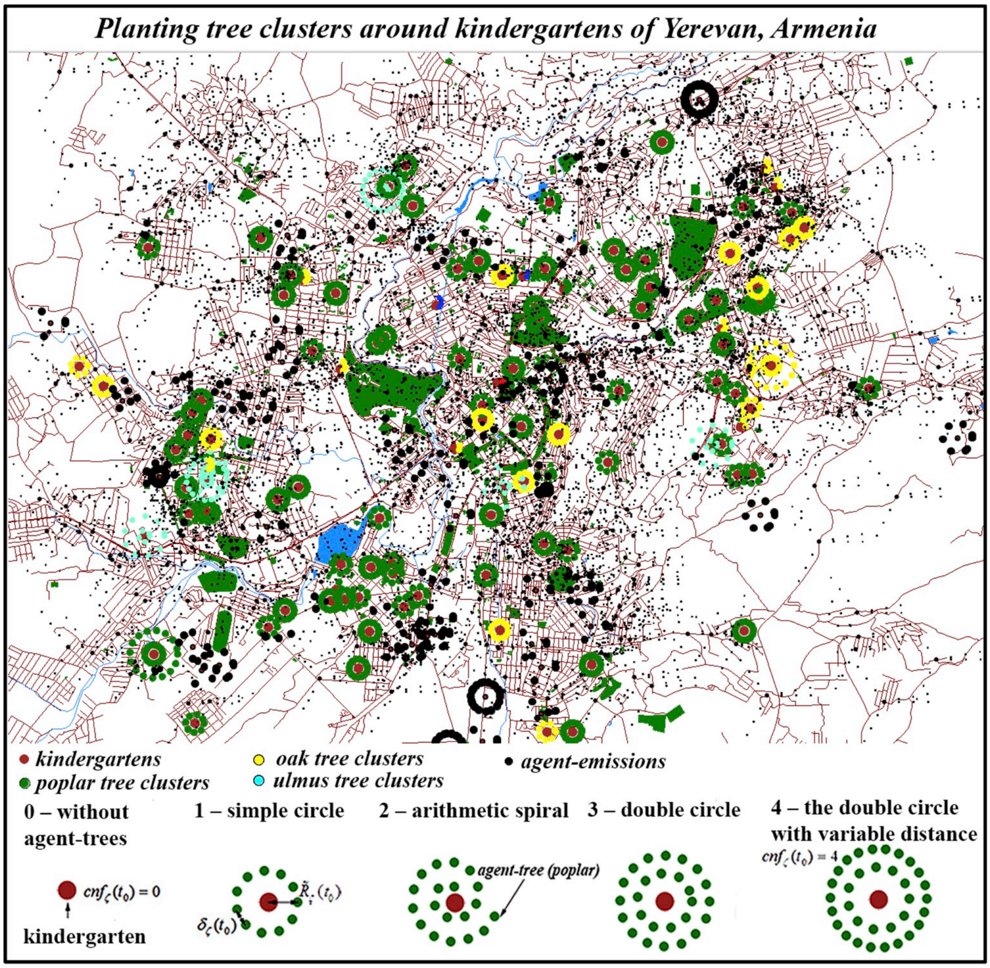

Fig. 14. Tree cluster configurations for planting around kindergartens of Yerevan, Armenia.

The model error estimated in protected urban areas (kindergartens) is:

$$\sqrt{\left(\frac{ADC* - \widehat{ADC*}}{\widehat{ADC*}}\right)^2 + \left(\frac{N* - \widehat{N}*}{\widehat{N}*}\right)^2} \leq \bar{\chi}_2, \tag{19}$$

where.

- $(ADC, \widehat{ADC}), (N, \widehat{N})$ are simulated and actual values of the average daily air pollution concentration in the area of the monitoring station (at the centre of the city) and the number of agent-trees, respectively;
- $(ADC*, \widehat{ADC}*), (N*, \widehat{N}*)$ are simulated and actual values of the average daily air pollution concentration in protected urban areas (kindergartens) and the number of agent-trees, respectively; and
- $\bar{\chi}_1$, $\bar{\chi}_2$ are the upper limits of the model error (10% and 5.14%, respectively).

Aggregated results of the model validation for selected scenarios 2 and 5 with using actual data for 2017 are presented in Table 12. These scenarios were implemented in practice in Yerevan, Armenia by 2017.

4. Discussion and conclusion

In this paper, a new approach to modelling the air pollution dynamics in a city with use of the agent-based model and heuristic optimisation was suggested. The main feature of the developed method involves the use of agent-trees interacting with agent-emissions, which describe the dynamics using a system of differential equations that consider absorptive-diffusive effects in real ecological systems. The research aims to solve the problem of optimal allocation and configuration of tree clusters in the city of Yerevan, Armenia to minimise the average daily pollution concentration observed in defined areas.

As was demonstrated in the work, there are two important optimisation problems in the minimisation of air pollution. The first involves reducing the air pollution concentration over a whole city through planting agent-trees around emission sources (Problem A). Some effective scenarios were computed for solving this problem (Tables 7–8 and Figs. 9–13). The second optimisation problem involves reducing the air pollution concentration in selected urban areas, e.g., planting agent-trees around kindergartens (Problem B). Two additional scenarios were computed for solving this problem (Tables 9 and 10 and Fig. 14), and one of the scenarios is the most preferable. This scenario

Table 9
Optimal numbers of agent-trees and greenery budget values for Problem B(planting around kindergartens).

Scenarios	Number of agent-trees	Number of trees	Greenery budget (mUSD)
Scenario 4. *Planting agent-trees around kindergartens without greenery near emission sources*	1441	14410	12.55
Scenario 5. *Planting agent-trees around kindergartens and agent-enterprises*	854	8540	7.41

Table 10
Average daily pollution concentration and greenery budget for Problem B(planting around kindergartens).

Configurations of tree clusters	Kind of trees	Average daily pollution concentration (me/m^3)	Greenery budget (mUSD)
Without tree clusters		0.127	0.00
Simple circle (for all tree clusters)	Poplar	0.053	9.71
	Oak	0.052	7.55
	Maple	0.054	6.47
	Pine	0.053	10.79
	Ulmus	0.059	10.79
Arithmetic spiral (for all tree clusters)	Poplar	0.081	2.24
	Oak	0.083	1.74
	Maple	0.093	1.49
	Pine	0.087	2.49
	Ulmus	0.082	2.49
Double circle (for all tree clusters)	Poplar	0.046	19.42
	Oak	0.047	15.11
	Maple	0.052	12.95
	Pine	0.051	21.58
	Ulmus	0.052	21.58
Double circle with variable distance between agent-trees (for all tree clusters)	Poplar	0.049	29.13
	Oak	0.051	22.66
	Maple	0.053	19.42
	Pine	0.051	32.37
	Ulmus	0.050	32.37
Scenario 4	different trees	0.032	12.55
Scenario 5	different trees	0.045	7.41

assumed planting agent-trees around kindergartens and agent-enterprises at the same time. Thus, the greenery budget would be separated between planting around emissions sources and protected urban areas. Such a greenery strategy is more effective because it requires a lower number of agent-trees while achieving low values of the average daily pollution concentration.

The important result of the research is the calculated greater efficiency of using combined configurations of tree clusters consisting of different kinds of trees and different geometries of planting (e.g., simple circle and arithmetic spiral) in comparison with using homogeneous configurations (Tables 8 and 10). This allows solving considered optimisation problems through the Pareto optimal solutions to provide the best decisions for reducing air pollution through agent-trees, which cannot be achieved by other means.

Thus, using the case study of the city of Yerevan in Armenia, the agent-based model allowed the Pareto optimal solution to be determined using a genetic algorithm. The system helped answer important questions about urban greenery, including where plants should be located in a city, which trees are better for reducing the air pollution concentration, how many tree clusters are needed and what is the optimal greenery budget (Tables 7–10 and Appendix A).

In comparison with other studies devoted to investigation of the influence of plants on air pollutant removal (e.g., Fuiii et al., 2005; Omasa et al., 2002; Bell and Treshow, 2002), this work focuses on the problem of interactions between air pollutants and greenery on a global scale including the whole city. Examination of the internal (chemical) processes of absorption of different air pollutants by different plants is outside the scope of the given work, but optimisation of the greenery strategy and control of the allocation of different tree clusters in the city taking into account the dynamics of air pollutants is a core focus of the presented investigation. Such an approach allows for the simulation of the dynamics of daily air pollution concentration taking into account

Table 11
Comparison of all considered scenarios.

Configurations of tree clusters	Number of trees	Average daily pollution concentration (me/m^3)	Greenery budget (mUSD)
Scenario 1. *Expensive complex greenery*	7200	0.048	6.32
Scenario 2. *Compromise greenery*	5440	0.064	3.44
Scenario 3. *Inexpensive greenery*	3370	0.069	2.95
Scenario 4. *Planting agent-trees around kindergartens without greenery near emission sources*	14410	0.032	12.55
Scenario 5. *Planting agent-trees around kindergartens and agent-enterprises*	8540	0.045	7.41

Table 12
Aggregated results of model validation.

Configurations of tree clusters	Simulated values		Actual values for 2017		Model error
	Number of agent-trees	Average daily pollution concentration (me/m^3)	Number of agent-trees	Average daily pollution concentration (me/m^3)	
Scenario 2. *Compromise greenery*	5440	0.064	5350	0.071	10.00%
Scenario 5. *Planting agent-trees around kindergartens and agent-enterprises*	8540	0.045	8300	0.047	5.14%

the combined influence of many other urban agents (factories, vehicles, trees, human populations) to protect both selected urban areas and the whole city.

There is still much worthwhile work to be investigated in the future. The most interesting and important research issues include 1) further specification of the model through including other agents, particularly agent-buildings, which can be additional natural barrier for air pollutants; 2) simulation of the strategy of vertical greening for tall buildings located near protected urban areas; 3) further refinement of the methodology for estimation of the air pollution concentration through improving the model of interaction between different air pollutants and taking into account the wide set of climate effects (e.g., temperature, air humidity, and wind turbulence); and 4) further improving the optimisation problems through taking into account the population distribution and the remoteness of different population clusters from emission sources.

Acknowledgements

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Appendix A. Optimal configurations of tree cluster planting around enterprises

No. of agent-enterprises	Coordinates of tree cluster centres		Optimal configurations of tree clusters			
	Longitude	Latitude	Geometry planting of agent-trees	Kind of trees	Distance between nearest agent-trees, metres	Radius of planting zone, metres
1	44.452886	40.185255	arithmetic spiral	maple	200	250
2	44.515191	40.186029	arithmetic spiral	maple	200	250
3	44.452882	40.185183	arithmetic spiral	maple	200	250
4	44.459556	40.183264	simple circle	maple	200	250
5	44.446861	40.138059	arithmetic spiral	maple	200	250
6	44.445827	40.174123	arithmetic spiral	maple	200	250
7	44.566993	40.221453	arithmetic spiral	maple	200	250
8	44.549951	40.203825	double circle	maple	200	250
9	44.508014	40.211234	arithmetic spiral	maple	200	250
10	44.521031	40.142562	arithmetic spiral	maple	200	250
11	44.400036	40.152160	arithmetic spiral	maple	200	250
12	44.518752	40.122132	double circle with variable distance	oak	200	250
13	44.518006	40.120192	arithmetic spiral	maple	200	250
14	44.485206	40.148622	arithmetic spiral	maple	200	250
15	44.460888	40.144316	arithmetic spiral	maple	200	250
16	44.427134	40.185669	arithmetic spiral	maple	200	250
17	44.461560	40.162804	arithmetic spiral	maple	200	250
18	44.489247	40.141717	arithmetic spiral	maple	200	250
19	44.572290	40.164796	simple circle	maple	200	250
20	44.532944	40.152099	simple circle	maple	200	250
21	44.546347	40.195269	arithmetic spiral	maple	200	250
22	44.500074	40.146946	arithmetic spiral	maple	200	250
23	44.499244	40.144289	simple circle	maple	200	250
24	44.507508	40.180254	simple circle	maple	200	250
25	44.490130	40.179375	arithmetic spiral	maple	200	250
26	44.523051	40.138597	arithmetic spiral	maple	200	250
27	44.473250	40.150027	arithmetic spiral	maple	200	250
28	44.429087	40.184458	arithmetic spiral	maple	200	250
29	44.426235	40.187411	arithmetic spiral	maple	200	250
30	44.507207	40.181125	arithmetic spiral	maple	200	250
31	44.464907	40.191119	arithmetic spiral	maple	200	250
32	44.529165	40.191523	arithmetic spiral	maple	200	250
33	44.502422	40.173353	arithmetic spiral	maple	200	250
34	44.493609	40.173447	arithmetic spiral	maple	200	250
35	44.450710	40.138904	simple circle	maple	200	250
36	44.525030	40.188061	simple circle	maple	200	250
37	44.526432	40.181716	arithmetic spiral	maple	200	250
38	44.502340	40.124714	double circle with variable distance	oak	200	250
39	44.412927	40.197716	arithmetic spiral	maple	200	250
40	44.593618	40.187313	arithmetic spiral	maple	200	250
41	44.570344	40.190286	arithmetic spiral	maple	200	250
42	44.549218	40.092105	arithmetic spiral	maple	200	250
43	44.529402	40.210127	arithmetic spiral	maple	200	250
44	44.523100	40.130684	arithmetic spiral	maple	200	250
45	44.509941	40.125821	arithmetic spiral	maple	200	250
46	44.498413	40.209968	arithmetic spiral	maple	200	250
47	44.444196	40.186415	arithmetic spiral	maple	200	250
48	44.481816	40.214362	arithmetic spiral	maple	200	250
49	44.436104	40.138133	arithmetic spiral	maple	200	250
50	44.533168	40.224208	arithmetic spiral	maple	200	250
51	44.531171	40.152329	arithmetic spiral	maple	200	250
52	44.536695	40.186394	arithmetic spiral	maple	200	250
53	44.493192	40.143951	arithmetic spiral	maple	200	250

54	44.558715	40.236147	double circle with variable distance	oak	200	250
55	44.524415	40.169180	double circle with variable distance	oak	200	250
56	44.569396	40.212193	arithmetic spiral	maple	200	250
57	44.534373	40.145602	arithmetic spiral	maple	200	250
58	44.466120	40.212868	arithmetic spiral	maple	200	250
59	44.522173	40.190181	arithmetic spiral	maple	200	250
60	44.572992	40.218547	arithmetic spiral	maple	200	250
61	44.557955	40.174979	arithmetic spiral	maple	200	250
62	44.465508	40.196313	arithmetic spiral	maple	200	250
63	44.510599	40.133524	double circle with variable distance	oak	200	250
64	44.516954	40.180059	simple circle	maple	200	250
65	44.521633	40.198632	arithmetic spiral	maple	200	250
66	44.494178	40.142460	simple circle	maple	200	250
67	44.538600	40.226738	arithmetic spiral	maple	200	250
68	44.562511	40.216550	arithmetic spiral	maple	200	250
69	44.463694	40.143946	arithmetic spiral	maple	200	250
70	44.498398	40.152903	arithmetic spiral	maple	200	250
71	44.434629	40.212409	arithmetic spiral	maple	200	250
72	44.464118	40.209714	arithmetic spiral	maple	200	250
73	44.521437	40.171011	simple circle	maple	200	250
74	44.513663	40.207475	simple circle	maple	200	250
75	44.504072	40.164685	arithmetic spiral	maple	200	250
76	44.521986	40.151798	arithmetic spiral	maple	200	250
77	44.444853	40.142108	arithmetic spiral	maple	200	250
78	44.616689	40.178025	simple circle	maple	200	250
79	44.498021	40.144575	arithmetic spiral	maple	200	250
80	44.510805	40.179524	arithmetic spiral	maple	200	250
81	44.437445	40.171254	double circle with variable distance	oak	200	250
82	44.497487	40.143960	arithmetic spiral	maple	200	250
83	44.443283	40.163645	arithmetic spiral	maple	200	250

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2019.02.003.

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