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Cluster-Based Optimization of an Evacuation Process Using a Parallel Bi-Objective Real-Coded Genetic Algorithm

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***Abstract*: *This work presents a novel approach to the design of a decision-making system for the cluster-based optimization of an evacuation process using a Parallel bi-objective Real-Coded Genetic Algorithm* (*P-RCGA*)*. The algorithm is based on the dynamic interaction of distributed processes with individual characteristics that exchange the best potential decisions among themselves through a global population. Such an approach allows the HyperVolume performance metric* (*HV metric*) *as reflected in the quality of the subset of the Pareto optimal solutions to be improved. The results of P-RCGA were compared with other well-known multi-objective genetic algorithms* (*e.g.,* ε *-MOEA, NSGA-II, SPEA2*)*. Moreover, P-RCGA was aggregated with the developed simulation of the behavior of human agent-rescuers in emergency through the objective functions to optimize the main parameters of the evacuation process.*

***Keywords*: *Cluster-based multi-objective optimization, human crowd behavior, real-coded genetic algorithms, multi-agent systems, fuzzy clustering.*

1. Introduction

Determining the best outcome of an evacuation in emergency is a topical issue. A great deal of research has been conducted in the field of modelling human crowd behavior in emergencies and the simulation of evacuation processes (e.g., [4, 7, 14, 21-23, 28]). There are medical facts that prove that a rapid evacuation is one of the most important factors for the survival rate of the patient population in emergency [15]. Therefore, the decision-making system of the effective evacuation process should be based on looking for the best trade-offs, maximizing the number of evacuated agents and minimizing the time for evacuation.

Studies by Dirk Helbing relating to the modelling the human crowd behavior are pioneering works. These have aimed at using simulation methods for identifying the best evacuation plans by taking panic into account. In one of his well-known works published in Nature [22], for the first time, it was possible to reproduce a number of crowd-specific phenomena, such as traffic jams, the involvement of new people in panic, and other effects based only on describing the interacting agents and their individual behavior at the molecular level. Molecular dynamics methods are used in Helbing's models in which psychological and social factors are considered as interaction potentials between human molecules. This approach, despite its many advantages, is not applicable practically for the optimization of real evacuation processes due to the high computational complexity associated with the increasing dimensionality of such a system.

Such difficulties can be overcome within the phenomenological approach, which is a simpler analogue description of the states of agents and their interactions. The approach was implemented in a study by Akopov and Beklaryan [4]. In the model, the states of agents and their characteristics, the rules of the agent interaction and the decision-making of agents are defined a priori. At the same time, the spatial dynamics of agents is described by a system of differential equations with variable structure that takes into account various scenarios for agents that are interacting with each other and with simple objects, such as column-obstacles. One of the model characteristics is the suggested definition of the personal space of an agent, which forms the phenomenon of the 'turbulence effect' of the crowd and panic. The advantage of the approach is the reduction in the computational complexity needed to determine the coordinates of moving agents whilst maintaining the accuracy of the behavior model of agents. In the model, a class of intellectual agents called agent-rescuers are responsible for the evacuation procedure based on computing crowd clusters formed because of panic and the attraction of agents to each other.

The computation procedure of crowd clusters is based on the suggested modified Fuzzy Clustering Algorithm (FCA) [8]. In this work, for the first time fuzzy clustering is used for the determination of crowd clusters in emergency taking into account natural restrictions for the evacuation (such as wall, obstacles, etc.) which can isolate individuals from their clusters. For the first time FCA was proposed by Bezdek [11, 12].

For the implementation of both – the model of evacuated agents and the model of agent-rescuer behavior, Agent-Based Modelling (ABM) (e.g., [2-4]) together with suggested bi-objective genetic algorithm are employed.

Developing effective Genetic Algorithms (GAs) that identify Pareto solutions in multi-objective optimization problems is a current theme of research in evolutionary computations with numerous applications in practice. As known, in most well-known Multi-Objective Evolutionary Algorithms (MOEAs), e.g., SPEA [32], SPEA2 [13], NSGA-II [16], and ε-MOEA [18], binary coding of chromosomes is used, as well as classic heuristic operators of binary crossover and mutation. However, the binary representation of chromosomes causes a significant loss in time-efficiency when searching in continuous spaces with large dimensionality when the demand for the precision of solutions is greatly required. The main problem is the dependency of the chromosome length on the required precision (the number of mantissa bits) in binary coding. At the same time, reducing the precision of solutions causes a reduction in the value of the HyperVolume metric (HV metric), which should be maximized in multi-objective minimization problems. Therefore, it has been suggested to use real-coded heuristic operators in multi-objective genetic algorithms.

The first RCGA (Real-Coded Genetic Algorithm) was developed by Herrera [24, 25] and is used for solving single objective optimization problems. Both binary genetic algorithms and real-coded genetic algorithms have many applications in technical systems and decision-making systems (e.g., [5, 10, 26, 29-31]). Real-coded genetic algorithms are characterized by the best precision of solutions looking in a continuous space.

An important direction for the application of RCGAs has been their use as a core in MOEAs to improve the precision of solutions and metrics such as hypervolume, rate of convergence, time processing and other characteristics.

Parallel RCGAs can be applied for solving large-scale black-box (i.e., derivative-free) optimization problems when the objective functions are computed as a result of simulation modelling. Examples of such approach are MAGAMO [6], MA-RCGA [1], and F-RCGA [9] where using interacting agent-processes allows for a significant improvement in the rate of convergence.

This work aims to design a parallel real-coded genetic algorithm for the cluster-based optimization of an evacuation process. The bi-objective box-constrained optimization problem for a model of human crowd behavior in emergency is formulated and solved using the suggested Parallel RCGA (P-RCGA). The first objective is the total number of evacuated agents that should be maximized and the second objective is the evacuation time that should be minimized.

2. Model of an evacuation process

Further, the abstract description of the suggested cluster-based model of agent-rescuer behavior and the solving of the bi-objective optimization problem will be considered. This model is based on phenomenological concepts of human crowd behavior in emergencies described in our previous studies [4, 8]. Here:

- T is the set of time moments (in minutes), and $|T|$ is the total number of time moments, $t_0 \in T$, $t_{|T|} \in T$ are the initial and finite time moments, $t_j \in T$, $j = 0, \ldots, |T|$ are all time moments;
- $I(t_j)$ is the set of indexes of usual agents that should be evacuated at moment t_j $(t_j \in T)$, and $|I(t_j)|$ is the total number of agents to be evacuated;
- $K(t_j)$ is the set of indexes of agent-rescuers that evacuate usual agents in emergency at moment t_j $(t_j \in T)$, and $|K(t_j)|$ is the total number of agent-rescuers;
- $C(t_j)$ is the set of indexes of crowd clusters at moment t_j $(t_j \in T)$ that are computed with the help of the previously suggested fuzzy clustering algorithm [8], and $|C(t_j)|$ is the total number of crowd clusters;

- $O(t_j)$ is the set of indexes of obstacles (e.g., column-obstacles, rectangle-obstacles, etc.) that can be located on the path of an agent at moment t_j $(t_j \in T)$, and $|O(t_j)|$ is the total number of obstacles;
- $\{\mathbf{X}_o(t_j),\ \mathbf{Y}_o(t_j)\}$ is the set of point coordinates belonging to the *o*-th obstacle $(o \in O(t_j))$ at moment t_j $(t_j \in T)$;
- $E(t_j)$ is the set of indexes of emergency exits at moment t_j $(t_j \in T)$, and $|E(t_j)|$ is the total number of emergency exits;
- $\{x_i(t_j),\ y_i(t_j)\ \}$, $\{\tilde{x}_k(t_j),\ \tilde{y}_k(t_j)\ \}$ are the coordinates of locations of usual agents $(i \in I(t_j))$ and agent-rescuers $(k \in K(t_j))$ at time t_j $(t_j \in T)$, respectively;
- $\{\hat{x}_{ic}(t_j),\ \hat{y}_{ic}(t_j)\ \}$ are the coordinates of the *c*-th crowd cluster $(c \in C(t_j))$ that is nearest to the *i*-th usual agent $(i \in I(t_j))$ at moment t_j $(t_j \in T)$;
- $\{\widehat{x}_{kc}(t_j),\ \widehat{y}_{kc}(t_j)\ \}$ are the coordinates of the *c*-th crowd cluster $(c \in C(t_j))$ that can be assigned to the *k*-th agent-rescuer $(k \in K(t_j))$ at moment t_j $(t_j \in T)$;
- $\{\breve{x}_{ke}(t_j),\ \breve{y}_{ke}(t_j)\ \} \in \{g_e,\ h_e\}$ are the coordinates of the center of the *e*-th emergency exit $(e \in E(t_j))$ that is the nearest to the *k*-th agent-rescuer $(k \in K(t_j))$ at moment t_j $(t_j \in T)$, $\{g_e,\ h_e\}$ is the set of coordinates of all emergency exits;
- $\{s_i(t_j),\ \tilde{s}_k(t_j)\}$ are the known speeds of the *i*-th usual agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$ at time t_j $(t_j \in T)$;
- $\{a_1,\ b_1\}$, $\{a_1,\ b_2\}$, $\{a_2,\ b_1\}$, $\{a_2,\ b_2\}$ are the coordinates of the rectangle tops in the two-dimensional space defined as the emergency area (Fig. 1).

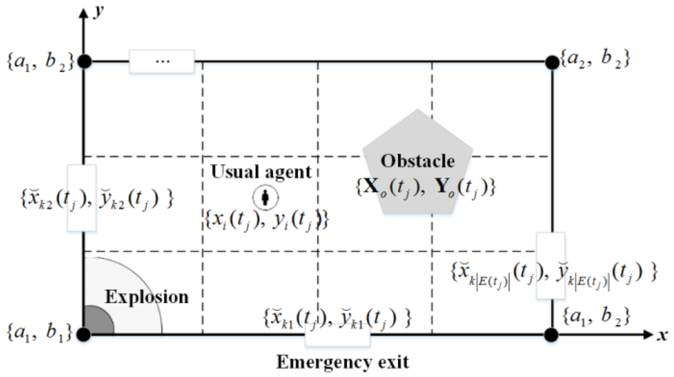

Fig. 1. Emergency area

- $\delta_i(t_j)$ is the Euclidean distance between the *i*-th usual agent $(i \in I(t_j))$ and the explosion epicenter having the internal radius $\hat{r}$ and the external radius $\widehat{R}$ at moment t_j $(t_j \in T)$ (Fig. 2);

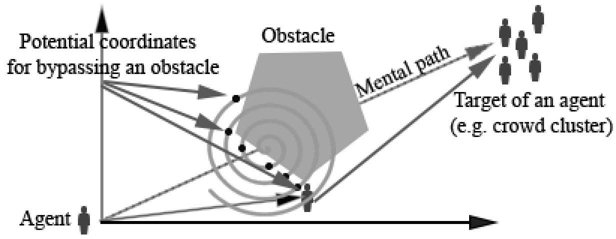

Fig. 2. An agent bypassing the nearest obstacle

- $p_i(t_j) \in [0,\ 1]$ is the known probability of destroying the *i*-th usual agent $(i \in I(t_j))$ due to the increase in the concentration of harmful substances in the air at moment t_j $(t_j \in T)$;
- $u_i(t_j) \in [0,\ 1]$ is a random number generated by the random-number generator;
- $\mathrm{st}_i(t_j) \in \{0,\ 1,\ 2,\ 3\}$ is the current state of the *i*-th usual agent $(i \in I(t_j))$ at moment t_j $(t_j \in T)$, $\mathrm{st}_i(t_j) = 0$ if the *i*-th usual agent is a normal state, i.e., it is not injured or destroyed, $\mathrm{st}_i(t_j) = 1$ if the *i*-th agent is injured and has a minimum speed, $\mathrm{st}_i(t_j) = 2$ if the *i*-th usual agent is destroyed, $\mathrm{st}_i(t_j) = 3$ if the *i*-th usual agent is evacuated (i.e., its coordinates are outside the emergency area); the transitions between these states depend on the location of the *i*-th usual agent in an emergency;
- $\mathrm{st}_k(t_j) \in \{0,\ 1,\ 2\}$ is the current state of the *k*-th agent-rescuer $(k \in K(t_j))$ at moment t_j $(t_j \in T)$, $\mathrm{st}_k(t_j) = 0$ if the agent-rescuer is moving towards the center of a crowd cluster to evacuate agents, $\mathrm{st}_k(t_j) = 1$ if the agent-rescuer is waiting for both uninjured agents and injured agents at the centre of a crowd cluster to collect them to start the evacuation, $\mathrm{st}_k(t_j) = 2$ if the agent-rescuer is moving towards the nearest emergency exit to evacuate the collected agents;
- $\tilde{\tau}_k(t_j)$ is the waiting time of the *k*-th agent-rescuer in the center of the crowd cluster while agents are collected to be evacuated;
- $\{\alpha_{ic}(t_j),\ \tilde{\alpha}_{kc}(t_j)\}$ are the angles of the motion directions of the *i*-th usual agent $(i \in I(t_j))$ towards the *c*-th crowd cluster $(c \in C(t_j))$ caused by the known "effect of crowd" [4], as well as the motion of the *k*-th agent-rescuer $(k \in K(t_j))$ towards the *c*-th crowd cluster $(c \in C(t_j))$ to evacuate agents, respectively;
- $\{\omega_{ik}(t_j),\ \tilde{\omega}_{ke}(t_j)\}$ are the angles of the motion directions of the *i*-th usual agent $(i \in I(t_j))$ towards the *k*-th agent-rescuer, as well as the motion of the *k*-th agent-rescuer $(k \in K(t_j))$ towards the *e*-th emergency exit $(e \in E(t_j))$, respectively;

- $\{\beta_{ip}(t_j),\ \tilde{\beta}_{kp}(t_j)\}$ are the angles of shifting the motion directions of the *i*-th agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$ regarding their previous directions caused by the nearest neighbor *p*-th agent $(p \in I(t_j))$ appearing on their paths;
- $\{\gamma_{io}(t_j),\ \tilde{\gamma}_{ko}(t_j)\}$ are the angles of the bypassing directions of the *i*-th usual agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$ around the nearest *o*-th obstacle $(o \in O(t_j))$;
- $\{\overline{x}_i^q(t_j),\ \overline{y}_i^q(t_j)\}$, $\{\overline{x}_k^q(t_j),\ \overline{y}_k^q(t_j)\}$ are the coordinates of the *i*-th usual agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$ moving along the mental path towards their targets at moment $t_j\ (t_j \in T)$, and $q = 1,\ 2\ ...,\ Q$ is the index of internal iterations, Q is the total number of iterations, e.g.,

$$\overline{x}_i^q(t_j) = \overline{x}_i^{q-1}(t_j) + s_i(t_j)\cos\alpha_{ic}(t_j),$$
$$\overline{y}_i^q(t_j) = \overline{y}_i^{q-1}(t_j) + s_i(t_j)\sin\alpha_{ic}(t_j);$$

- $\tilde{R}_k(t_j)$ is the radius of the visibility zone of the *k*-th agent-rescuer $(k \in K(t_j))$ that defines the ability of usual agents to find it in an emergency;
- $\{d_{ip}(t_j),\ d_{kp}(t_j)\}$ are the distances between the *i*-th usual agent $(i \in I(t_j))$ or the *k*-th agent-rescuer $(k \in K(t_j))$ and the nearest neighbor *p*-th agent $(p \in I(t_j))$;
- $\tilde{d}_{ik}(t_j)$ is the distance between the *i*-th usual agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$;
- $\{r_i(t_j),\ \tilde{r}_k(t_j)\}$ are the radiuses of personal spaces of the *i*-th usual agent $(i \in I(t_j))$ and the *k*-th agent-rescuer $(k \in K(t_j))$, depending on the density of agents around an appropriate agent at moment $t_j\ \ (t_j \in T)$:

(1)
$$r_i(t_j) = \begin{cases} r_i(0) \ \text{ if } \rho_i(t_j) \le \rho_1, \\ r_i(0)/2 \ \text{ if } \rho_1 < \rho_i(t_j) \le \rho_2, \\ r_i(0)/4 \ \text{ if } \rho_2 < \rho_i(t_j) \le \rho_3, \\ 2r_i(0) \ \text{ if } \rho_3 < \rho_i(t_j), \end{cases}$$

where ρ_1, ρ_2, ρ_3 are fixed threshold densities of agents, $r_i(0)$ is the initial radius of an agent, and $\rho_i(t_j)$ is the density of agents around the *i*-th usual agent $(i \in I(t_j))$,

(2)
$$\rho_i(t_j) = \sum_{i=1}^{|I(t_j)|} m_i(t_j),$$

where $\hat{\delta}_{ip}(t_j)$ is the Euclidean distance between the i-th usual agent $(i \in I(t_j)$ and the neighboring p-th agent $(p \in I(t_j))$ that is located inside the circle with a fixed radius of R_i with the coordinates of the center at $\{x_i(t_j),\ y_i(t_j)\}$.

The spatial dynamics of i-ths usual agents $(i \in I(t_j))$ is described by the following system of finite difference equations with the variable structure at moment t_j $(t_j \in T)$:

$$x_i(t_j) = \begin{cases} x_i(t_{j-1}) + s_i(t_{j-1})\cos\alpha_{ic}(t_{j-1}) \text{ if I is true,} \\ x_i(t_{j-1}) + s_i(t_{j-1})\cos\left(\alpha_{ic}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if II is true,} \\ x_i(t_{j-1}) + s_i(t_{j-1})\cos\omega_{ik}(t_{j-1}) \text{ if III is true,} \\ x_i(t_{j-1}) + s_i(t_{j-1})\cos\left(\omega_{ik}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if IV is true,} \\ x_i(t_{j-1}) + s_i(t_{j-1})\cos\gamma_{io}(t_{j-1}) \text{ if V is true,} \\ x_i(t_{j-1}) + s_i(t_{j-1})\cos\left(\gamma_{io}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if VI is true,} \\ 0 \text{ if VII is true,} \end{cases} \tag{3}$$

$$y_i(t_j) = \begin{cases} y_i(t_{j-1}) + s_i(t_{j-1})\sin\alpha_{ic}(t_{j-1}) \text{ if I is true,} \\ y_i(t_{j-1}) + s_i(t_{j-1})\sin\left(\alpha_{ic}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if II is true,} \\ y_i(t_{j-1}) + s_i(t_{j-1})\sin\omega_{ik}(t_{j-1}) \text{ if III is true,} \\ y_i(t_{j-1}) + s_i(t_{j-1})\sin\left(\omega_{ik}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if IV is true,} \\ y_i(t_{j-1}) + s_i(t_{j-1})\sin\gamma_{io}(t_{j-1}) \text{ if V is true,} \\ y_i(t_{j-1}) + s_i(t_{j-1})\sin\left(\gamma_{io}(t_{j-1}) \pm \beta_{ip}(t_{j-1})\right) \text{ if VI is true,} \\ 0 \text{ if VII is true.} \end{cases} \tag{4}$$

Here:

I. $\tilde{d}_{ik}(t_{j-1}) > \tilde{R}_k(t_{j-1})$ for any $k \in K(t_j)$ and $d_{ip}(t_{j-1}) > \left(r_i(t_{j-1}) + r_p(t_{j-1})\right)$ for all $p \in I(t_{j-1})$ and $\left(\overline{x}_i^q(t_{j-1}) \notin \mathbf{X}_o(t_{j-1}) \text{ and } \overline{y}_i^q(t_{j-1}) \notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

II. $\tilde{d}_{ik}(t_{j-1}) > \tilde{R}_k(t_{j-1})$ for any $k \in K(t_{j-1})$ and $d_{ip}(t_{j-1}) \le \left(r_i(t_{j-1}) + r_p(t_{j-1})\right)$ for the nearest $p \in I\left(r_i(t_{j-1}) + r_p(t_{j-1})\right)$ and $\left(\overline{x}_i^q(t_{j-1}) \notin \mathbf{X}_o(t_{j-1}) \text{ and } \overline{y}_i^q(t_{j-1}) \notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

III. $\tilde{d}_{ik}(t_{j-1}) \le \tilde{R}_k(t_{j-1})$ for the nearest $k \in K(t_j)$ and $d_{ip}(t_{j-1}) > (r_i(t_{j-1}) + r_p(t_{j-1}))$ for all $p \in I(t_{j-1})$ and

$\left(\bar{x}_i^q(t_{j-1}) \notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_i^q(t_{j-1}) \notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

IV. $\tilde{d}_{ik}(t_{j-1}) \le \tilde{R}_k(t_{j-1})$ for the nearest $k \in K(t_j)$ and $d_{ip}(t_{j-1}) \le (r_i(t_{j-1}) + r_p(t_{j-1}))$ for the nearest $p \in I(t_{j-1})$ and $\left(\bar{x}_i^q(t_{j-1}) \notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_i^q(t_{j-1}) \notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

V. $d_{ip}(t_{j-1}) > (r_i(t_{j-1}) + r_p(t_{j-1}))$ for all $p \in I(t_{j-1})$ and $\left(\bar{x}_i^q(t_{j-1}) \in \mathbf{X}_k(t_{j-1}) \text{ and } \bar{y}_i^q(t_{j-1}) \in \mathbf{Y}_k(t_{j-1})\right)$ at least for one $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

VI. $d_{ip}(t_{j-1}) \le (r_i(t_{j-1}) + r_p(t_{j-1}))$ for the nearest $p \in I(t_{j-1})$ and $\left(\bar{x}_i^q(t_{j-1}) \in \mathbf{X}_k(t_{j-1}) \text{ and } \bar{y}_i^q(t_{j-1}) \in \mathbf{Y}_k(t_{j-1})\right)$ at least for one $q = 1,\ 2\ ...,\ Q$ and $\mathrm{st}_i(t_{j-1}) \notin \{2,\ 3\}$,

VII. $\mathrm{st}_i(t_{j-1}) \in \{2,\ 3\}$.

The spatial dynamics of k-ths agent-rescuers $(k \in K(t_j))$ is described by the following system of finite difference equations with the variable structure at moment $t_j\ (t_j \in T)$:

$$(5) \qquad \tilde{x}_k(t_j) = \begin{cases} \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos \tilde{\alpha}_{kc}(t_{j-1}) \text{ if VIII is true,} \\ \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos\left(\tilde{\alpha}_{kc}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if IX is true,} \\ \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos \tilde{\omega}_{ke}(t_{j-1}) \text{ if X is true,} \\ \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos\left(\tilde{\omega}_{ke}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if XI is true,} \\ \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos \tilde{\gamma}_{ko}(t_{j-1}) \text{ if XII is true,} \\ \tilde{x}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \cos\left(\tilde{\gamma}_{ko}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if XIII is true,} \\ 0 \text{ if XIV is true,} \end{cases}$$

$$(6) \qquad \tilde{y}_k(t_j) = \begin{cases} \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin \tilde{\alpha}_{kc}(t_{j-1}) \text{ if VIII is true,} \\ \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin\left(\tilde{\alpha}_{kc}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if IX is true,} \\ \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin \tilde{\omega}_{ke}(t_{j-1}) \text{ if X is true,} \\ \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin\left(\tilde{\omega}_{ke}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if XI is true,} \\ \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin \tilde{\gamma}_{ko}(t_{j-1}) \text{ if XII is true,} \\ \tilde{y}_k(t_{j-1}) + \tilde{s}_i(t_{j-1}) \sin\left(\tilde{\gamma}_{ko}(t_{j-1}) \pm \tilde{\beta}_{kp}(t_{j-1})\right) \text{ if XIII is true,} \\ 0 \text{ if XIV is true,} \end{cases}$$

where

VIII. $\mathrm{st}_k(t_{j-1})=0$ and $d_{kp}(t_{j-1})>(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for all $p\in I(t_{j-1})$ and $\left(\bar{x}_k^q(t_{j-1})\notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q=1,\ 2\ ...,\ Q$,

IX. $\mathrm{st}_k(t_{j-1})=0$ and $d_{kp}(t_{j-1})\le(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for all $p\in I(t_{j-1})$ and $\left(\bar{x}_k^q(t_{j-1})\notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q=1,\ 2\ ...,\ Q$,

X. $\mathrm{st}_k(t_{j-1})=2$ and $d_{kp}(t_{j-1})>(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for all $p\in I(t_{j-1})$ and $\left(\bar{x}_k^q(t_{j-1})\notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q=1,\ 2\ ...,\ Q$,

XI. $\mathrm{st}_k(t_{j-1})=2$ and $d_{kp}(t_{j-1})\le(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for all $p\in I(t_{j-1})$ and $\left(\bar{x}_k^q(t_{j-1})\notin \mathbf{X}_o(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\notin \mathbf{Y}_o(t_{j-1})\right)$ for all $q=1,\ 2\ ...,\ Q$,

XII. $d_{kp}(t_{j-1})>(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for all $p\in I(\xi)$ and $\left(\bar{x}_k^q(t_{j-1})\in \mathbf{X}_k(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\in \mathbf{Y}_k(t_{j-1})\right)$ at least for one $q=1,\ 2\ ...,\ Q$ and $\mathrm{st}_k(t_{j-1})\ne 1$,

XIII. $d_{kp}(t_{j-1})\le(\tilde{r}_k(t_{j-1})+r_p(t_{j-1}))$ for the nearest $p\in I(t_{j-1})$ and $\left(\bar{x}_k^q(t_{j-1})\in \mathbf{X}_k(t_{j-1}) \text{ and } \bar{y}_k^q(t_{j-1})\in \mathbf{Y}_k(t_{j-1})\right)$ at least for one $q=1,\ 2\ ...,\ Q$ and $\mathrm{st}_k(t_{j-1})\ne 1$,

XIV. $\mathrm{st}_k(t_{j-1})=1$.

The angles of the motion direction of appropriate agents towards the *c*-th crowd cluster $(c\in C(t_j))$ at moment t_j $(t_j\in T)$ are:

$$\alpha_{ic}(t_j)=\arctan\frac{\hat{y}_{ic}(t_{j-1})-y_i(t_{j-1})}{\hat{x}_{ic}(t_{j-1})-x_i(t_{j-1})}, \tag{7}$$

$$\tilde{\alpha}_{kc}(t_j)=\arctan\frac{\widehat{y}_{kc}(t_{j-1})-y_i(t_{j-1})}{\widehat{x}_{kc}(t_{j-1})-x_i(t_{j-1})}, \tag{8}$$

$$i\in I(t_j),\quad k\in K(t_j).$$

The angles of shifting the motion directions of *i*-ths and *k*-ths agents $(i\in I(t_j),\ k\in K(t_j))$ regarding their previous directions caused by the nearest neighbor *p*-th agent $(p\in I(t_j))$ appearing at moment t_j $(t_j\in T)$ are:

$$\beta_{ip}(t_j)=\frac{\pi}{4}+\arctan\frac{y_p(t_{j-1})+r'_{ip}(t_{j-1})\sin(\pi/4)-y_i(t_{j-1})}{x_p(t_{j-1})+r'_{ip}(t_{j-1})\cos(\pi/4)-x_i(t_{j-1})}, \tag{9}$$

$$\tilde{\beta}_{kp}(t_{j-1})=\frac{\pi}{4}+\arctan\frac{y_p(t_{j-1})+r''_{kp}(t_{j-1})\sin(\pi/4)-\tilde{y}_k(t_{j-1})}{x_p(t_{j-1})+r''_{kp}(t_{j-1})\cos(\pi/4)-\tilde{x}_k(t_{j-1})}, \tag{10}$$

where

$$r'_{ip}(t_{j-1}) = r_i(t_{j-1}) + r_p(t_{j-1}) \,,$$
$$r''_{kp}(t_{j-1}) = \tilde{r}_k(t_{j-1}) + r_p(t_{j-1}) \,.$$

The angles of the motion directions of the *i*-th usual agent $(i \in I(t_j))$ towards the *k*-th agent-rescuer $(k \in K(t_j))$, as well as the motion of the *k*-th agent-rescuer $(k \in K(t_j))$ towards the *e*-th emergency exit $(e \in E(t_j))$ at moment t_j $(t_j \in T)$ are:

$$\omega_{ic}(t_j) = \arctan \frac{\hat{y}_{ic}(t_{j-1}) - y_i(t_{j-1})}{\hat{x}_{ic}(t_{j-1}) - x_i(t_{j-1})} \,, \tag{11}$$

$$\tilde{\omega}_{ke}(t_j) = \arctan \frac{\breve{y}_{ke}(t_{j-1}) - y_i(t_{j-1})}{\breve{x}_{ke}(t_{j-1}) - x_i(t_{j-1})} \,. \tag{12}$$

The angles of the bypassing directions of *i*-ths and *k*-ths agents $(i \in I(t_j),\ k \in K(t_j))$ around the nearest *o*-th obstacle $(o \in O(t_j))$ at moment t_j $(t_j \in T)$ are:

$$\gamma_{io}(t_j) = \arg\min \left| \alpha_i^*(t_{j-1}) - \tilde{\boldsymbol{\gamma}}_{io}(t_{j-1}) \right| , \tag{13}$$

$$\gamma_{ko}(t_j) = \arg\min \left| \tilde{\alpha}_k^*(t_{j-1}) - \tilde{\tilde{\boldsymbol{\gamma}}}_{ko}(t_{j-1}) \right| . \tag{14}$$

Here:

$\alpha_i^*(t_{j-1})$, $\tilde{\alpha}_k^*(t_{j-1})$ are the angles of the current motion direction of appropriate agents,

$\tilde{\boldsymbol{\gamma}}_{io}(t_{j-1})$, $\tilde{\boldsymbol{\gamma}}_{ko}(t_{j-1})$ are sets of angles of possible bypassing directions of appropriate agents around the nearest *o*-th obstacle $(o \in O(t_j))$ at moment t_j $(t_j \in T)$, and

$$\tilde{\boldsymbol{\gamma}}_{io}(t_j) = \arctan \frac{\tilde{\mathbf{y}}_{io}^*(t_{j-1}) - y_i(t_{j-1})}{\tilde{\mathbf{x}}_{io}^*(t_{j-1}) - x_i(t_{j-1})} \,, \tag{15}$$

$$\tilde{\tilde{\boldsymbol{\gamma}}}_{ko}(t_j) = \arctan \frac{\tilde{\tilde{\mathbf{y}}}_{ko}^*(t_{j-1}) - \tilde{y}_k(t_{j-1})}{\tilde{\tilde{\mathbf{x}}}_{ko}^*(t_{j-1}) - \tilde{x}_k(t_{j-1})} \,, \tag{16}$$

$\{\tilde{\mathbf{x}}_{io}^*(t_{j-1}),\ \tilde{\mathbf{y}}_{io}^*(t_{j-1})\}$, $\{\tilde{\tilde{\mathbf{x}}}_{ko}^*(t_{j-1}),\ \tilde{\tilde{\mathbf{y}}}_{ko}^*(t_{j-1})\}$ are the sets of possible coordinates of appropriate agents provided they bypass the nearest *o*-th obstacle $(o \in O(t_j))$. These coordinates are computed through constructing the mental path of the *i*-th usual agent $(i \in I(t_j))$ towards its target.

For the determination of the nearest accessible coordinates located outside the obstacle, the usual arithmetic spiral constructed at the intersection point of the mental path and the obstacle can be used (see Fig. 2).

The total number of evacuated usual agents at moment of the evacuation time $\tilde{T}$ $(\tilde{T} \in T)$ is

(17) $$N(\tilde{T}) = \sum_{j=0}^{\tilde{T}} m_i(t_j),$$

where

(18) $$m_i(t_j) = \begin{cases} 1 \text{ if } \mathrm{st}_i(t_j) = 3, \\ 0 \text{ if } \mathrm{st}_i(t_j) \neq 3, \end{cases} \quad i \in I(t_j),\ t_j \in T.$$

The model has the following set of control parameters:

- $\{|K(t_0)|,\ |E(t_0)|\}$, are total number of agent-rescuers and emergency exits at moment t_0;
- $\{g_e,\ h_e\},\ e \in E(t_0)$, are the coordinates of *e*-th emergency exits;
- $\{\hat{x}_{kc}(t_j),\ \hat{y}_{kc}(t_j)\},\ k \in K(t_0),\ c \in C(t_j),\ t_j \in T$, are the coordinates of the *c*-th crowd cluster computed with the fuzzy clustering algorithm [8] which are assigned to the *k*-th agent-rescuer;
- $\{\tilde{s}_k(t_0),\ \tilde{\tau}_k(t_0)\},\ k \in K(t_0)$, are the speed and waiting time (delay) of the *k*-th agent-rescuer.

The values of these parameters are defined at initial time t_0 (i.e., at the beginning of the emergency) with the exception being that the coordinates of crowd clusters are changed during the simulation time.

As a result, the main optimization problem of the evacuation process can be formulated as follows.

Problem A. The need to maximize the total number of evacuated agents and minimize the evacuation time through the set of control parameters:

(19) $$\begin{cases} \max\limits_{\{|K(t_0)|,\ |E(t_0)|,\ \{g_e,\ h_e\},\ \{\hat{x}_{kc}(t_j),\ \hat{y}_{kc}(t_j)\},\ \{\tilde{s}_k(t_0),\ \tilde{\tau}_k(t_0)\}\}} N(\tilde{T}), \\ \min\limits_{\{|K(t_0)|,\ |E(t_0)|,\ \{g_e,\ h_e\},\ \{\hat{x}_{kc}(t_j),\ \hat{y}_{kc}(t_j)\},\ \{\tilde{s}_k(t_0),\ \tilde{\tau}_k(t_0)\}\}} \tilde{T}, \end{cases}$$

s.t.,

$$0 \le |K(t_0)| \le \bar{K},\ 0 \le |E(t_0)| \le \bar{E},$$

$$a_1 \le g_e \le a_2,\ b_1 \le h_e \le b_2,\ a_1 \le \hat{x}_{kc}(t_j) \le a_2,\ b_1 \le \hat{y}_{kc}(t_j) \le b_2,\ 0 \le s_k(t_0) \le \bar{s},$$

$$0 \le \tau_k(t_0) \le \bar{\tau},\ k \in K(t_0),\ e \in E(t_0),\ c \in C(t_j),\ t_j \in T.$$

Here, $\bar{K}$, $\bar{E}$, $\bar{\tau}$, $\bar{s}$ are the maximum permitted values of appropriate parameters (upper limits).

3. Parallel bi-objective real-coded genetic algorithm

To solve the problem (19), a novel parallel real-coded genetic algorithm for bi-objective optimization was developed (P-RCGA). The algorithm is based on the previously suggested parallel Multi-Agent Real-Coded Genetic Algorithms – MA-RCGA [1] and F-RCGA [9], as well as on the multi-objective genetic algorithm developed for multi-objective optimization – AGAMO [6]. P-RCGA extends the features of these algorithms through the ability to solve large-scale multi-objective optimization problems using real-coded heuristic operators, as the application of cluster-based approach to control of agent-rescuers behavior.

The aggregated scheme of P-RCGA implemented for each agent-process is shown in Fig. 3.

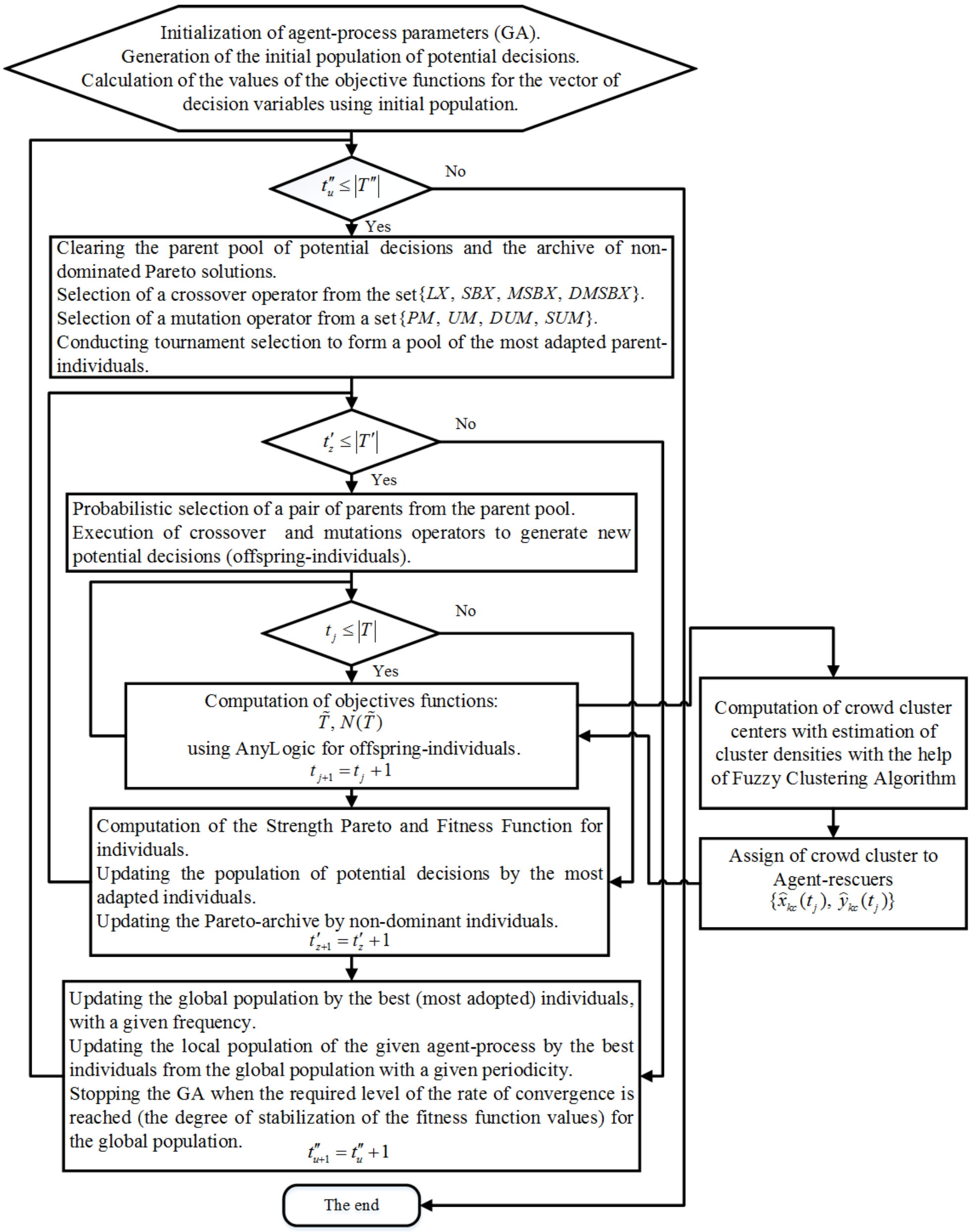

Fig. 3. Parallel real-coded genetic algorithm for multi-objective optimization

P-RCGA uses different crossover and mutation operators suggested in [1, 19, 20, 24, 26, 31, 32].

In particular, a set of crossovers $\{\text{LX, SBX, MSBX, DMSBX}\}$ and mutations $\{\text{PM, UM, DUM, SUM}\}$ is employed, for instance, LX is the Laplace Crossover [19], SBX is the Simulated Binary Crossover [26], MSBX is the Modified Simulated Binary Crossover [1], etc. The probabilistic selection of such operators in the genetic algorithm is implemented to achieve the maximum diversity of a population of potential decisions.

P-RCGA uses both external iterations $t''_u \in \{t''_1, t''_2, ..., t''_{|T''|}\}$, where $|T''|$ is the number of external iterations, and internal iterations $t'_z \in \{t'_1, t'_2, ..., t'_{|T'|}\}$, where $|T'|$ is the number of internal iterations for the generation of offspring-individuals that are potential decisions, as well as the internal simulation time $(t_j \in \{t_1, t_2, ..., t_{|T|}\})$ provided by the AnyLogic simulation tool. AnyLogic is used for the computation of objectives and fitness functions using offspring-individuals provided by the genetic algorithm. The main feature of P-RCGA (Fig. 3) is the suggested procedure of the computation of crowd cluster centers with following estimation of cluster densities with the help of fuzzy clustering algorithm [8].

The aggregated architecture of the decision-making system developed for the optimization of an evacuation process is shown in Fig. 4.

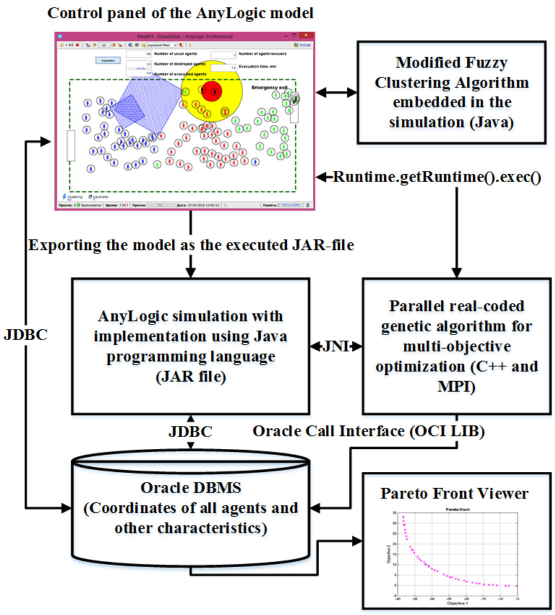

Fig. 4. Aggregated architecture of the developed decision-making system

The scheme of the parallelization proposed for the developed parallel real-coded genetic optimization algorithm is presented in Fig. 5.

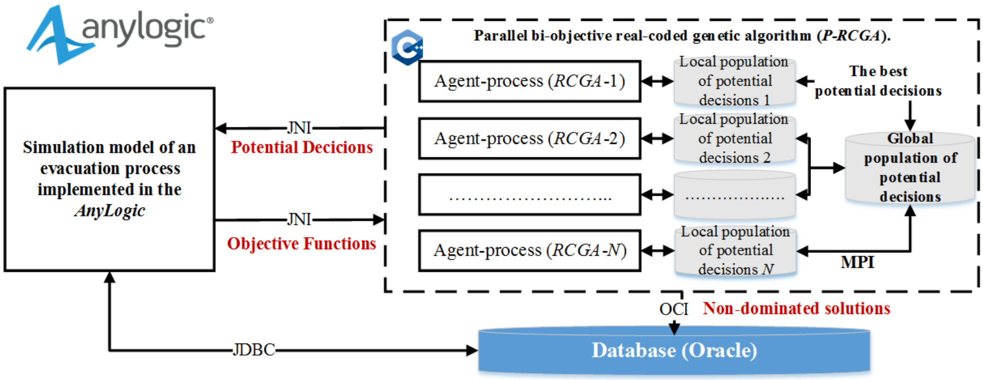

Fig. 5. Parallelization scheme of P-RCGA

As shown in Fig. 5, the developed algorithm (P-RCGA) uses the multi-processes architecture. Within the proposed framework, each agent-process generates and updates own local populations of potential decisions with following exchanging by the best potential decisions (individuals) through the global population with the use of MPI (the Message Passing Interface). The sets of parent-individuals (e.g., consisting of 100 elements) selected in each local population with own potential of decisions are transferred to the global population and the other set of parent-individuals (e.g., consisting of 10 elements) are retrieved back to update local populations. At the same time, the suggested simulation model of an evacuation process implemented in the AnyLogic is responsible for the computation of objective functions for the given set of decision variables (potential decisions) provided by agent-processes at each iteration of P-RCGA (Fig. 5). Moreover, such well-known technologies and interfaces are used as JDBC, JNI, OCI, etc., for providing the connections between the simulation model (AnyLogic), database (Oracle) and parallel genetic algorithm (implemented in C^{++}).

4. Results and discussion

For an estimation of P-RCGA, different performance metrics are used, in particular, the processing time and the hypervolume, amongst other characteristics. The hypervolume metric (Zitzler and Thiele [32]) measures the size of the space enclosed by all solutions on the Pareto front and a user-defined reference point (a slightly worse point than the nadir point). This indicator guarantees strict monotonicity regarding the Pareto dominance.

The following test instances suggested in [17, 27] are used for the validation of P-RCGA: ZDT1 is the first unconstrained problem having the convex front, DTLZ2 is the second multi-objective test problem having a spherical Pareto-optimal front, DTLZ7 is the third multi-objective test problem having the discontinuous front (Table 1). To simplify, the number of decision variables and objective functions in test instances equals to 2.

Table 1. Test instances for P-RCGA

Title	Objectives to be minimized	Feasible ranges
ZDT1	$\begin{cases} f_1 = x, \\ f_2 = g\left(1 - \sqrt{\dfrac{f_1}{g}}\right), \end{cases}$ where $g = 1 + 9y$	$0 \le x \le 1$ $0 \le y \le 1$
DTLZ2	$\begin{cases} f_1 = (1+g)\cos\left(x\dfrac{\pi}{2}\right), \\ f_2 = (1+g)\sin\left(x\dfrac{\pi}{2}\right), \end{cases}$ where $g = (x-0.5)^2 + (y-0.5)^2$	$0 \le x \le 1$ $0 \le y \le 1$
DTLZ7	$\begin{cases} f_1 = x, \\ f_2 = (1+g)h, \end{cases}$ where $g = 1 + \dfrac{9}{2}(x+y)$, $h = 2 - \dfrac{f_1}{(1+g)}\left(1 + \sin(3\pi f_1)\right)$	$0 \le x \le 3$ $0 \le y \le 4$

The performance metrics values computed for the suggested P-RCGA in comparison with the most known multi-objective GAs, in particular, ε-MOEA [18], NSGA-II [13], SPEA2 [16] using test instances are presented in Table 2.

Table 2. Comparison of P-RCGA with other multi-objective GAs using test instances

GA	Performance metrics	Test instances		
		ZDT1	DTLZ2	DTLZ7
P-RCGA	Hypervolume	Min: 0.434 Median: 0.598 Max: 0.611	Min: 0.219 Median: 0.222 Max: 0.234	Min: 0.681 Median: 0.711 Max: 0.789
	Processing time, s	12	10	14
ε -MOEA	Hypervolume	Min: 0.321 Median: 0.459 Max: 0.539	Min: 0.213 Median: 0.213 Max: 0.214	Min: 0.386 Median: 0.428 Max: 0.745
	Processing time, s	24	18	22
NSGA-II	Hypervolume	Min: 0.136 Median: 0.479 Max: 0.544	Min: 0.212 Median: 0.212 Max: 0.213	Min: 0.602 Median: 0.657 Max: 0.695
	Processing time, s	29	32	38
SPEA2	Hypervolume	Min: 0.416 Median: 0.515 Max: 0.545	Min: 0.213 Median: 0.212 Max: 0.213	Min: 0.608 Median: 0.672 Max: 0.708
	Processing time, s	18	22	29

Mainly standard binary coded heuristic operators are used in ε -MOEA, SPEA2 and NSGA-II. In contrast, P-RCGA is based on real-coded crossover and mutation operators implemented on the individual level of agent-processes to generate offspring-individuals and select the best potential decisions. Thus, the application of real-coded heuristic operators combined with multi-agent architecture of P-RCGA improves the quality of the Pareto front in bi-objective optimization of an evacuation process.

In Fig. 6 the dynamics of the Inverted Generational Distance (IGD) is shown, that defines the remoteness of the Pareto front computed with the use of P-RCGA from the known reference front for considered test instances.

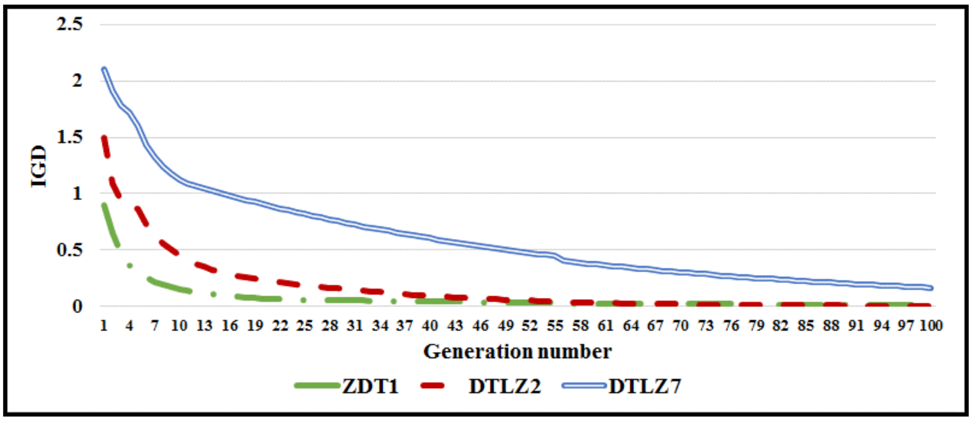

Fig. 6. Dynamics of IGD for the Pareto front computed with the use of P-RCGA

The evolutionary dynamics of non-dominated solutions generated by different (e.g., 4) agent-processes in P-RCGA for considered test instances is shown in Fig. 7.

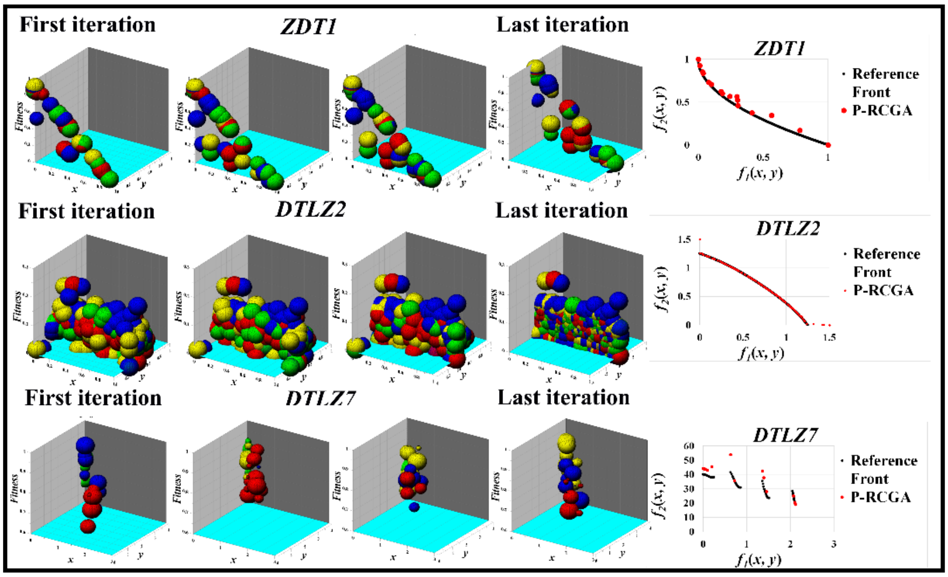

Fig. 7. Evolutionary dynamics of non-dominated solutions in P-RCGA

As seen from Fig. 7, each agent-process generates own sets of non-dominated solutions which cardinalities are increased during the process of an evolutionary searching.

The Pareto front computed with the use of P-RCGA in solving the Problem A is shown in Fig. 8.

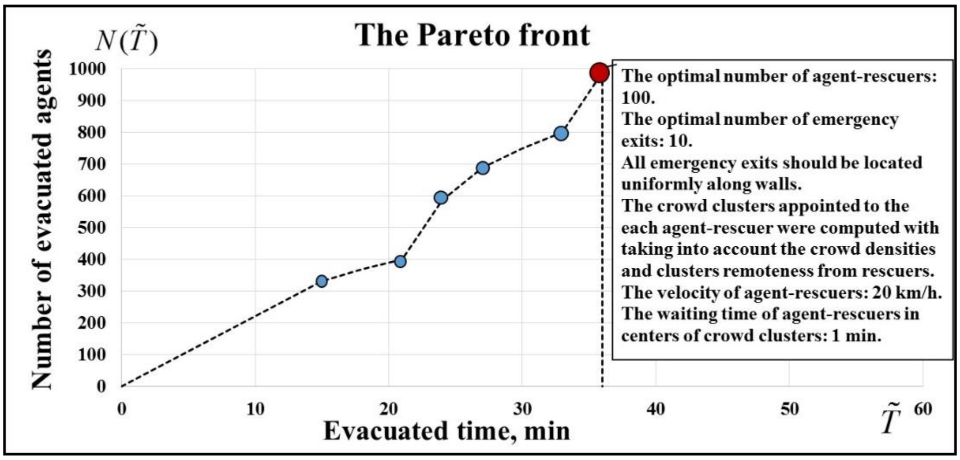

Fig. 8. The Pareto front for the bi-objective optimization problem of an evacuation process computed with the use of P-RCGA

5. Conclusion

This paper aims to design a cluster-based optimization system for evacuation process in emergency using a suggested Parallel Real-Coded Genetic Algorithm (P-RCGA). The most important parameter of such systems is the evacuation time that should be minimized because of the probability of intoxication by harmful substances. On the other hand, agent-rescuers cannot have enough time for the fast evacuation of all usual agents. Therefore, the optimal control of important parameters such as the velocity and motion directions of agent-rescuers, number of emergency exits and other characteristics of an evacuation process is required.

A new parallel real-coded genetic algorithm P-RCGA (Fig. 3) and the decision-making system for the optimization of an evacuation process (Fig. 4) are suggested. A parallelization scheme of P-RCGA based on the interaction of agent-processes is suggested (Fig. 5). The system usage allows the Pareto-optimal solutions on the evacuation process to be searched (Fig. 8). P-RCGA was verified using well-known test instances (Table 1) and compared with other multi-objective genetic algorithms (Table 2). As a result, it was shown that using real-coded heuristic operators in combination with the suggested multi-agent parallel architecture of P-RCGA significantly improves the quality of the Pareto-front (a hypervolume metric and Inverted Generational Distance).

Further research work will aim to design a complex 3D-simulator of an evacuation process aggregated with a real-coded genetic algorithm using fuzzy rules to control agent-rescuer behavior.

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