Evolutionary Multiobjective Optimization for Pedestrian Route Guidance with Multiple Scenarios

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***Abstract*—Crowd-related accidents often occur in both normal and emergency situations. To prevent these problems, it is highly suggested to investigate and simulate the risks of overcrowding in a large-scale gathering by using a multi-agent system. Such simulation enables the improvement of safe and efficient pedestrian route guidance, depending on multiple scenarios with complicated environmental and traffic conditions. In this paper, for practical safety pedestrian route guidance, we propose a multi-objective evolutionary optimization method to handle multiple scenarios in a large-scale firework event. The pedestrian dataset is obtained with a multi-agent traffic simulator, CrowdWalk. As the optimization of route guidance is a multi-objective optimization problem, we modify a natural evolution strategy based multi-objective optimization algorithm by replacing the Pareto dominance relation with the scenario dominance relation. This aims for the flexibility of pedestrian route guidance in response to traffic demands. The computational results demonstrate that the method can find a well-balanced set of solution to multiple scenarios and maintain a trade-off among multiple objectives in real world applications.**

***Index Terms*—evolutionary algorithm, pedestrian simulation, multiobjective optimization, multiscenario optimization.**

I. Introduction

Managing crowds is an important issue for keeping participant safety in large-scale events. In addition to evacuation during a disaster, it has also been reported that unexpected accidents can occur simply by gathering a large number of participants at a particular location [1]. To clarify the risk of a crowd accident and prevent overcrowding, it is useful to simulate pedestrian flow using a multi-agent system [2]–[4]. The simulator can provide detailed information about the congestion, and optimize the safe crowd management plan.

In this paper, we consider the optimization for the pedestrian route guidance during the fireworks event. After the event, numerous people surge to the nearest station and traffic lights control the pedestrian flow from the fireworks venue to the station. To obtained efficient and safety route guidance, multiple objective functions should be brought into consideration and need to be satisfied simultaneously. Here, two objective functions are considered. The first objective function is the traveling time. The second objective function is the congestion degree. Since the station capacity is limited, the minimization of the traveling time of pedestrians may increase the risk of accidents due to overcrowding at the station. It is desirable to reduce the traveling time while alleviating congestion.

To evaluate these objective functions, we first specify a histogram of participants departing the venue for reproducing real-world environments on the pedestrian simulation. The concept of the pedestrian simulator is described in Fig. 1. However, since it is difficult to estimate the histogram in advance, the specified histogram does not always correspond to the actual pedestrian traffic. From a practical point of view, the route guidance must be evaluated over several different pedestrian traffic conditions, which we refer to as scenarios. That is, route guidance optimization can be considered as a multiscenario, multiobjective (MSMO) problem. Recently, the MSMO problem is widely studied in the research field of engineering, such as the design of distributed energy supply systems [5] and tractor-trailer design problems [6].

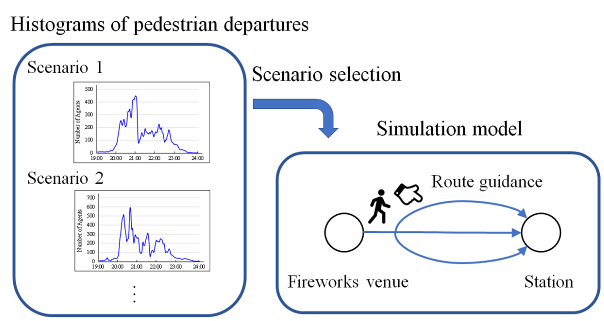


Fig. 1. The concept of the pedestrian simulator with multiple scenarios.

Let us consider the following K-scenario M-objective minimization problem with a decision vector $\mathbf{x}$ and its feasible region $\mathbf{X}$:

$$\begin{aligned}&\text{Minimize}\ \{f_1^k(\mathbf{x}), f_2^k(\mathbf{x}), ..., f_M^k(\mathbf{x})\}\\&\text{subject to}\ \mathbf{x} \in \mathbf{X},\ k = 1, 2, ..., K,\end{aligned} \tag{1}$$

where $f_i^k(\mathbf{x})$ is an i-th objective function with k-th scenario. Let us consider two objective vectors with a single-scenario case. The objective vector $\mathbf{a}^k = (a_1^k, a_2^k, ..., a_M^k)$ and $\mathbf{b}^k = (b_1^k, b_2^k, ..., b_M^k)$ are two points in the M-dimensional objective space with k-th scenario. The Pareto dominance relation "$\succ$"

and the weak Pareto dominance relation "$\succeq$" are defined as follows:

$$\text{Pareto Dominance} : \mathbf{a} \succ \mathbf{b} \Leftrightarrow \forall i, a_i \leq b_i \text{and} \exists j, a_j < b_j. \tag{2}$$

$$\text{Weak Pareto Dominance} : \mathbf{a} \succeq \mathbf{b} \Leftrightarrow \forall i, a_i \leq b_i. \tag{3}$$

In a multiscenario case, it might happen that a solution **a** Pareto dominate solution **b** in one scenario, but **a** dose not Pareto dominate **b** in another scenario. Thus, existing multiobjective evolutionary algorithms (MOEAs) cannot directly applicable to the MSMO problem. One straightforward idea to handle multiple scenarios is to identify the worst scenario and then find an optimal design for it [7]. The other idea for the MSMO problem is to consider the scenario dominance relation between two solutions [5], [6]. The scenario dominance "$\succ_s$" is defined as follows:

$$\text{Scenario dominance} : \mathbf{a} \succ_s \mathbf{b} \Leftrightarrow \forall k, \mathbf{a}^k \succeq \mathbf{b}^k \text{and} \exists l, \mathbf{a}^l \succ \mathbf{b}^l. \tag{4}$$

In [5], a scenario dominance relation is combined with MOEA (donated as S-NSGA-II). In [6], the concept of ϵ-domination [8] is combined with scenario dominance.

Since the evaluation of the route guidance needs a time-consuming simulation, in this work, we propose an evolutionary MSMO method based on a natural evolution strategy (NES). More precisely, we modify the NES-based MOEA (MO-NES) [9] where the candidate solutions are sampled efficiently from the principle of the natural gradient descent. In the proposed method, the scenario dominance relation is utilized to compare the candidate solution and the current solution in the NES procedure.

Section II describes the procedure of the route guidance optimization, and the pedestrian simulator CrowdWalk [10]. Section III gives the detail of the proposed method (MSMO-NES). In Section III, we also examine the performance of MSMO-NES on the numerical problem. Then, Section IV reports the performance of the proposed method through the simulation of the Kanmon Strait fireworks in Kita Kyushu City in Japan. In the experiment, the proposed method is compared with two MSMO algorithms and show that the proposed method can obtain a well-balanced solution set to multiple scenarios and maintain a trade-off among multiple objectives. Finally, this paper is concluded in Section V.

II. Route Guidance Optimization

A. Overview

Fig. 2 shows an overview of the route guidance optimization. The route guidance optimization can be divided into two components: (i) the pedestrian simulation, (ii) fitness evaluation for the route guidance. The following subsections explain each component in detail.

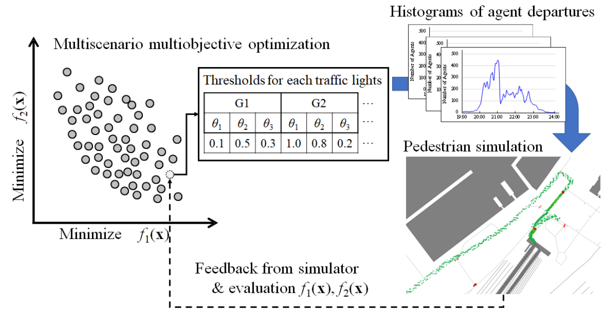


Fig. 2. The overview of the route guidance optimization.

B. A Model for Pedestrian Simulation

Simulation using a multi-agent system is widely studied in the research fields of ecology, economics and traffic engineering. CrowdWalk [10] is an activity tracker for multi-agent traffic simulations assuming a large number of pedestrians. For treating tens of thousands of pedestrians smoothly, CrowdWalk simplifies every pedestrian flow in one-dimensional space while updating each position according to the movement model based on the driving force and the social influence.

To create a simulation model, the map and the departure time of each pedestrian are to be specified. The map consists of links and nodes, where the links and nodes represent the routes for the traffic and intersections of the routes, respectively. Each agent (i.e., pedestrian) leaves from the venue for the station at a pre-specified time.

Fig. 3 shows the location of the nearest station, the fireworks venue and nine traffic lights at the simulation model for the Kanmon Strait fireworks. There are also three routes, Routes 1-3, are designated from the venue to the station. Since congestions mainly occur when the spectators moving from the venue to the station after the event is over, we assume all pedestrians moving from the venue to the station in the simulation model. Before the pedestrian simulator is conducted, a histogram of the number of pedestrians departing from the venue at each time step is to be specified. As shown in Fig. 1, a single histogram represents a single scenario. To obtain a practically efficient and safety route guidance, we prepare multiple scenarios considered simultaneously.

In the simulation model, the pedestrian flow is controlled by the nine traffic lights. More precisely, in this framework, the route guidance optimization is conducted by the optimization of the control of the nine traffic lights. There are also three points where pedestrian traffic is measured (i.e., points from C1 to C3 in Fig. 3). The number of pedestrians, in practice, are obtained via pedestrian detection for the movies taken by RGB-D cameras. The pedestrian traffic information is utilized in the control of the nine traffic lights. For the detail of the control of the traffic lights, please refer to the next subsection.

Finally, we introduce detailed settings in the simulation model. The simulation map consists of 11 nodes and links connecting each other. These nodes include a single node represents the station that is the destination of all pedestrians

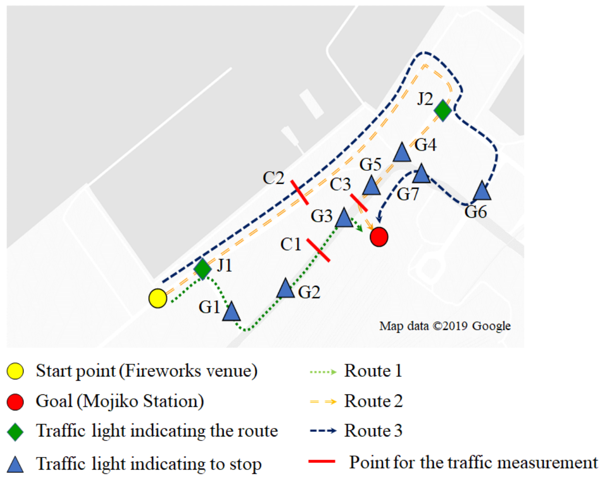


Fig. 3. Map of the simulation model for the Kanmon Strait fireworks in Kita Kyushu City in Japan. The points from C1 to C3 are the data points measuring the pedestrian traffic. The points from G1 to G7 and J1 and J2 represent the traffic lights.

and another node represents the venue where pedestrians depart for the station. At the station node, an entry restriction into the station is conducted since the capacity is limited. The entry restriction is automatically operated based on the train schedule.

Of the other nine nodes for traffic lights, the seven nodes are to control the stop-and-go movement of pedestrians (G1 to G7 in Fig. 3). The rest of two nodes are to divide a pedestrian flow into two routes at the points J1 and J2. The pedestrians select Route 1 or 2 at J1, and then Route 2 or 3 at J2. In other words, all the nine traffic lights in this simulation model have only two conditions.

C. Design Variables Representation and Fitness Evaluation

In this framework, the control of the nine traffic lights is optimized. Each traffic light has only two conditions and their conditions are changed according to the number of pedestrians at the three points C1, C2, and C3 in Fig. 3. The number of pedestrians and the condition of each traffic lights are updated per minute.

To simplify the control of the traffic lights, thresholds for the numbers of pedestrians at the three points and a default condition are specified for each traffic light. Let us consider the threshold vector $\theta^i = (\theta_1^i, \theta_2^i, \theta_3^i)$ for the i-th traffic lights and the number of pedestrians $\mathbf{p}^i = (p_1, p_2, p_3)$ at the specific time step. When the volume of traffic at any point is not larger than the threshold (i.e., $\forall j, p_j(t) \leq \theta_j^i$), the i-th traffic light indicates the default condition at the next step. Otherwise, it indicates another condition. For the traffic lights from G1 to G7, the default condition is passable. For J1 and J2, the default condition is specified in Routes 1 and 2, respectively.

In the route guidance optimization, the design variables represent the thresholds of each traffic light. That is, the design variable vector $\mathbf{x}$ has 9×3 = 27 elements. Since the maximum number of pedestrians who can go through each point is limited due to the limitation of the width of the street, the number of pedestrians is normalized into the range [0, 1]. Therefore, the range of each element of the design variable is also specified in [0, 1].

Next, we describe how to evaluate the fitness function under each scenario. We consider two objective functions in this framework. The first objective function $f_1(\mathbf{x})$ is the traveling time of all pedestrians. The average of the traveling time values of overall pedestrians is calculated as follows:

$$f_1(\mathbf{x}) = \sum_{n=1}^{N} \frac{Arrival_n - Departure_n}{N}, \tag{5}$$

where N is the number of all pedestrians, $Arrival_n$ and $Departure_n$ is an arrival time and a departure time of n-th pedestrian, respectively.

The second objective function $f_2(\mathbf{x})$ is the number of pedestrians in the overcrowded area. For calculating $f_2(\mathbf{x})$, we consider the local population density around each pedestrian. The fitness function of $f_2(\mathbf{x})$ is as follows:

$$f_2(\mathbf{x}) = \sum_{n=1}^{N} \begin{cases} 1 & (\text{if } d_n > 2.17), \\ 0 & (\text{otherwise}), \end{cases} \tag{6}$$

where d_n is the local population density around the n-th pedestrian. The threshold of overcrowding is defined as 2.17 [ped/m^2] or more based on Fruin's standard level services [11].

When we consider the K-scenario problem, the route guidance optimization handles $2K$ objective values. This optimization can be formulated as follows:

$$\begin{aligned} &\text{Minimize}\left\{f_1^1(\mathbf{x}), f_2^1(\mathbf{x})\right\}, \text{Minimize}\left\{f_1^2(\mathbf{x}), f_2^2(\mathbf{x})\right\}, ..., \\ &\text{Minimize}\left\{f_1^K(\mathbf{x}), f_2^K(\mathbf{x})\right\}, \end{aligned} \tag{7}$$

where $\mathbf{x}$ is the design variable vector and $f_i^k(\mathbf{x})$ is an i-th objective function with k-th scenario.

III. Natural Evolution Strategy For MSMO

For a multiscenario, multiobjective route guidance optimization, all scenarios are considered simultaneously. The optimization methodology tries to find a solution set where the trade-off relationships in all scenarios are well represented so that decision-makers can analyze them to choose a preferred solution. In other words, the desirable solution set needs to keep a good balance among multiple scenarios and multiple objectives.

Since the evaluation of the route guidance needs a time-consuming simulation, in this work, we modify MO-NES [9] to determine an appropriate route guidance set among the multiple scenarios. MO-NES is one of the representative MOEAs for solving single scenario problems with continuous variables. The candidate solutions are sampled efficiently from the principle of the natural gradient descent.

A. MO-NES Algorithm

Here, we briefly describe the procedure of MO-NES. In MO-NES, a (1+1)-ES style hill-climber is derived from the xNES algorithm [12] and the multiple (1+1)-xNES hill-climbers are utilized to define the search distribution to approximate the Pareto front. The number hill-climbers is same as the population size P. The search distributions of the (1+1)-xNES hill-climber is denoted by three parameters (μ, σ, A). These parameters represent the center, global step size, and full covariance matrix, respectively. In each iteration, *P* hill-climbers generate one candidate solution each. The search distributions of the hill-climbers are updated by the principle of natural gradient descent. The *i*-th candidate solution is generated as follows:

$$\begin{aligned} &\mu' \leftarrow \mu_i + \sigma_i A_i z_i, z_i \sim N(0, I), \\ &\sigma' \leftarrow \sigma, A' \leftarrow A, i = 1, 2, ..., P, \end{aligned} \tag{8}$$

where (μ', σ', A') are the parameters of new hill-climber based on the new sample solution from the *i*-th hill-climber, *P* is the number of population and *I* denotes the unit matrix. We regard the center of the new hill-climber μ'_i as the design variable vector of the *i*-th candidate solution.

After *P* candidates are sampled by *P* hill-climbers, an indicator-based ranking scheme is conducted to determine the success/failure of the samplings. In the scheme, current solutions and candidate solutions are merged into a single solution set and ranked according to (i) the Pareto dominance relation, and (ii) hypervolume contribution [13]. In more detail, the merged solution set is split into multiple fronts using nondominated sorting [14]. Then the solutions in each front are sorted by the hypervolume contribution. The lower rank indicates the better solution.

Let us assume the current solution μ_i and the candidate solution μ'_i for the *i*-th hill-climber. To determine the success/failure of the sampling of the *i*-th hill-climber, the rank of the candidate solution $rank(\mu'_i)$ and the current solution $rank(\mu_i)$ is compared. If $rank(\mu'_i)$ is smaller than $rank(\mu_i)$, the *i*-th sampling is counted as a success. Otherwise, the sampling is failure. According to the success/failure of the samplings, the search distributions of the hill-climbers are updated by the principle of natural gradient descent as follows:

$$\begin{aligned} &\text{If } rank(\mu'_i) < rank(\mu_i) \text{ then} \\ &\qquad \sigma \leftarrow \sigma \exp \eta_\sigma^+, \sigma' \leftarrow \sigma' \exp \eta_\sigma^+, \\ &\qquad A' \leftarrow A' \exp \eta_A^+ [z_i z_i^T - I]. \\ &\text{else} \\ &\qquad \sigma \leftarrow \sigma / \exp \eta_\sigma^-, \sigma' \leftarrow \sigma' / \exp \eta_\sigma^-, \end{aligned} \tag{9}$$

where $\eta_\sigma^+, \eta_\sigma^-, \eta_A^+$ is the learning rates to the global step size, and full covariance matrix. Finally, the next population is selected to keeping the best *P* out of 2*P* solutions according to the ranking. The procedure of MO-NES is stated in Fig. 4.

The MO-NES Algorithm

Step 1: Search distributions of the (1+1)-xNES hill-climbers are randomly generated.

Step 2: Evaluate initial population $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_P)$.

Step 3: Repeat following steps, until a stopping condition is met.

3.1: Candidate solution set $\boldsymbol{\mu}' = (\mu'_1, \ldots, \mu'_P)$ is sampled by each hill-climber.

3.2: Evaluate $\boldsymbol{\mu}'$ and current population $\boldsymbol{\mu}$ and candidates $\boldsymbol{\mu}'$ are merged into a solution set.

3.3: Perform the indicator-based selection scheme on $\boldsymbol{\mu}$ and $\boldsymbol{\mu}'$ and compute ranks $rank(\mu_1), \ldots, rank(\mu_P), rank(\mu'_1), \ldots, rank(\mu'_P)$.

3.4: For each (say *i*-th) samplings, $rank(\mu_i)$ and $rank(\mu'_i)$ are compared and the success/failure of the *i*-th samplings are determined.

3.5: Update the search distributions of each hill-climbers as (9).

3.6: The new current population is constructed based on the ranking.

Fig. 4. The procedure of the MO-NES algorithm.

B. Modification to MO-NES for MSMO (MSMO-NES)

To handling the MSMO problem, we made two modifications to MO-NES. One is the modification to the determination of the success/failure of the samplings. In the original MO-NES, current solutions and candidate solutions are merged into a single solution set for the ranking assignment based on the Pareto dominance relation. In the proposed method, the current solution and the candidate solution of each hill-climber are directly compared by the scenario dominance relation (4). The comparison of the scenario dominance relation can be classified into the following three cases: (a) the candidate solution scenario dominates current solution, (b) both solutions are nondominated (c)the current solution scenario dominates the candidate solution.

In cases (a) and (c), the sampling is counted as a success and failure, respectively. In case (b), the hypervolume contributions of multiple scenario is comprehensively compared. First, the hypervolume contribution on each scenario is calculated. Then, the rankings of the hypervolume contribution with each scenario are determined. We denote these rankings as scenario-wise rankings. Each solution is assigned *K* scenario-wise ranks, corresponding to *K* scenarios. Finally, a total ranking of the scenario-wise ranks of both solutions are compared. The solution having a smaller total ranking is regarded as the better solution. Table I illustrates the process of assignment of ranks and calculation of the scenario-based ranking with five solutions for three-scenario optimization problem.

TABLE I
CALCULATION OF SCENARIO-BASED RANKING

Solution	Hypervolume contribution			Scenario-wise ranking			Total ranking
	SC1*	SC2	SC3	SC1	SC2	SC3	
A	0.2	0	0.8	3	5	1	9
B	0	0.1	0	4	4	5	13
C	0	0.2	0.4	4	3	3	10
D	0.7	0.3	0.1	2	2	4	8
E	0.9	0.8	0.7	1	1	2	4

*SC1, SC2, SC3 means Scenario 1, Scenario 2, Scenario 3, respectively.

The other modification is the selection of the next population. The original MO-NES selects the best *P* solutions from

$2P$ solutions as the next population according to the indicator-based ranking scheme. In the proposed method, the current solution is replaced only by a better candidate from the same hill-climber. This modified MO-NES algorithm is denoted as multiscenario MO-NES (or MSMO-NES).

C. Performance examination in numerical problem

Here, we present results from the proposed method on the following bi-scenario bi-objective problem (BSBOP) [15]. All four objective functions are to be minimized.

$$f_1(\mathbf{x}) = \begin{cases} (x_1-2)^2+(x_2-1)^2 & \text{for Scenario1,} \\ (x_1-1)^2+(x_2+1)^2 & \text{for Scenario2,} \end{cases}$$
$$f_2(\mathbf{x}) = \begin{cases} x_1^2+(x_2-3)^2 & \text{for Scenario1,} \\ (x_1+1)^2+(x_2-1)^2 & \text{for Scenario2,} \end{cases} \quad (10)$$
$$\text{subject to } x_1^2 - x_2 \le 0, x_1 \le 1, x_2 \le 1.$$

We compare the proposed method with two existing MSMO algorithms. One is a worst-case aggregation approach [7] where all scenarios combine for each objective function in an aggregated manner. For the worst-case aggregation, the aggregate function can be the max function evaluating the worst value for all K scenarios as follows:

$$f_m^{agg}(\mathbf{x}) = \max_{1 \le k \le K} f_m^k(\mathbf{x}). \quad (11)$$

Since the aggregate function transforms the multiscenario problem into a single scenario problem, any MOEAs can be used to find a set of trade-off Pareto-optimal solutions. In this paper, we adopt NSGA-II which is used in [7].

The other MSMO algorithm is a scenario-based multiobjective evolutionary algorithm (S-NSGA-II [5]) where NSGA-II is modified to use the scenario dominance relation. The parameters of MSMO algorithms are shown in Table II. The algorithms run for a maximum 5,000 solution evaluations for BSBOP.

TABLE II
PARAMETERS OF THE MULTISCENARIO MULTIOBJECTIVE ALGORITHMS

Parameter	Value
Population size	100
Maximum number of solution evaluations	5,000 for BSBOP 1,000 for Pedestrian Route Guidance
Crossover in NSGA-II variants	SBX crossover (distribution index: 15)
Mutation in NSGA-II variants	Polynomial mutation (distribution index: 20)
Learning rates to the global step size	$(\eta_\sigma^+, \eta_\sigma^-)$: 1/5 $d^{1.5}$, $d^{1.5}$, d: Number of variables
Learning rates to the full covariance matrix	η_A^+ : 1/4 $d^{1.5}$

Figure 5 shows the obtained solutions on Scenario 1 objective space. We can see a clear difference in the distribution of obtained solutions among the three algorithms. The trade-off between the objectives is well observed by the nondominated solution set in S-NSGA-II. In contrast, the solution set obtained from MSMO-NES appears to be scattered widely over the objective function space. However, the convergence of the nondominated solution of MSMO-NES is not inferior to S-NSGA-II. The aggregation approach also shows the trade-off, however, this solution set is dominated by the obtained solutions from MSMO-NES and S-NSGA-II. That is, the trade-off information obtained by the aggregation approach is less informative for decision making in Scenario 1 objective space.

Similarly, Fig. 6 shows the obtained solutions on Scenario 2 objective space. It is clearly observed that the convergence of MSMO-NES is better than the other algorithms. In Fig. 7, the solutions are replotted in the worst-case aggregated objective space by (11). Since the worst-case aggregated objectives are directly optimized in the aggregation approach, it is not surprising that the aggregation approach shows the good convergence and diversity in this objective space. We can also see that the obtained solutions by S-NSGA-II converge in a specific area. MSMO-NES obtains the well-distributed solution set in Fig. 7. When considering the comprehensive performance in all objective function spaces, MSMO-NES obtains the widely spread and well-converged solution set in any objective function space. On the other hand, the number of nondominated solutions is smaller than the other methods.

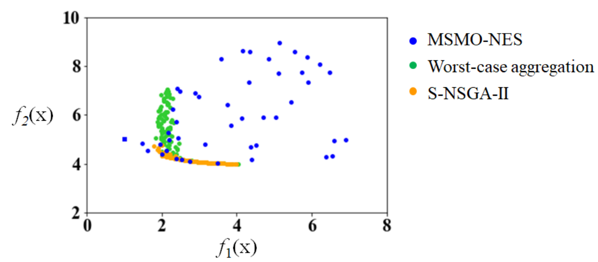


Fig. 5. Obtained solutions by the three different MSMO algorithms plotted on Scenario 1 objective space for BSBOP.

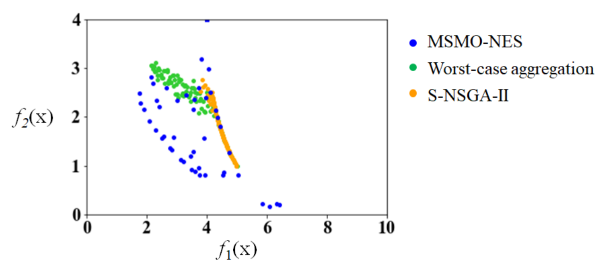


Fig. 6. Obtained solutions by the three different MSMO algorithms plotted on Scenario 2 objective space for BSBOP.

IV. MULTISCENARIO OPTIMIZATION FOR PEDESTRIAN ROUTE GUIDANCE

In this section, the performance of the MSMO-NES is examined throughout the route guidance optimization using

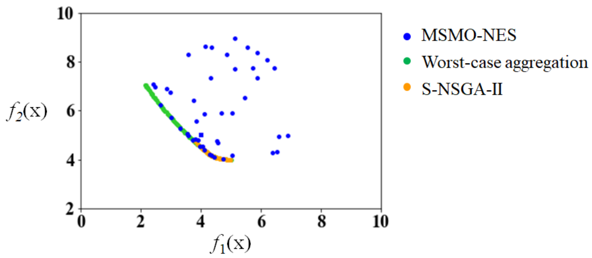
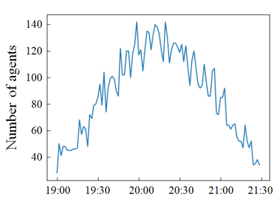
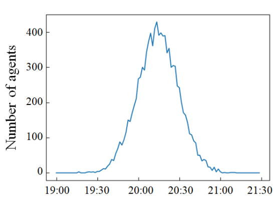


Fig. 7. Obtained solutions by the three different MSMO algorithms plotted on the worst-case aggregated objective space for BSBOP.

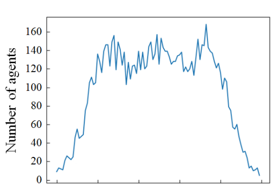
the pedestrian simulation of the Kanmon Strait fireworks. In the route guidance optimization, the number of people departing from the fireworks venue to the station strongly affect the performance of the route guidance. Since it is difficult to estimate the trend of participation in the mass gathering event, the route guidance must be evaluated over several different pedestrian traffic conditions. For this purpose, we assume four histograms of the number of people departing from the venue to the station. Each route guidance is evaluated with all traffic condition scenarios. That is, this route guidance optimization problem is a four-scenario optimization problem. Fig. 8 shows the four histograms of the number of pedestrians departing from the venue. The total number of pedestrians in the histograms is around 10,000. Figs. 9 - 12 show the obtained solutions on Scenarios 1 to 4. Due to the heavy calculation cost of the pedestrian simulator, the algorithms run for a maximum 1,000 solution evaluations in this section. Other parameters are same as specified in Section 3.C.



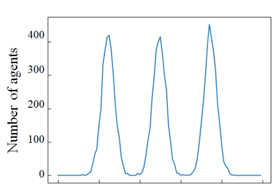
(a) Histogram for scenario 1.



(b) Histogram for scenario 2.



(c) Histogram for scenario 3.



(d) Histogram for scenario 4.

Fig. 8. Four histograms of participants departing the fireworks venue in the route guidance optimization.

From the comparison of the number of pedestrians at the peak in the histograms in Fig. 8, the four scenarios are categorized into two cases. In Scenarios 1 and 3, the max number of pedestrians is around 140 and a stable number

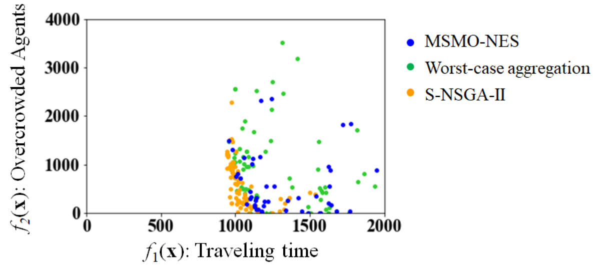


Fig. 9. Obtained solutions by the three different MSMO algorithms plotted on Scenario 1 objective space for the route guidance optimization.

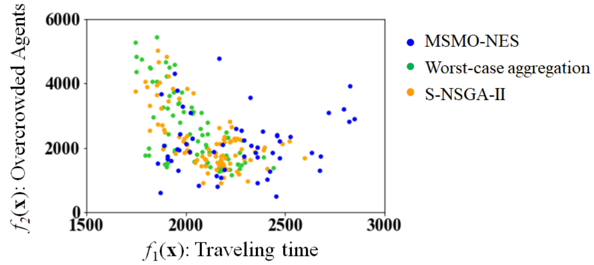


Fig. 10. Obtained solutions by the three different MSMO algorithms plotted on Scenario 2 objective space for the route guidance optimization.

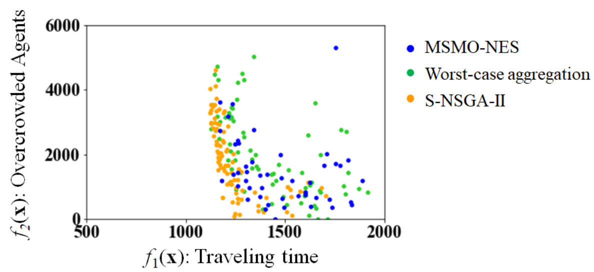


Fig. 11. Obtained solutions by the three different MSMO algorithms plotted on Scenario 3 objective space for the route guidance optimization.

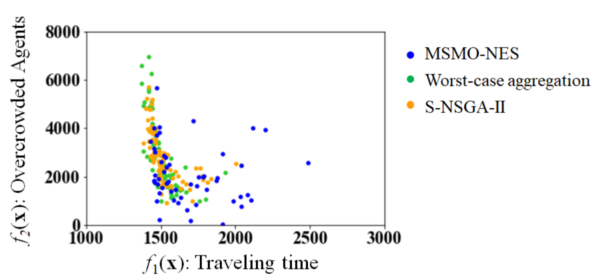


Fig. 12. Obtained solutions by the three different MSMO algorithms plotted on Scenario 4 objective space for the route guidance optimization.

of pedestrians move over a long period. We denote these scenarios as stable scenarios. On the other hand, in Scenarios 2 and 4, the max number of pedestrians is around 400 and a large number of pedestrians move at once. We denote these scenarios as unstable scenarios. From Figs. 9 and 11, solutions obtained by S-NSGA-II are well-converged toward the left hand side. That is, S-NSGA-II is good at the minimization of traveling time in the stable scenarios. For the unstable scenarios, MSMO-NES is good at the minimization of the number of overcrowded pedestrians in contrast.

Obtained hypervolume values on each objective space are also summarized in Table III. The best result over the three algorithms is highlighted in bold for each objective space. To calculate the hypervolume values, we specify the reference point $\mathbf{r}$ as $\mathbf{r}$ = (3,000, 7,000). MSMO-NES obtain the highest hypervolume value in 3 objective spaces out of 5. One interesting observation is that the obtained hypervolume of the aggregation approach is worse than that of MSMO-NES. This may suggest the difficulty to solve the aggregated function calculated from a large number of scenarios.

TABLE III
OBTAINED HYPERVOLUME VALUES

	MSMO-NES	Worst-case aggregation	S-NSGA-II
Scenario 1	9.586E+06	1.426E+07	**1.437E+07**
Scenario 2	**1.416E+07**	7.400E+06	7.126E+06
Scenario 3	7.338E+06	1.261E+07	**1.281E+07**
Scenario 4	**1.255E+07**	9.627E+06	9.586E+06
Worst-case	**1.072E+07**	6.845E+06	6.439E+06

V. CONCLUSIONS

In this work, we proposed the multiscenario multiobjective evolutionary optimization method (MSMO-NES) for the pedestrian route guidance optimization problem. The experimental results showed that MSMO-NES is able to find a solution set that represents the trade-offs in each objective function space well. Future research topics include an automatic generation of scenarios that evoke undiscovered risks and a dynamic selection of conflicting scenarios during a multiscenario search. The development of data mining techniques to be used to extract the knowledge from the obtained route guidance is also an interesting topic.

REFERENCES

[1] J. J. Fruin, "The causes and prevention of crowd disasters," *Engineering for crowd safety*, vol. 1, no. 10, pp. 99–108, 1993.

[2] W. Zhonghua, W. Yongyan, and L. Yang, "Application of pedestrian simulation software in beijing olympic games a case study of olympic badminton venue," in *2009 WRI World Congress on Software Engineering*, vol. 2, 2009, pp. 254–261.

[3] A. Johansson and D. Helbing, "Pedestrian flow optimization with a genetic algorithm based on boolean grids," in *Pedestrian and Evacuation Dynamics 2005*, 2007, pp. 267–272.

[4] S. Shigenaka, S. Takami, Y. Ozaki, M. Onishi, T. Yamashita, and I. Noda, "Evaluation of optimization for pedestrian route guidance in real-world crowded scene," in *18th International Conference on Autonomous Agents and MultiAgent Systems*, 2019, pp. 2192–2194.

[5] R. Wang, F. Zhang, and T. Zhang, "Multi-objective optimal design of hybrid renewable energy systems using evolutionary algorithms," in *2015 11th International Conference on Natural Computation (ICNC)*, 2015, pp. 1196–1200.

[6] K. Deb, L. Zhu, and S. Kulkarni, "Handling multiple scenarios in evolutionary multiobjective numerical optimization," *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 6, pp. 920–933, 2017.

[7] ——, "Multi-scenario, multi-objective optimization using evolutionary algorithms: Initial results," in *2015 IEEE Congress on Evolutionary Computation (CEC)*, 2015, pp. 1877–1884.

[8] M. Laumanns, L. Thiele, K. Deb, and E. Zitzler, "Combining convergence and diversity in evolutionary multiobjective optimization," *Evolutionary Computation*, vol. 10, no. 3, pp. 263–282, 2002.

[9] T. Glasmachers, T. Schaul, and J. Schmidhuber, "A natural evolution strategy for multi-objective optimization," in *Parallel Problem Solving from Nature, PPSN XI*, 2010, pp. 627–636.

[10] T. Yamashita, T. Okada, and I. Noda, "Implementation of simulation environment for exhaustive analysis of huge-scale pedestrian flow," *SICE Journal of Control, Measurement, and System Integration*, vol. 6, no. 2, pp. 137–146, 2013.

[11] (2013) Fruin - levels of service. [Online]. Available: http://www.gkstill.com/Support/crowd-flow/fruin/LoS.html

[12] T. Glasmachers, T. Schaul, S. Yi, D. Wierstra, and J. Schmidhuber, "Exponential natural evolution strategies," in *12th Annual Conference on Genetic and Evolutionary Computation, GECCO'10*, 2010, p. 393–400.

[13] E. Zitzler and L. Thiele, "Multiobjective optimization using evolutionary algorithms—a comparative case study," in *Parallel Problem Solving from Nature, PPSN V*. Springer, 1998, pp. 292–301.

[14] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[15] M. M. Wiecek, V. Y. Blouin, G. M. Fadel, A. Engau, B. J. Hunt, and V. Singh, "Multi-scenario multi-objective optimization with applications in engineering design," in *Multiobjective Programming and Goal Programming*, 2009, pp. 283–298.