Empirical Analysis of Island Model on Large Scale Global Optimization

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***Abstract*—Evolutionary algorithms (EAs) have shown their great capability of handling optimization problems. In the domain of large scale global optimization, many distributed EAs (dEAs) have been proposed for maintaining population diversity so as to enhance their efficacy. One well-known variant of dEA is the island model EA, in which several populations form islands communicating through migration. There are several key factors that affect the performance and search behavior of island model EA, such as population size of each island and migration topology. While most studies of dEA focus on low or medium dimensional problems, an investigation into the effects of these factors on high dimensional problems is greatly needed. This study presents an empirical analysis of island model EA on large scale global optimization problems. The analysis examines the solution quality, convergence speed, and population diversity of island model EA with different migration topologies, population sizes, migration rates, and migration frequencies on four benchmark function of 1,000 dimensions. The results render guidelines for using island model EA to solve large scale global optimization problems.**

***Index Terms*—Distributed evolutionary algorithm, island model, large-scale global optimization, differential evolution.**

I. Introduction

Evolution algorithms (EAs) have attained many successes in tackling optimization problems [1], [2]. Following the concept of Darwinism, EA initializes a population of diverse chromosomes (a.k.a. individuals) and then uses natural selection and genetic operators for evolving solutions. Many dialects of EA have been proposed, including genetic algorithm [3], [4], ant colony optimization [5], particle swarm optimization [6], differential evolution (DE) [7], and so on.

One issue in application of EAs is that, as the dimension of problem increases, it becomes more challenging for EA to find the optimal solutions. A family of EAs named as distributed EA (dEA) was proposed to handle this issue. The dEA has two types, i.e., fine-grained cellular model and coarse-grained island model. The former leverages a structured population and restricts mating to neighboring individuals. The latter manipulates multiple populations and allows reproduction to occur only with the individuals in the same island; in addition, the communication among islands relies on migration of individuals. Five factors are crucial to the performance of island model: population size of each island, migration topology, migration frequency, migration rate, and migration policy. These factors influence the convergence and population diversity during evolution. Some studies have investigated these factors on small or medium dimensional problems [8], [9], [10], [11]. However, study of dEA on high dimensional problems is lacking.

This study aims to render an empirical analysis of island model EA on large scale global optimization (LSGO) problems. LSGO is an emerging topic of computational intelligence area. Many problems and real-world applications are related to LSGO, such as evolutionary deep neural network [12], [13], deoxyribonucleic acid analysis [14], and molecular simulation [15]. In particular, LSGO faces severe challenges on balancing exploration and exploitation; additionally, maintenance of diversity becomes more difficult on LSGO. In this study, we investigate the effects of key factors in island model EA, including population size, migration topology, migration frequency, and migration rate, on the solution quality, convergence speed, and diversity on LSGO functions of 1,000 dimensions.

The contributions of this study are summarized as follows:

- Empirical analysis on the effectiveness and efficiency of key factors in island model EA
- Inspection of the correlation between migration frequency and migration rate
- Investigation on the relation between population diversity and convergence
- Appropriate setting of population size, migration topology, migration frequency, and migration rate for the island model EA on LSGO

The remaining sections are organized as follows. Section II reviews previous work on island model. Section III describes the island model DE in detail, and Section IV presents the empirical analysis on a set of test functions. Concluding remarks of this study are given in Section V.

II. Related Work

Island model parallelizes EA and helps to maintain population diversity for better performance. Many studies have applied island model to enhance the efficiency of EAs. Enrique [16] adopted island model genetic algorithm with ring topology and accomplished super-linear speedup. Burczynski *et al.* [17] leveraged an island master/slave EA to lessen the cost at fitness evaluation, and achieved approximate linear acceleration. Some studies employed island model for effectiveness.

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Algorithm 1 Pseudocode of island model EA

N_{I}: number of islands, N_{P}: population size, $\mathcal{F}$: migration frequency, $\mathcal{R}$: migration rate, $\mathcal{T}$: migration topology, $\mathcal{P}$: migration policy

for $i \leftarrow 1$ to N_{I} **do**
    Initialize (Pop_i, N_{P})
    Evaluate (Pop_i)
end for
$t \leftarrow 1$
while $t < T$ **do**
    for $i \leftarrow 1$ to N_{I} **do**
        $Ofsp_i \leftarrow$Recombine (Pop_i)
        Evaluate $(Ofsp_i)$
        $Pop_i \leftarrow$Survival selection $(Pop_i \cup Ofsp_i)$
    end for
    if $t \mod \mathcal{F} = 0$ **then** ▷ Migration frequency met
        for $i \leftarrow 1$ to $\mathcal{R}$ **do** ▷ Migration rate
            $j \leftarrow$Neighbor $(\mathcal{T}, Pop_i)$ ▷ Neighboring island
            $Pop_j \leftarrow$Migrate $(Pop_i, Pop_j, \mathcal{P})$ ▷ Policy
        end for
    end if
    $t \leftarrow t + 1$
end while

Palomo-Romero [18] used island model genetic algorithm with ring topology on facility layout problem. In [19], island model was applied to NSGA-II with a new migration policy based on partial order relation for multi-objective optimization.

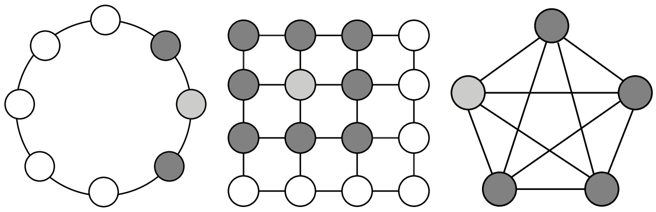
Some studies focused on the effects of migration factors such as migration topology, migration rate, migration frequency, and migration policy. Skolicki and Jong [8] investigated the migration rate and migration frequency on real-valued test functions with low dimensions. The results suggested using low migration rate and low migration frequency to prevent from premature convergence. Rucinski *et al.* [10] presented an analysis on migration topology, where 14 migration topologies were considered. The results on three numerical optimization problems with 250 dimensions show significant difference among topologies, indicating the importance of migration topology. Fernández *et al.* [20] explored the impacts of migration topology and migration frequency on island model genetic programming. The results suggested using a low migration interval.

III. Methodology

This study aims to investigate the effects of island model on LSGO. The following subsections describe island model and the adopted DE in detail.

A. Island Model

Island model EA is commonly used for preserving diversity during evolution. Algorithm 1 shows the process of island model EA. In island model EA, each population performs recombination, evaluation, and survival selection, separately. Migration is controlled by the migration frequency $\mathcal{F}$. When migration occurs, each island select $\mathcal{R}$ islands to migrate to. The selection individuals to be migrated depends upon the migration policy $\mathcal{P}$.



(a) Ring (b) Lattice (c) Fully connected

Figure 1: Migration topologies and neighborhood

Restated, the performance of island model EA is affected by several factors, including population size of each island, migration topology, migration rate, migration frequency, and migration policy.

Population size (N_{p}): Population size determines the diversity at initialization, and the selection pressure during evolution. In island model EA, small population size may let the population be easily occupied by migrators. On the contrary, large population size is able to keep diversity after migration, but results in slow convergence.

Migration Topology ($\mathcal{T}$) : Migration topology defines the connectivity of islands and therefore determines the neighborhood of each island. Figure 1 illustrates three commonly adopted topologies, i.e., ring, lattice, and fully connected. In the ring topology, each island has two neighboring islands, and these islands form a ring shape. Hence, the ring topology has a connectivity of 2. The lattice topology has grid shape, and its neighboring islands are those with one difference at the location of either vertical or horizontal position. The degree of connectivity of lattice topology is eight. In the fully connected topology, each island is a neighbor of any other island. It has a degree of connectivity of $N_{\mathrm{I}}-1$, where N_{I} denotes the number of islands. The migration topology also determines the flow of migration. Two commonly exploited strategies are broadcast and peer-to-peer. The former migrates an individual to all the neighboring islands, while the latter migrates an individual to $\mathcal{R}$ islands. This study considers the peer-to-peer strategy for assessing the effect of migration rate $\mathcal{R}$.

Migration Frequency ($\mathcal{F}$): The timing of migration depends on the migration frequency. Migration frequency is associated with the interval between two migrations. It significantly influences the decreasing speed of population diversity. An appropriate setting of migration frequency can lead to good convergence.

Migration Rate ($\mathcal{R}$): Aside from migration frequency, migration rate defines the quantity of each migration, namely, the number of neighboring islands to be migrated. This number influences the population diversity.

Migration Policy ($\mathcal{P}$): Migration policy decides the individuals to replace and to be replaced when migration, with the form of X-to-Y, which represents the individual X replaces individual Y. The commonly used migration

Algorithm 2 Pseudocode of differential evolution

N_{p}: population size, F: scaling factor, p_c: crossover rate

Initialize (Pop, N_{P})
Evaluate (Pop)
$t \leftarrow 1$
while $t < T$ **do**
  for $i \leftarrow 1$ to N_{P} **do**
    $j_{\mathrm{rand}} \sim \{1, ..., D\}$
    $r_1, r_2, r_3 \sim \{1, ..., N_{\mathrm{p}}\}$
    for $j \leftarrow 1$ to D **do**
      $p \sim (0, 1)$
      if if $p < p_c$ or $j = j_{\mathrm{rand}}$ **then**
        $\hat{x}_{i,j} \leftarrow x_{r_1,j} + F \cdot (x_{r_2,j} - x_{r_3,j})$
      else
        $\hat{x}_{i,j} \leftarrow x_{i,j}$
      end if
    end for
    Evaluate $(\hat{x}_i)$
    if $f(\hat{x}_i) < f(x_i)$ **then**
      $x_i \leftarrow \hat{x}_i$
    end if
  end for
  $t \leftarrow t + 1$
end while

policies include best-to-worst, best-to-random, and random-to-random, which stand for the best individual substituting to the worst individual, the best individual substituting to a random individual, and a random individual substituting to a random individual, respectively. This study adopts the best-to-random policy according to the suggestion in [21], [22], [23].

B. Island Model Differential Evolution

This study utilizes the island model differential evolution (IM-DE) to investigate the effects of key factors in island model. IM-DE carries out DE in each island for evolution. DE is a famous EA that has achieved many successes in dealing with numerical optimization problems. In DE, each individual in the population is called target vector, while each generated offspring is named as trial vector. There are several variants of DE proposed. This study adopts the DE/rand/1/bin mutation strategy due to its good performance. According to the DE/rand/1/bin mutation strategy, the i^{th} trial vector $\hat{x}_{i,j}$ of j^{th} dimension is determined by

$$\hat{x}_{i,j} = \begin{cases} x_{r_1,j} + F \cdot (x_{r_2,j} - x_{r_3,j}) & \text{if } p < p_c \text{ or } j = j_{\mathrm{rand}} \\ x_{i,j} & \text{otherwise} \end{cases}, \tag{1}$$

where F represents the scaling factor, p_c denotes the crossover rate, p and j_{rand} are two random numbers with $p \sim (0, 1)$, and $j_{\mathrm{rand}} \sim \{1, ..., D\}$, and D is the problem dimension. The subscripts r_1, r_2, and r_3 are three different numbers with $r_1, r_2, r_3 \sim \{1, ..., N_{\mathrm{p}}\}$. For any trial vector, the replacement occurs if it gains better fitness than the corresponding target vector; otherwise, the trial vector is discarded.

Table I: Parameter setting of DE

Parameter	Value
Crossover Rate	0.9
Scale Factor	[0.5, 1.0]
Mutation Strategy	DE/rand/1/bin
Population Size	5, 20, 50, 100 per island

Table II: Parameter setting of island model

Parameter	Value
Number of Islands	100
Migratory Topology	Ring, lattice, and fully connected
Migratory Rate	1, 2, 5 individuals
Migratory Frequency	5, 20, 50, 100
Migratory Policy	Best substitutes random
Synchronization	Synchronous

Algorithm 2 shows the pseudocode of DE. At initialization, a population of N_{p} individuals are generated at random. In each generation, N_{p} trial vectors are generated by (1). Each trial vector $\hat{x}_i$ is compared to corresponding target vector x_i for survival selection. The process terminates until the maximum generation T is met.

IV. Experimental Results

This study carries out a series of experiments to investigate the effects of population size, migration topology, migration frequency, and migration rate of island model on LSGO. The test suite includes four 1,000-dimensional functions (i.e., F_1, F_4, F_{12}, and F_{15}) of different types selected from CEC 2013 Competition on Large Scale Global Optimization [24], where the four types are fully separable functions, functions with a separable subcomponent, overlapping functions, and non-separable functions. The maximum number of function evaluations is set to 3×10^7 for observation of search behavior.

A. Parameter setting

Tables I and II list the parameter setting of DE and island model, respectively. The setting of DE follows [7]: crossover rate 0.9 and scaling factor in [0.5,1.0]. Four population sizes (5, 20, 50, and 100) are tested in the experiments. For the island model, the number of islands is fixed to 100 and migration policy uses best-to-random. As aforementioned, this study considers three commonly adopted migration topology, i.e., ring (Rg), lattice (Lt), and fully connected (Fc). Three migration rates are considered, i.e., 1, 2, and 5. Note that the ring topology has a maximum migration rate of 2. The present study ponders four values of migration frequency 5, 20, 50, and 100.

B. Results

The experiments are organized as follows. First, we look into the effects of population size of each island, migration topology, migration rate, and migration frequency in terms of the ranking of solution quality, convergence speed, and population diversity. Then, the effects of the expected migration rate are examined to explore the correlation of migration rate and

Table III: Rank of ring (Rg), lattice (Lt), and fully connected (Fc) topologies

Function	Migration topology ($\mathcal{T}$)		
	Rg	Lt	Fc
F_1	3	2	1
F_4	2	2	1
F_{12}	3	2	1
F_{15}	3	1	1

Table IV: Rank of IM-DE with population size $N_{\mathrm{P}} \in \{5, 20, 50, 100\}$

Function	Population size (N_{P})			
	5	20	50	100
F_1	1	2	3	4
F_4	1	2	3	4
F_{12}	1	2	3	4
F_{15}	1	2	3	4

Table V: Rank of IM-DE with migration rate $\mathcal{R} \in \{1, 2, 5\}$

Function	Migration rate ($\mathcal{R}$)		
	1	2	5
F_1	3	2	1
F_4	3	2	1
F_{12}	3	2	1
F_{15}	3	2	1

Table VI: Rank of IM-DE with migration frequency $\mathcal{F} \in \{5, 20, 50, 100\}$

Function	Migration frequency ($\mathcal{F}$)			
	5	20	50	100
F_1	1	1	3	4
F_4	1	2	3	4
F_{12}	1	1	3	4
F_{15}	3	1	2	3

migration frequency. Finally, we compare the performance of DE and IM-DE to examine our suggested guidelines of island model on the LSGO problems. Considering the stochastic nature of EA, this study performs 30 trials for each experiment.

Migration Topology: Table III presents the ranks of the three topologies of ring (Rg), lattice (Lt), and fully connected (Fc), where the ranks are obtained by non-parametric Mann-Whitney U-test with significant level 0.05. On the four test functions, the fully connected topology obtains the best rank, while the ring topology has the worst rank. The lattice has the best rank on F_{15}, second on F_1 and F_{12}, and worst on F_4. Figure 2 further shows the variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE. Similarly, the fully connected topology achieves fastest convergence; the ring topology has slowest convergence on all the four test functions. In addition, the fully connected topology gains lowest population diversity, whereas ring topology has highest diversity during evolution. These results show the relation of topologies to convergence and diversity.

Population Size: Regarding the rank of the four population sizes, Table IV shows that the population size 5 gets the best rank on the four test functions. The rank of population size degrades as the size increases. As for convergence speed and diversity, Fig. 3 shows the variation of median best fitness (MBF) and population diversity against the number of function evaluations. The results demonstrate that IM-DE with population size 5 achieves the fastest convergence speed and the lowest diversity on all test functions. By contrast, IM-DE with population size 100 has the slowest convergence and highest population diversity. These results reveal that small population leads to faster convergence and better solution quality with rapidly decreasing diversity.

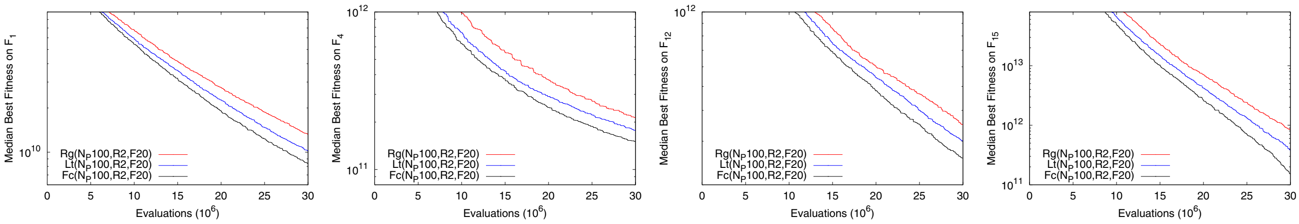
Migration Rate: Table V presents the rank of IM-DE with migration rate $\mathcal{R} \in \{1, 2, 5\}$. The IM-DE with $\mathcal{R} = 5$ achieves the best rank; on the contrary, migration rate $\mathcal{R} = 1$ performs worst. Similarly, on the MBF and population diversity (Fig. 4), IM-DE with $\mathcal{R} = 5$ converges fastest with lowest diversity, while that with $\mathcal{R} = 1$ converges slowest with highest diversity. These results show the relation of diversity and the performance of IM-DE in solution quality and convergence speed.

Migration Frequency: Table VI lists the rank of IM-DE with migration frequency $\mathcal{F} \in \{5, 20, 50, 100\}$. The IM-DE with migration frequency $\mathcal{F} = 5$ achieves the best rank on F_1, F_4, and F_{12}, whilst the one with $\mathcal{F} = 20$ gains best rank on F_1, F_{12}, and F_{15}. Comparing the frequencies $\mathcal{F}$ =5 and $\mathcal{F}$ =20, the former performs better on the function with a separable subcomponent, namely F_4, but does worse on the non-separable function F_{15}. In addition, the ranks degrade as the migration interval increases from 20 to 100.

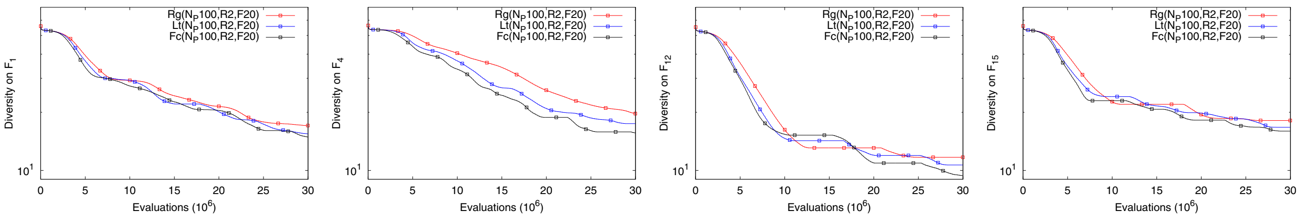
Figure 5 shows the convergence of IM-DE with migration frequency $\mathcal{F} \in \{5, 20, 50, 100\}$. As the migration interval increases, the convergence of IM-DE slows but its population diversity increases. These results indicate that a relatively low migration interval with high migration frequency can bring about good performance.

Expected Migration Rate: This study further investigates the correlation of migration rate and migration frequency using the expected migration rate. Figure 6 plots the MBF of IM-DE with three different expected migration rates 0.02, 0.05, and 0.10. The convergence speed of IM-DE with similar expected migration rate obtains similar convergence curve. Furthermore, as the expected migration rate increases, the convergence accelerates. The IM-DE with highest expected migration rate gains the fastest convergence speed.

Comparison of Appropriate and Inappropriate Settings: To examine the suggested guidelines of migration topology, population size, migration rate, and migration frequency, we compare the solution quality and convergence speed for DE with $N_{\mathrm{P}} = 100$ and IM-DE with appropriate setting Fc($N_{\mathrm{P}}5, \mathcal{R}5, \mathcal{F}5$) and inappropriate setting Rg($N_{\mathrm{P}}100, \mathcal{R}1, \mathcal{F}100$). According to Table VII and Fig. 7,

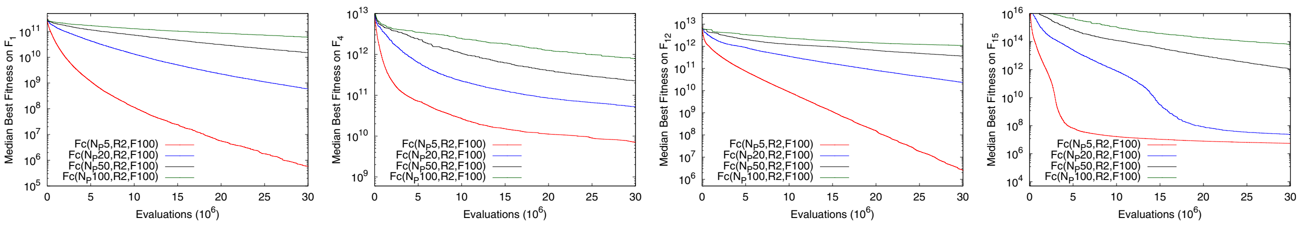


(a) MBF

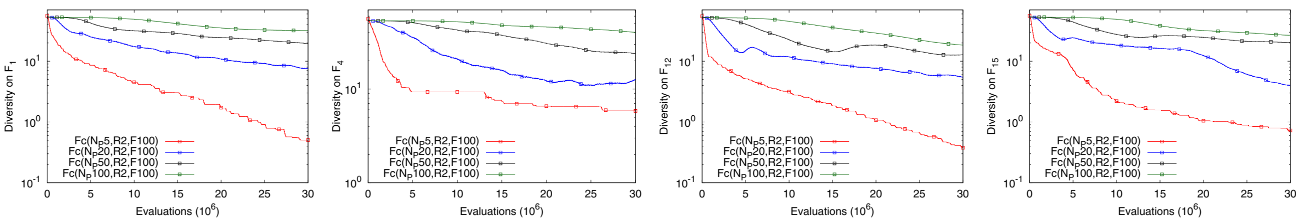


(b) Diversity

Figure 2: Variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE with ring (Rg), lattice (Lt), and fully connected (Fc) topologies on the four test functions



(a) MBF



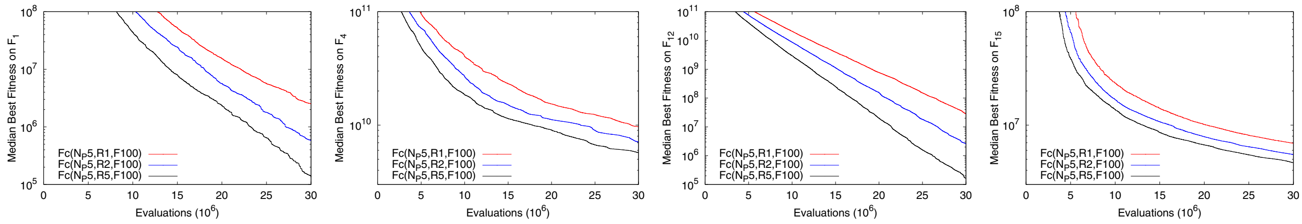
(b) Diversity

Figure 3: Variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE with population sizes $N_{\mathrm{P}} \in \{5, 20, 50, 100\}$ on the four test functions

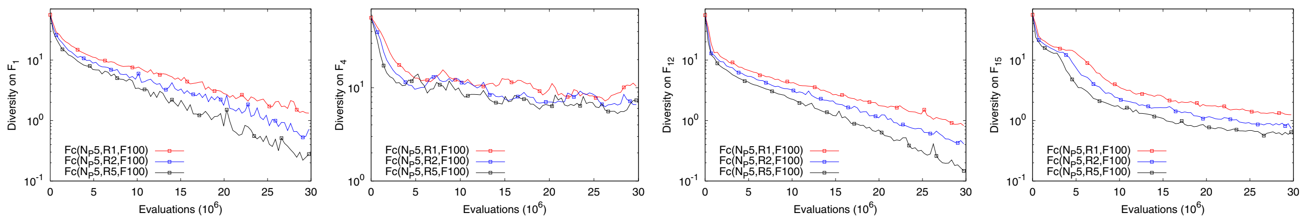
IM-DE with appropriate setting outperforms DE and IM-DE with inappropriate setting in solution quality and convergence speed. In addition, DE is superior to IM-DE with inappropriate setting. As for population diversity, IM-DE with appropriate setting has relatively low diversity, whereas DE and IM-DE with inappropriate setting keep relatively high diversity. These results indicate that island model with appropriate settings can improve the effectiveness and efficiency of DE; however, an inappropriate setting may harm the performance of DE.

V. Conclusions

Large scale global optimization is an emerging topic in computational intelligence. Many real-world applications require handling hundreds or thousands of decision variables. Island model EA is a promising EA for handling high dimensional problems. This study presents an empirical analysis on the key factors of island model on LSGO problems, including population size, migration topology, migration rate, and migration frequency. A series of experiments is conducted on DE and IM-DE to test their performance and examine the effects of their key factors on LSGO. The results show the relation between migration rate and migration frequency. The expected migration rate controls the variation of population diversity and thus has a significant influence over the solution quality and convergence speed. The results also validate the

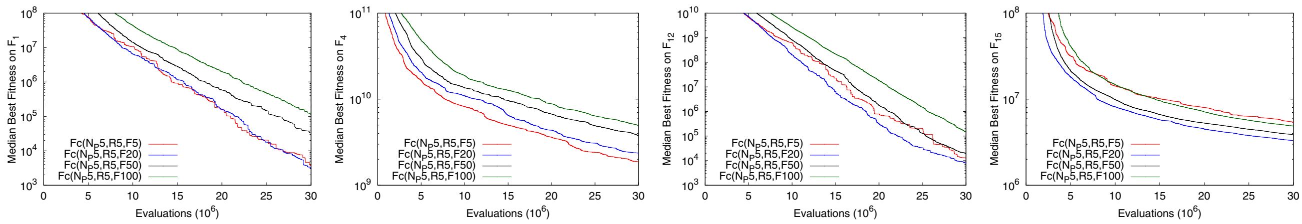


(a) MBF

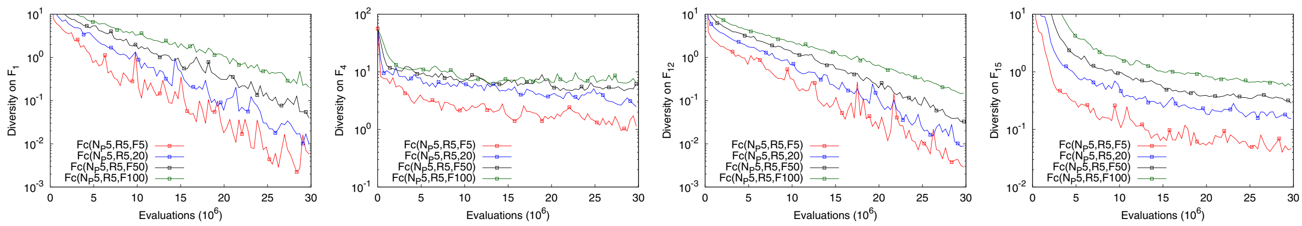


(b) Diversity

Figure 4: Variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE with migration rate $\mathcal{R} \in \{1, 2, 5\}$ on the four test functions



(a) MBF



(b) Diversity

Figure 5: Variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE with migration frequency $\mathcal{F} \in \{5, 20, 50, 100\}$ on the four test functions

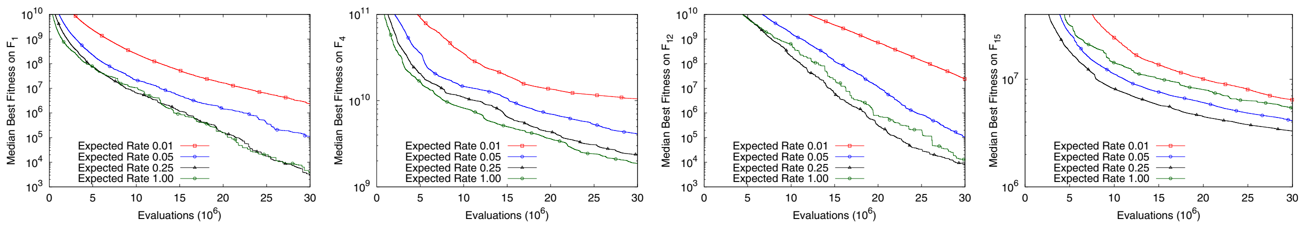
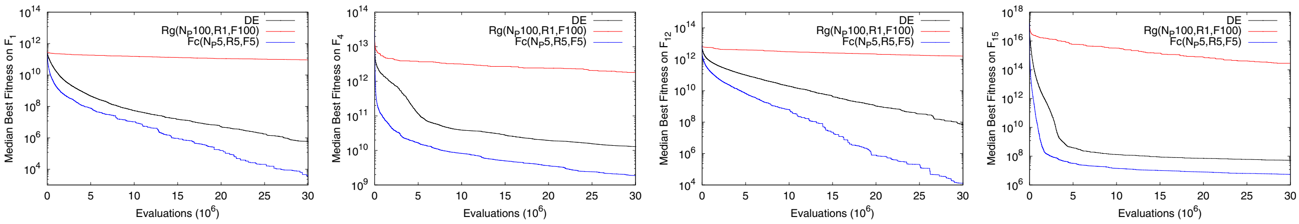


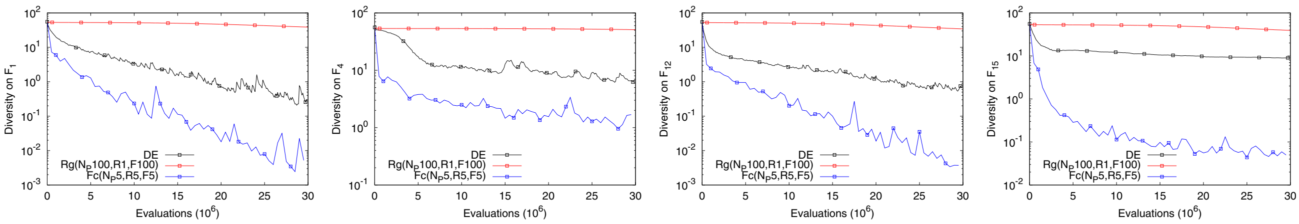
Figure 6: Variation of median best fitness (MBF) against number of function evaluations for IM-DE with different expected migration rates 0.02 (red), 0.05 (blue), and 0.10 (black) on the four test functions

Table VII: MBF and Mann-Whitney U-test for DE and IM-DE with Fc($N_{\mathrm{P}}5, \mathcal{R}5, \mathcal{F}5$) and Rg($N_{\mathrm{P}}100, \mathcal{R}1, \mathcal{F}100$) settings. The symbol $+$ denotes the former method is significantly superior to the latter method.

	MBF			p-value		
Function	DE	Appropriate	Inappropriate	DE Inappropriate	Appropriate DE	Appropriate Inappropriate
F_1	8.19E+05	**3.79E+03**	9.07E+10	1.18E-09 (+)	1.56E-13 (+)	1.18E-09 (+)
F_4	1.32E+10	**1.87E+09**	1.83E+12	1.18E-09 (+)	2.42E-13 (+)	1.18E-09 (+)
F_{12}	1.21E+08	**1.22E+04**	1.61E+12	1.18E-09 (+)	2.63E-12 (+)	1.18E-09 (+)
F_{15}	5.42E+07	**5.36E+06**	2.82E+14	1.18E-09 (+)	5.66E-16 (+)	1.18E-09 (+)



(a) MBF



(b) Diversity

Figure 7: Variation of median best fitness (MBF) and population diversity against number of function evaluations for IM-DE with appropriate (Fc($N_{\mathrm{P}}20, \mathcal{R}5, \mathcal{F}5$)) and inappropriate (Rg($N_{\mathrm{P}}100, \mathcal{R}1, \mathcal{F}100$)) settings on the four test functions

importance of appropriate setting of island model.

There remains some directions for future work. This study examines the behavior of island model on four LSGO problems. The performance analysis can be extended to the whole set of LSGO functions. Further analysis on different problems, such as large scale combinatorial problems and large scale scheduling problems, is a possible direction. This study considers DE as the baseline EA for analysis. Analysis on the island model with different EAs is also promising.

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