IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received April 29, 2019, accepted July 5, 2019, date of publication July 10, 2019, date of current version January 2, 2020.

Digital Object Identifier 10.1109/ACCESS.2019.2928059

A Two-Phase Multiobjective Local Search for the Device Allocation in the Distributed Integrated Modular Avionics

QING ZHOU[1], JINYAN WANG[1], GUOQUAN ZHANG[1], KEQING GUO[2,3], XINYE CAI[2,3], LISONG WANG[2,3], AND YUHUA HUANG[2,3]

[1]Science and Technology on Avionics Integration Laboratory, China Aeronautical Radio Electronics Research Institute, Shanghai 200233, China
[2]Department of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[3]Collaborative Innovation Center of Novel Software Technology and Industrialization, Nanjing 210023, China

Corresponding author: Xinye Cai (xinye@nuaa.edu.cn)

This work was supported in part by the Aeronautical Science Foundation of China under Grant 20175552042.

ABSTRACT In the distributed integrated modular avionics (DIMA), it is desirable to assign the DIMA devices to the installation locations of the aircraft for obtaining the optimal quality and cost, subject to the resource and safety constraints. Currently, the routine device assignments in DIMA are conducted manually or by experience, which becomes more and more difficult with the increasing number of devices. Especially, in the face of large-scale device assignment problems (DAPs), the manual allocation will become an almost impossible task. In this paper, a bi-objective safety-constraint device assignment model in DIMA is formulated with the integer encoding for better scalability. A two-phase multiobjective local search (2PMOLS) is proposed for addressing it. In the first phase of 2PMOLS, the fast convergence of the population toward the Pareto front (PF) is achieved by the weighted sum approach. In the second phase, Pareto local search is conducted on the solutions delivered in the first phase for the extension of the PF approximation. 2PMOLS is compared with three decomposition-based approaches and one domination-based approach on DAPs of different sizes in the experimental studies. The experimental results show that 2PMOLS outperforms all the compared algorithms, in terms of both the convergence and diversity. It has also been demonstrated that the solution obtained by 2PMOLS is better in terms of both objectives (mass and ship set costs), compared with the solution designed by the domain expert. The experimental results show that 2PMOLS performs increasingly better with the increase of the problem size, compared with other algorithms, which indicates it has better scalability.

INDEX TERMS Distributed integrated modular avionics, device assignment, Pareto local search, multiobjective optimization.

I. INTRODUCTION

Integrated modular avionics (IMA) is the product of the standardization of avionic software and hardware. IMA is a computing platform made up of general integrated modules, on which multiple aircraft tasks (atomic concepts separated by aircraft system functions) can reside. The key concept is to share resources provided by standardized hardware with the standardized software interfaces allowing the parallel integration of aircraft systems on fewer devices than before.

The associate editor coordinating the review of this manuscript and approving it for publication was Genny Tortora.

As the concept of IMA can greatly reduce the weight of the avionic system, it becomes the mainstream direction for the development of the avionic system. However, IMA requires very precise design of the system as a whole (e.g, the device configuration in the physical space), which is more prominent in the distributed architecture-based IMA (DIMA). In DIMA, the standardized equipments can be distributed in multiple locations of the aircraft, thus such an architecture can further reduce the cable length and the task response time relative to IMA. Nevertheless, how to design the overall architecture of the DIMA is a very difficult task with the following factors taken into consideration:

1) the device used by DIMA,
2) the topological structure consisting of devices,
3) resources provided by device for aircraft tasks,
4) aircraft hardware installation position,
5) aircraft avionic integrated design process in the system resources, security, reliability and other constraints based on some metric (e.g., the total weight and cost of avionics systems).

The current avionic system mainly relies on the designing experience of the domain experts. With the rapid growth of the aircraft functions and modules, system resource requirements, as well as the requirements on the system reliability, safety and other aspects continue to grow. Under this circumstance, the manual design and verification become both inaccurate and difficult, modeling, validation and the optimal design of DIMA become an inevitable trend.

As the avionic system contributes significantly to the ship set cost, and mass of an aircraft, the optimal design of the DIMA architecture gradually becomes an active research field. For example, the mathematical models have been established for promoting and improving the design through the validation and evaluation of the model-based avionic architecture in [1]. The feasibility of the optimal design of hardware mapping has been demonstrated in [2]. Compared to the manual design, significant improvements of the model-based design has been presented in [2].

Sagaspe *et al.* proposed an allocation approach of avionics shared resources in [3] to analyze the safety of the avionic systems with the considerations of the computational and communication resources. They further proposed an constraint-based shared resource allocation approach in [4] to help decide whether a set of systems can be implemented on an IMA architecture while enforcing safety requirements. However, their approach can neither be applied to the multi-objective avionic model, nor suitable for large-scale problems.

Lohse *et al.* used heuristic methods to optimize the IMA distribution [5]. As a result, the weight of the small avionic systems can be significantly reduced. However, their approach did not consider the safety and reliability constraints for designing the avionic system.

Annighofer and Thielecke [2] models the DIMA by mapping the devices to the installation locations in an aircraft. The binary programming is employed to optimize the total weight on the model. Later, they have extended their work to multiobjective modeling and optimization in [6].

Zhang and Xiao [7] modeled the DIMA system as a cyber-physical system (CPS) containing a physical layer and a function layer. The improvement of the system is conducted through the conventional lexicographic optimization with the binary encoding.

While the optimal design of the model-based IMA/DIMA architecture becomes a promising research field, nevertheless, the following issues have not been well-addressed. First of all, the avionic system has high requirements for the reliability and safety. Most of the aforementioned works do not consider these features in the design. Second, the scalability of the existing IMA/DIMA models is poor due to the use of the binary encoding. This leads to the fact that the existing work of model-based IMA/DIMA design is limited to small subsystems. Third, the model-based IMA/DIMA architecture design faces the complex constraints, large-scale of systems and multiple objectives (e.g., total weight and cost of the avionics system) to be optimized, how to design an effective algorithm to adapt to its needs is of great importance.

In this paper, the device assignment problem in DIMA is modeled with the safety constraints using the integer encoding for better scalability. A two-phase multiobjective local search (2PMOLS) is further proposed for addressing it. The rest of this paper is organized as follows. In Section II, the background with regard to multiobjective optimization and decomposition methods are introduced. The local search and Pareto local search for combinatorial multiobjective optimization problems (CMOPs) are also presented in this section. Section III elaborates the mathematical model of the device assignment problem. Section IV presents the proposed algorithm for addressing DAP. The experimental setups are presented in Section V. The systematic experiments are conducted to verify the effectiveness of proposed algorithm in Section VI. The DIMA architecture obtained is also analyzed in this Section. Finally, a summary alongside with the future research direction are provided in Section VII.

II. BACKGROUND

A. MULTIOBJECTIVE OPTIMIZATION

In DIMA architecture design, the device assignment problem has multiple possibly conflicting objectives (e.g., mass and costs) to be optimized. Such a problem is called a multiobjective optimization problem (MOP), which can be stated as follows:

$$\begin{aligned} \text{minimize} \quad & F(x) = (f_1(x), \ldots, f_m(x)) \\ \text{subject to} \quad & x \in \Omega \end{aligned}$$

where Ω is the *decision space*, $F : \Omega \rightarrow R^m$ consists of m real-valued objective functions. The *attainable objective set* is $\{F(x)|x \in \Omega\}$. In the case when Ω is a finite set, (1) is called a combinatorial MOP (CMOP).

Let $u, v \in R^m$, u is said to *dominate* v, denoted by $u \prec v$, if and only if $u_i \leq v_i$ for every $i \in \{1, \ldots, m\}$ and $u_j < v_j$ for at least one index $j \in \{1, \ldots, m\}$.[1] A solution $x^* \in \Omega$ is *Pareto-optimal* to (1) if there exists no solution $x \in \Omega$ such that $F(x)$ dominates $F(x^*)$. $F(x^*)$ is then called a *Pareto-optimal (objective) vector*. In other words, any improvement in one objective of a Pareto optimal solution is bound to deteriorate at least another objective. The set of all the Pareto-optimal solutions is called the *Pareto set* (*PS*) and the

[1] In the case of maximization, the inequality signs should be reversed.

image of (PS) on the objective vector space is called *Pareto front* (PF) [8].

B. DECOMPOSITION METHODS

Over the past decades, multiobjective evolutionary algorithms (MOEAs) [9]–[12] have been recognized as a major methodology for approximating the PFs in the MOPs [13], [14]. Based on their selection mechanism, they can be further divided into the domination-based (e.g., [11], [15]–[20]), indicator-based (e.g., [21]–[25]) and decomposition approaches (e.g., [12], [26]–[33]). In the decomposition-based approaches, an MOP is usually decomposed into a number of single objective subproblems and solve them in a collaborative manner. A representative of such approaches is multiobjective evolutionary algorithm based on decomposition (MOEA/D) [12]. The commonly used decomposition methods [8] include Weighted Sum, Tchebycheff and Penalty-based Boundary Intersection, which can be defined as follows.

Let $\lambda^i = (\lambda_1, \ldots, \lambda_m)^T$ be a direction vector for i-th subproblem, where $\lambda_j \geq 0, j \in 1, \ldots, m$ and $\sum_{j=1}^{m} \lambda_j = 1$.

1) **Weighted Sum (WS) Approach:** The i-th subproblem is defined as

$$\begin{aligned} \text{minimize} \quad & g^{ws}(x|\lambda^i) = \sum_{j=1}^{m} \lambda_j^i f_j(x), \\ \text{subject to} \quad & x \in \Omega. \end{aligned} \tag{1}$$

Its search direction vector is defined as λ^i.

2) **Tchebycheff (TCH) Approach:** The i-th subproblem is defined as

$$\begin{aligned} \text{minimize} \quad & g^{tch}(x|\lambda^i, z^*) = \max_{1 \leq j \leq m} \{|f_j(x) - z_j^*|/\lambda_j^i\}, \\ \text{subject to} \quad & x \in \Omega. \end{aligned} \tag{2}$$

where Ω is the feasible region, but $\lambda_j = 0$ is replaced by $\lambda_j = 10^{-6}$ because $\lambda_j = 0$ is not allowed as a denominator in (2). Its search direction vector is defined as λ^i.

3) **Penalty-based Boundary Intersection (PBI) Approach:** This approach is a variant of Normal-Boundary Intersection approach [34]. The i-th subproblem is defined as

$$\begin{aligned} \text{minimize} \quad & g^{pbi}(x|\lambda^i, z^*) = d_1^i + \beta d_2^i, \\ & d_1^i = (F(x) - z^*)^T \lambda^i / ||\lambda^i||, \\ & d_2^i = ||F(x) - z^* - (d_1^i / ||\lambda^i||)\lambda^i||, \\ \text{subject to} \quad & x \in \Omega. \end{aligned} \tag{3}$$

where $||.||$ denotes L_2-norm and β is the penalty parameter. Its search direction vector is defined as λ^i.

C. LOCAL SEARCH AND PARETO LOCAL SEARCH

By using decomposition-based approaches, such as MOEA/D, a single-objective local search heuristic can be easily applied to a CMOP. Thus the local search heuristics and/or meta-heuristics (e.g. iterative local search [35], guided local search [36], tabu search [37], variable neighborhood search [38], ant colony optimization [39] and simulated annealing [40]) have been widely adopted to approximate the PFs of CMOPs.

Pareto local search (PLS) can be considered as an extension of the single objective local search [41]–[43]. It explores the neighborhood of a set of nondominated solutions for approximating PF [44], [45], which can be used as either stand-alone algorithms [46], [47] or even as components of the hybrid algorithms [42], [48]. Usually, a classical PLS can be divided into the following three components [49].

1) **Selection step** determines how to select the starting solutions for neighborhood exploration. In the PLS [41], these solutions are selected uniformly at random among the unexplored ones.
2) **Acceptance criterion** determines which solutions can be stored into the external archive. In the PLS, all the nondominated solutions identified in the neighborhood exploration are accepted.
3) **Neighborhood exploration** is conducted on the starting solutions. In particular, it defines the neighborhood of a solution, which is to be explored before switching to a different solution. The PLS always explores the entire neighborhood of a solution.

III. MATHEMATICAL MODEL OF DEVICE ASSIGNMENT PROBLEM

In the distributed integrated modular avionics (DIMA), it is desirable to assign the DIMA devices to the installation locations of the aircraft for obtaining the optimal quality and cost, subject to the resource and safety constraints. This is called device assignment problem (DAP) in this paper. The inputs of DAP are the device types, the number of devices, the resources required for the device and the installation locations [6].

For DAP, a solution can be encoded as follows.

$$x_D = \{x_{D_1}, x_{D_2}, \ldots, x_{D_i}, \ldots, x_{D_t}\}, \quad x_{D_i} \in [1, n]. \tag{4}$$

In this vector, D_i stands for the i-th device; and t is the number of the devices in DIMA architecture. n is the number of the installation locations. Each entry in the solution vector consists of the variable from 1 to n represents a possible assignment. The value of the variable x_{D_i} indicates that the device i is assigned to a installation location, e.g. $x_{D_i} = z$ means that the i-th device is assigned to z-th installation location. The DIMA device types include the core processing module (CPM) and the remote data concentrator(RDC). When these devices are installed, they require the installation locations to provide the resources, such as slots, peripherals, cooling facilities, and power supply.

In the model, we use a resource vector

$$R^j = \{R_1^j, R_2^j, \ldots, R_s^j, \ldots, R_S^j\}. \tag{5}$$

to describe the type of resources and the amount of resources available to the installation location j. Correspondingly, we use another resource vector

$$r^i = \{r_1^i, r_2^i, \ldots, r_s^i, \ldots r_S^i\}. \tag{6}$$

to represent the type of installation resource and the quantity necessary for device i to run.

For each valid device assignment, the amount of resources for each resource type consumed by all devices at each installation location does not exceed the total number of resources of that type at that installation location. This is illustrated by a **Resource Constraints** expression, for a given location j,

$$\sum_{x_{D_i}=j} r_s^i \leq R_s^j, \quad s = 1, \ldots, S. \tag{7}$$

which means that all types of resources consumed by the devices on the installation location j do not exceed the limit.

In the DIMA architecture, the safety of the avionic systems must be taken into account. Thus, in the model, each system has a redundant backup. But the mutual redundancy between the system devices cannot be placed in the same installation location, must be isolated. Such that **Segregation Constraints** is expressed as follows:

$$x_{D_i} \neq x_{D_j}, \quad i \neq j. \tag{8}$$

It is revealed that the device i and the device j that are redundant with each other cannot exist at any same position. The expression can also represent other devices that need to be isolated in addition to redundant devices.

The following two objectives are considered for optimization in DAP.

Mass is one of the most important objectives for evaluating the entire aircraft. Since Mass has a significant impact on the fuel consumption of the aircraft, which further affects the efficiency of the aircraft. The Mass of the avionics system is mainly composed of hardware modules, cables and installation facilities. In the device assignment problem, the Mass is mainly composed of the weight of the cables. The cable mass is the weight of the connecting cable between the task hosted on the device and the desired peripheral. In the objective function f_{Mass}, it calculates all the cables Mass $M_{i,x_{D_i}}$ produced by each assignment possible x_{D_i}. If the cable is not required, the cable Mass is 0. Finally all the cables mass is accumulated. Such that,

$$f_{Mass} = \sum_{i=1}^{t} M_{i,x_{D_i}}. \tag{9}$$

Ship set costs (SSC) is another important object considered in DIMA field. In the avionics system, SSC is a recurrent expense in the production process of each aircraft. In device assignment problem, SSC is total cost of peripheral used in each assignment. which means the SSC objective is

$$f_{SSC} = \sum_{i=1}^{t} C_{i,x_{D_i}}. \tag{10}$$

where $C_{i,x_{D_i}}$ is produced by each possible assignment x_{D_i}.

IV. A TWO-PHASE MULTIOBJECTIVE LOCAL SEARCH ALGORITHM

To solve DIMA device assignment problem, a two-phase multiobjective local search (2PMOLS) is proposed. In the first phase, the weighted-sum approach is adopted for the fast convergence of the population towards PFs. In the second phase, PLS is conducted on the obtained solutions in the first phase for the extension of PFs.

Algorithm 1 shows the workflow of 2PMOLS for DAPs. 2PMOLS maintains:

- the starting population SP, which consists of the starting solutions for LS;
- the external population EP, in which all the obtained nondominated solutions are stored;
- a uniformly generated set of weight vectors $W = \{\lambda^1, \ldots, \lambda^N\}$.

The symbol $\downarrow$ represents the input while $\uparrow$ represents the output, $\updownarrow$ represents both the input and output of a algorithm.

Algorithm 1 2PMOLS

Input: a stopping criterion;
Output: EP.
1 $Initialization(EP \updownarrow, W \downarrow)$;
```
/* first phase */
```
2 $Phase\_1(SP \downarrow, EP \updownarrow, W \downarrow)$;
```
/* second phase */
```
3 $Phase\_2(SP \downarrow, EP \updownarrow)$;
4 If the stopping criteria is satisfied, stop and output the EP. Otherwise go to Step3.

Algorithm 2 Initialization

Input: $EP = \{x^1, \ldots, x^N\}$
Output: EP, W
1 Decompose a DAP into N subproblems by the weight vectors $W = \{\lambda^1, \ldots, \lambda^N\}$. For each $i = 1, \ldots, N$, solution x^i is generated randomly or by a heuristic and associated with i-th subproblem.
2 Compute the Euclidean distance between any two weight vectors and obtain T closest weight vectors to each weight vector. For each $i = 1, \ldots, N$, set $B(i) = \{i_1, \ldots, i_T\}$, where $\lambda^{i_1}, \ldots, \lambda^{i_T}$ are the T closest weight vectors to λ^i.

A. INITIALIZATION

The initialization procedure is presented in Algorithm 2. First, a DAP is decomposed into N subproblems by the uniformly generated weight vectors W. EP is initialized randomly or by a heuristic. For each $i \in \{1, \ldots, N\}$, a solution x^i is associated with the i-th subproblem. After that, the Euclidean distance between any two weight vectors is calculated. For each weight vector, its T closest vectors are chosen as the neighborhood.

B. PHASE ONE

The Algorithm 3 seeks the fast convergence of the population for obtaining a good PF approximation. For each solution $x \in SP$, the local search (LS) is conducted by generating its neighboring solutions $N(x)$. After that, each solution $y \in N(x)$ is used to update the neighborhood of x by the weighted-sum approach based on Eq. (1).

Algorithm 3 *Phase_1*

```
Input  : SP = {x^1, ..., x^N}, EP, W
Output: EP.
Set TP = EP, SP = EP.
while SP is not empty do
    foreach x^i ∈ SP do
        /* N(x) is the neighborhood of x */
        foreach y ∈ N(x^i) do
            if j ∈ B(i)&&g^ws(y|λ^j) ≤ g^ws(x^j|λ^j) then
                set x^j = y;
            end
        end
    end
    SP = EP\TP.
end
```

C. PHASE TWO

In Algorithm 4, Pareto local search(PLS) is conducted on each solution $x \in SP$ by generating its neighbors $N(x)$, which is then used to update EP as follows. For each $y \in N(x)$, if there is no solution in EP which can dominate it, then y will be added into EP and all the solutions in EP that are dominated by y will be removed. All the new generated non-dominated solutions that successfully update EP are stored in SP as the starting solutions for the next round of the local search.

Algorithm 4 *Phase_2*

```
Input  : SP,EP
Output: EP.
Set TP = EP, SP = EP.
while SP is not empty do
    foreach x ∈ SP do
        /* N(x) is the neighborhood of x */
        foreach y ∈ N(x) do
            add y to EP, if there is no solution in EP
            which can dominate y, remove all the
            solutions in EP that are dominated by y.
        end
    end
    SP = EP\TP.
end
```

V. EXPERIMENTAL SETUPS

A. CASE STUDY

A320-like aircraft is used for our empirical study. In the A320 aircraft, it has seven installation locations, namely AVIONICS-BAY, NOSE-LEFT, NOSE-RIGHT, MID-LEFT, MID-RIGHT, TAIL-LEFT and TAIL-RIGHT. Different installation locations have different access time, and different types or numbers of the resources, which will lead to differences in constraints and objectives. The mass and cost of cable routes will result in the differences in the Mass and SSC objective. The goal is to assign the devices to these seven installation locations so that the two objectives (Mass and SSC) are optimized. An instance named 14-7 indicates that 14 devices are to be installed into 7 locations. In this paper, seven instances of different scales are selected, i.e., 14-7, 28-7, 40-7, 50-7, 60-7, 100-7, 140-7.

B. PARAMETERS SETTINGS

- 2PMOLS: In phase 1, the weighted sum method is adopted to decompose the multiobjective problem into a number of single objective optimization subproblems. The number of subproblems is set to 60 and the size of the neighborhood of each subproblem is set to 20. In phase 2, PLS is adopted for obtaining more approximated Pareto optimal solutions.
- MOEA/D-LS: MOEA/D [12] based on three decomposition methods, weighted sum (WS), Tchebycheff (TCH) and penalty boundary intersection (PBI) is adopted. For a fair comparison, MOEA/D (WS, TCH, PBI) is combined with local search heuristic (MOEA/D-LS). The number of subproblems for these algorithms are set to 60 for all instances and the size of the neighborhood of each subproblem is set to 20. For PBI, the penalty parameter θ is set to 5.
- NSGA-II-LS: NSGA-II [11] is a classical Pareto-dominance based algorithm and NSGA-II-LS is the combination of NSGA-II and local search heuristic. The population size in NSGA-II-LS is set to 60.

The neighborhood $N(x)$ of a solution x is generated as follows: Randomly remove 2 devices from x and then add the devices one by one to the locations considering the resource at each location and segregation constraints between devices. Repeat the process until all the possible assignments are taken into account.

TABLE 1. The c-metric (%) values between 2PMOLS and MOEA/D-LS (WS, TCH and PBI), NSGA-II-LS on seven DAP instances of different scales.

instance	MOEA/D-LS(WS)		MOEA/D-LS(TCH)		MOEA/D-LS(PBI)		NSGA-II-LS	
	C(A,B)	C(B,A)	C(A,B)	C(B,A)	C(A,B)	C(B,A)	C(A,B)	C(B,A)
14-7	**6.67**	0	**5.89**	0	**22.62**	0	0	0
28-7	**9.64**	0	1.14	**63.41**	0	**70.48**	0	**80.19**
40-7	**42.71**	0	**47.28**	0	**81.10**	0	**43.77**	0
50-7	**59.61**	0	**28.6**	0	**33.47**	0	**32.85**	0
60-7	**29.08**	6.32	**41.22**	14.92	**51.18**	12.69	**83.68**	9.99
100-7	**100**	0	**100**	0	**100**	0	**100**	0
140-7	**87.18**	1.07	**99.56**	0	**100**	0	**99.37**	0

A corresponds to 2PMOLS.
B corresponds to the compared algorithm.

TABLE 2. The performance of 2PMOLS, MOEA/D-LS (WS, TCH, PBI) and NSGA-II-LS in terms of average I_H values on seven DAP instances of different scales.

instance	2PMOLS	MOEA/D-LS (WS)	MOEA/D-LS (TCH)	MOEA/D-LS (PBI)	NSGA-II-LS
14-7	**1.93E+05**	1.54E+05$^-$	1.88E+05$^-$	1.88E+05$^-$	1.91E+05$^-$
28-7	**1.23E+07**	1.22E+07$^-$	7.09E+06$^-$	5.36E+06$^-$	1.19E+07$^-$
40-7	**3.67E+07**	3.63E+07$^-$	2.37E+07$^-$	1.76E+07$^-$	2.77E+07$^-$
50-7	**3.59E+07**	3.49E+07$^-$	2.36E+07$^-$	1.66E+07$^-$	3.03E+07$^-$
60-7	**7.73E+07**	7.57E+07$^-$	5.51E+07$^-$	3.38E+07$^-$	4.62E+07$^-$
100-7	**1.39E+08**	1.27E+08$^-$	6.05E+07$^-$	4.36E+07$^-$	6.07E+07$^-$
140-7	**3.10E+08**	2.93E+08$^-$	1.48E+08$^-$	1.04E+08$^-$	1.20E+08$^-$

The best I_H value is highlighted in bold.
'+', '−' and '≈' indicate that the result is significantly better, significantly worse and statistically similar to that of 2PMOLS on this test instance, respectively (wilcoxon's rank sum test at the 0.05 significance level).

Stopping criterion: Each of the compared algorithms is terminated when there is no newly added solutions for local search.

For a fair comparison, all the compared algorithms are run independently for 20 times on each test instance. All the compared algorithms use the same method to initialize populations and use the same parameter settings as in the original paper. All the compared algorithms are coded in Java and the experiments are conducted on a PC equipped with Intel 3.4 GHz CPU and 16G RAM.

C. PERFORMANCE METRICS

Two performance metrics are used to measure the performance of the compared multiobjective algorithms, as follows.

1) Hypervolume indicator(I_H) [50]: Let $z^* = (f_1^*, \ldots, f_m^*)$ be a reference point in the objective space which is dominated by all Pareto optimal objective vectors. Calculating the area from z^* to Pareto front of the objective space to obtain the I_H. The higher the I_H, the better the approximation. It can be defined as

$$I_H(P) = volume(\bigcup_{f \in P}[f_1, z_1^r] \times \ldots [f_m, z_m^r]). \quad (11)$$

In our experiments, the reference points are set as 1.1 times of the largest objective values of the nondominated solutions obtained by all the compared algorithms.

2) Set coverage (c-metric) [50]: Let A and B be two approximations to the PF of an MOP. $C(A, B)$ is defined as the percentage of the solutions in B dominated by at least one solution in A:

$$C(A, B) = \frac{|u \in B | \exists v \in A : v \ dominates \ u|}{|B|} \times 100\% \quad (12)$$

$C(B, A)$ is not necessarily equal to $1 - C(A, B)$. $C(A, B) = 1$ indicates that all solutions in B are dominated by solutions in A while $C(A, B) = 0$ means that no solution in B is dominated by a solution in A.

VI. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. COMPARISONS WITH MOEA/D-LS (WS, TCH AND PBI) AND NSGA-II-LS

In this section, 2PMOLS is compared with MOEA/D-LS (WS, TCH, PBI) and NSGA-II-LS on DAP instances. We can observe from Table 1 that 2PMOLS has the best performance

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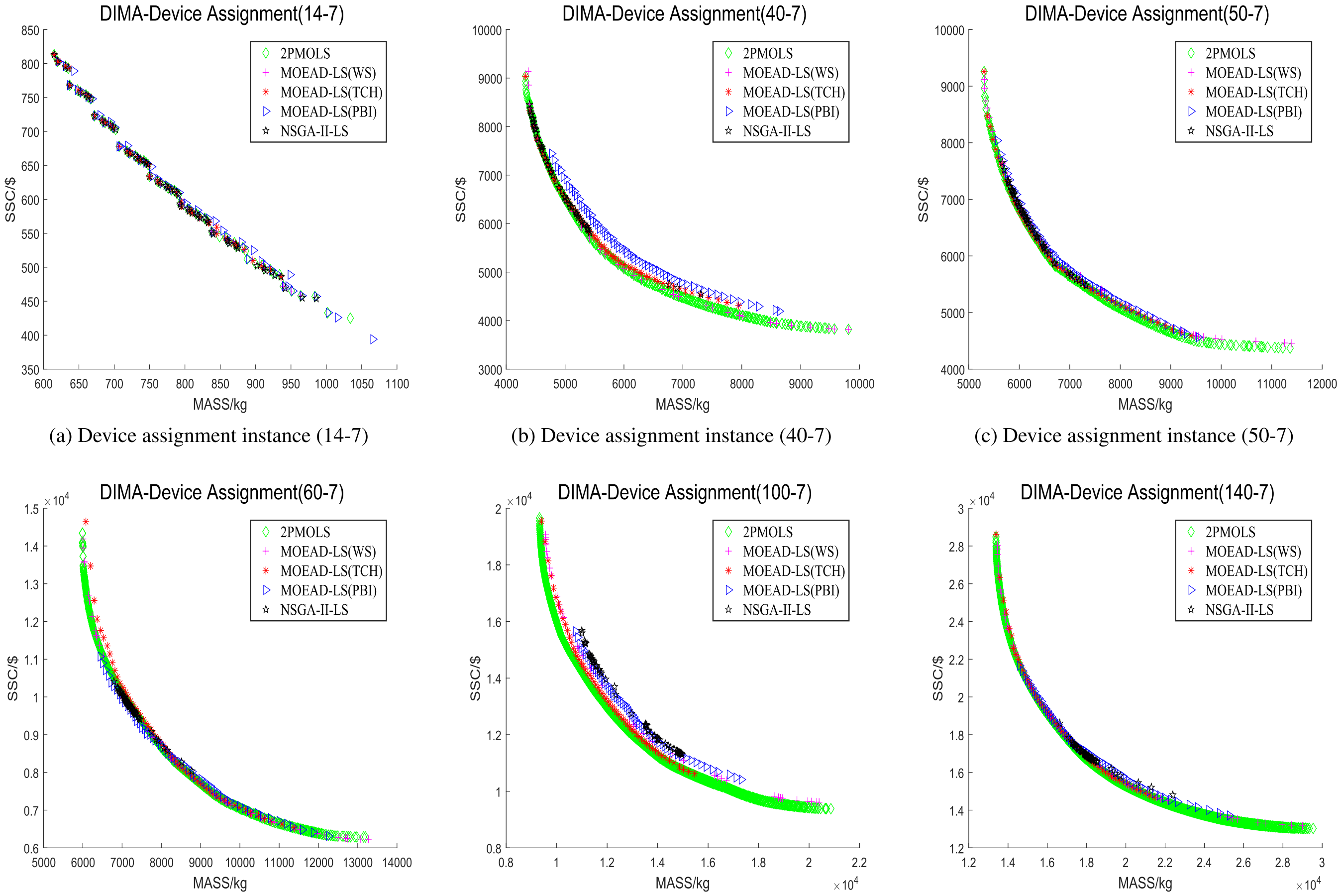

(a) Device assignment instance (14-7)
(b) Device assignment instance (40-7)
(c) Device assignment instance (50-7)
(d) Device assignment instance (60-7)
(e) Device assignment instance (100-7)
(f) Device assignment instance (140-7)

FIGURE 1. The nondominated solutions obtained by 2PMOLS, MOEA/D-LS (WS, TCH and PBI) and NSGA-II-LS on different DAP instances.

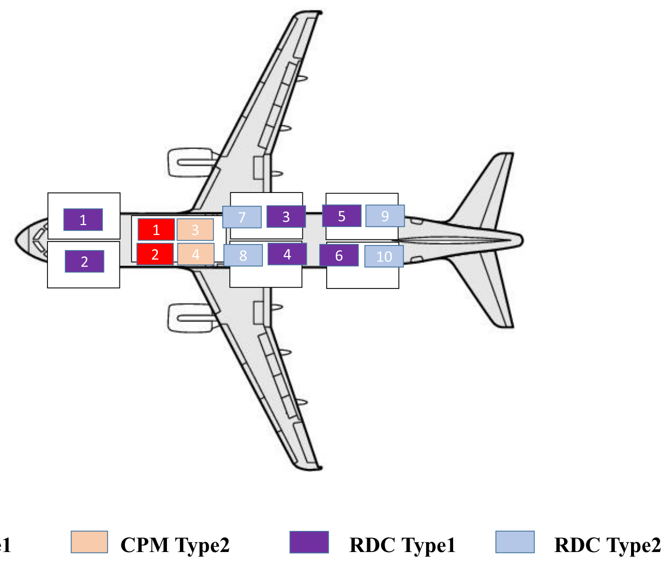

FIGURE 2. Device assignment designed by a domain expert.

except for 28-7 in terms of c-metric. This indicates that 2PMOLS has the best overall convergence. It is interesting to see that 2PMOLS performs increasingly better with the increasing scale of DAP instance compared with other algorithms, which indicates that 2PMOLS has much better scalability.

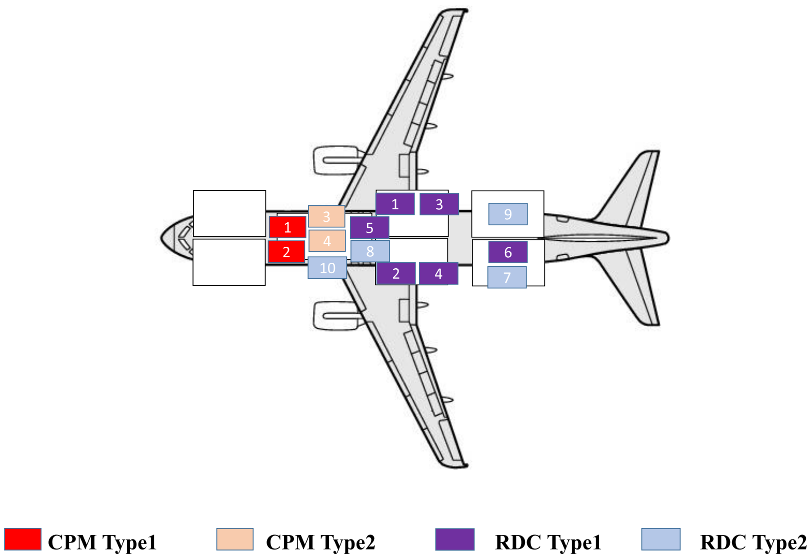

FIGURE 3. A solution of the device assignment obtained by 2PMOLS.

TABLE 3. The CPU time (s) spent by 2PMOLS, MOEA/D-LS (WS, TCH and PBI) and NSGA-II-LS on seven DAP instances of different scales.

instance	2PMOLS	WS	TCH	PBI	NSGA-II-LS
14-7	0.4	0.1	0.2	0.4	0.2
28-7	0.6	0.3	0.3	0.8	0.7
40-7	1.0	0.4	0.5	2.1	0.9
50-7	1.7	0.5	0.8	3.1	1.6
60-7	2.5	0.6	1.5	7.6	2.6
100-7	120.2	0.8	3.5	9.6	3.2
140-7	203.4	3.1	4.9	35.3	9.6

All the compared algorithms were coded in JAVA and all the algorithms were tested on a PC with 3.4GHz CPU.

To further validate the performance of 2PMOLS, the hypervolume values obtained by all five compared algorithms are presented in Table 2. It can be observed clearly that 2PMOLS performs significantly better than all the other compared algorithms, which indicates that 2PMOLS has the best overall performance in terms of both convergence and diversity. For 28-7 instance, although the convergence performance of 2PMOLS in terms of c-metric is worse than that of other compared algorithms, its over performance in terms of hypervolume is significantly better than that of all the other compared algorithms. This indicates 2PMOLS has the superior performance in terms of diversity.

To better visualize the performance of all the compared algorithms, the nondominated sets delivered by five compared algorithms in the run with the median hypervolume value on seven DAP instances with different scales are given in Fig. 1. It can be observed that 2PMOLS has the best performance on all the instances.

In addition, the final CPU time in seconds for all the five compared algorithms are given in Table 3. It can be observed that MOEA/D-LS (WS) has the fastest convergence speed, followed by MOEA/D-LS (TCH). The convergence speed of 2PMOLS is very close to that of MOEA/D-LS (PBI) on 14-7, 28-7, 40-7, 50-7 and 60-7 instances. However, in the two large-scale problems (100-7 and 140-7), the computational time of 2PMOLS is more than other compared algorithms due to the use of PLS.

In 14-7 instance, a manually designed DIMA device architecture by a human expert is given in Figure 2. For comparison, a solution obtained by 2PMOLS and selected by a human expert is decoded and presented in Figure 3. This solution is (2, 2, 2, 2, 3, 4, 3, 4, 2, 6, 6, 2, 5, 2). It can be observed that all the computing devices (CPM) are assigned to AVIONICS-BAY, since that the cooling resources needed by the computing device are only available in the AVIONICS-BAY. In addition, the mass of the manual assignment is 7.69 kg (its SSC is 715), whereas the optimal mass of the device assignment obtained by 2PMOLS is 7.07 kg (its SSC is 678). The results show that the model-based optimal design by 2PMOLS makes a significant improvement over manual design by a human expert on both objectives.

B. COMPUTATIONAL COMPLEXITY OF 2PMOLS

Let us assume the number of subproblems is N; the neighborhood size for each subproblem is T; the size of the external population is M and on average each initial solution will generate Y solutions by local search. In the idealization process (Algorithm 2), computing T closest neighboring weight vector requires $O(NlogN)$, where sorting N weight vectors requires $O(NlogN)$ and finding T closest neighboring weight vectors requires $O(TN)$. In phase 1 (Algorithm 3), the local search for each solutions requires $O(Y)$ computations; thus updating T neighboring subproblems for N subproblems requires $O(TNY)$ computations. In phase 2 (Algorithm 4), the local search for the external population requires $O(MY)$ computations and updating the external population requires $O(M^2Y)$ computations. Therefore, the total computational complexity of 2PMOLS is $O(M^2Y)$.

VII. CONCLUSION

In this paper, the device assignment problem in DIMA is modeled with the safety constraints using the integer encoding for better scalability. A two-phase multiobjective local search (2PMOLS) is further proposed for addressing it. 2PMOLS is compared with three decomposition-based approaches and one domination-based approach on DAPs of different sizes in the experimental studies. The experimental results show that 2PMOLS outperforms all the compared algorithms, in terms of both the convergence and diversity. It has also been demonstrated that the solution obtained by 2PMOLS is better in terms of both objectives (mass and ship set costs), compared with the solution designed by the domain expert.

REFERENCES

[1] C. Fraboul and F. Martin, "Modeling and simulation of integrated modular avionics," in *Proc. 6th Euromicro Workshop Parallel Distrib. Process.*, Madrid, Spain, 1998, pp. 102–110.

[2] B. Annighöfer and F. Thielecke, "Supporting the design of distributed integrated modular avionics systems withbinary programming," in *Deutscher Luft-und Raumfahrtkongress*. Berlin, Germany, 2012.

[3] L. Sagaspe, G. Bel, P. Bieber, F. Boniol, and C. Castel, "Safe allocation of avionics shared resources," in *Proc. 9th IEEE Int. Symp. High-Assurance Syst. Eng.*, Oct. 2005, pp. 25–33.

[4] L. Sagaspe and P. Bieber, "Constraint-based design and allocation of shared avionics resources," in *Proc. IEEE/AIAA 26th Digit. Avionics Syst. Conf.*, Oct. 2007, pp. 2.A.5-1–2.A.5-10.

[5] F. Lohse, V. Zerbe, and T. Luetzelberger, "Architecture analysis and optimization of reconfigurable, complex systems," in *Proc. IEEE 14th Int. Conf. Intell. Eng. Syst.*, May 2010, pp. 221–225.

[6] B. Annighöfer and F. Thielecke, "Multi-objective mapping optimization for distributed integrated modular avionics," in *Proc. IEEE/AIAA 31st Digit. Avionics Syst. Conf.*, Oct. 2012, pp. 6B2-1–6B2-13.

[7] C. Zhang and J. Xiao, "Modeling and optimization in distributed integrated modular avionics," in *Proc. IEEE/AIAA 32nd Digit. Avionics Syst. Conf. (DASC)*, Oct. 2013, pp. 2E1-1–2E1-12.

[8] K. Miettinen, *Nonlinear Multiobjective Optimization*. Dordrecht, The Netherlands: Kluwer, 1999.

[9] X. Cai, Y. Li, Z. Fan, and Q. Zhang, "An external archive guided multiobjective evolutionary algorithm based on decomposition for combinatorial optimization," *IEEE Trans. Evol. Comput.*, vol. 19, no. 4, pp. 508–523, Aug. 2015.

[10] X. Cai, Z. Mei, Z. Fan, and Q. Zhang, "A constrained decomposition approach with grids for evolutionary multiobjective optimization," *IEEE Trans. Evol. Comput.*, vol. 22, no. 4, pp. 564–577, Aug. 2018.

[11] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.

[12] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Trans. Evol. Comput.*, vol. 11, no. 6, pp. 712–731, Dec. 2007.

[13] K. Deb and K. Miettinen, *Multiobjective Optimization: Interactive and Evolutionary Approaches*, vol. 5252. Berlin, Germany: Springer, 2008.

[14] C. A. C. Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*, 2nd ed. New York, NY, USA: Springer, Sep. 2007.

[15] E. Zitzler and S. Künzli, "Indicator-based selection in multiobjective search," in *Proc. 8th Int. Conf. Parallel Problem Solving Nature*, Birmingham, U.K., Sep. 2004, pp. 832–842.

[16] J. Knowles and D. Corne, "Approximating the nondominated front using the Pareto archived evolution strategy," *Evol. Comput.*, vol. 8, no. 2, pp. 149–172, Jun. 2000.

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

[18] G. G. Yen and H. Lu, "Dynamic multiobjective evolutionary algorithm: Adaptive cell-based rank and density estimation," *IEEE Trans. Evol. Comput.*, vol. 7, no. 3, pp. 253–274, Jun. 2003.

[19] C. A. C. Coello, G. T. Pulido, and M. S. Lechuga, "Handling multiple objectives with particle swarm optimization," *IEEE Trans. Evol. Comput.*, vol. 8, no. 3, pp. 256–279, Jun. 2004.

[20] M. Li, S. Yang, and X. Liu, "Shift-based density estimation for Pareto-based algorithms in many-objective optimization," *IEEE Trans. Evol. Comput.*, vol. 18, no. 3, pp. 348–365, Jun. 2014.

[21] E. Zitzler and S. Künzli, "Indicator-based selection in multiobjective search," in *Parallel Problem Solving From Nature—PPSN VIII* (Lecture Notes in Computer Science), vol. 3242, X. Yao, Ed. Birmingham, U.K.: Springer-Verlag, Sep. 2004, pp. 832–842.

[22] M. Basseur and E. Zitzler, "Handling uncertainty in indicator-based multiobjective optimization," *Int. J. Comput. Intell. Res.*, vol. 2, no. 3, pp. 255–272, 2006.

[23] C. Igel, N. Hansen, and S. Roth, "Covariance matrix adaptation for multi-objective optimization," *Evol. Comput.*, vol. 15, no. 1, pp. 1–28, 2007.

[24] N. Beume, B. Naujoks, and M. Emmerich, "SMS-EMOA: Multiobjective selection based on dominated hypervolume" *Eur. J. Oper. Res.*, vol. 181, no. 3, pp. 1653–1669, 2007.

[25] J. Bader and E. Zitzler, "HypE: An algorithm for fast hypervolume-based many-objective optimization," *Evol. Comput.*, vol. 19, no. 1, pp. 45–76, Mar. 2011.

[26] T. Murata, H. Ishibuchi, and M. Gen, "Specification of genetic search directions in cellular multi-objective genetic algorithms," in *Proc. 1st Int. Conf. Evol. Multi-Criterion Optim. (EMO)*, Zürich, Switzerland, Mar. 2001, pp. 82–95.

[27] A. J. Nebro, J. J. Durillo, F. Luna, B. Dorronsoro, and E. Alba, "MOCell: A cellular genetic algorithm for multiobjective optimization," *Int. J. Intell. Syst.*, vol. 24, no. 7, pp. 726–746, Jul. 2009.

[28] J. J. Durillo, A. J. Nebro, C. A. C. Coello, F. Luna, and E. Alba, "A comparative study of the effect of parameter scalability in multi-objective metaheuristics," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Hong Kong, Jun. 2008, pp. 1893–1900.

[29] J. D. Schaffer and J. J. Grefenstette, "Multi-objective learning via genetic algorithms," in *Proc. 9th Int. Joint Conf. Artif. Intell. (IJCAI)*, Los Angeles, CA, USA, 1985, pp. 593–595.

[30] E. J. Hughes, "Multiple single objective Pareto sampling," in *Proc. Congr. Evol. Comput. (CEC)*, Canberra, ACT, Australia, vol. 4, Dec. 2003, pp. 2678–2684.

[31] E. J. Hughes, "MSOPS-II: A general-purpose many-objective optimiser," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Sep. 2007, pp. 3944–3951.

[32] X. Cai, Z. Yang, Z. Fan, and Q. Zhang, "Decomposition-based-sorting and angle-based-selection for evolutionary multiobjective and many-objective optimization," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2824–2837, Sep. 2017.

[33] X. Cai, Z. Mei, and Z. Fan, "A decomposition-based many-objective evolutionary algorithm with two types of adjustments for direction vectors," *IEEE Trans. Cybern.*, vol. 48, no. 8, pp. 2335–2348, Aug. 2018.

[34] I. Das and J. E. Dennis, "Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems," *SIAM J. Optim.*, vol. 8, no. 3, pp. 631–657, Jul. 1998.

[35] L. Paquete and T. Stützle, "Design and analysis of stochastic local search for the multiobjective traveling salesman problem," *Comput. Oper. Res.*, vol. 36, no. 9, pp. 2619–2631, 2009.

[36] A. Alsheddy and E. E. P. K. Tsang, "Guided Pareto local search based frameworks for biobjective optimization," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2010, pp. 1–8.

[37] E. L. Ulungu, J. Teghem, P. H. Fortemps, and D. Tuyttens, "MOSA method: A tool for solving multiobjective combinatorial optimization problems," *J. Multi-Criteria Decis. Anal.*, vol. 8, no. 4, pp. 221–236, 1999.

[38] Y.-C. Liang and M.-H. Lo, "Multi-objective redundancy allocation optimization using a variable neighborhood search algorithm," *J. Heuristics*, vol. 16, no. 3, pp. 511–535, 2010.

[39] C. García-Martínez, O. Cordón, and F. Herrera, "A taxonomy and an empirical analysis of multiple objective ant colony optimization algorithms for the bi-criteria TSP," *Eur. J. Oper. Res.*, vol. 180, no. 1, pp. 116–148, Jul. 2007.
[40] S. Bandyopadhyay, S. Saha, U. Maulik, and K. Deb, "A simulated annealing-based multiobjective optimization algorithm: AMOSA," *IEEE Trans. Evol. Comput.*, vol. 12, no. 3, pp. 269–283, Jun. 2008.
[41] L. Paquete and T. Stützle, *A Two-Phase Local Search for the Biobjective Traveling Salesman Problem*. Berlin, Germany: Springer, 2003.
[42] T. Lust and J. Teghem, "Two-phase Pareto local search for the biobjective traveling salesman problem," *J. Heuristics*, vol. 16, no. 3, pp. 475–510, 2010.
[43] T. Lust, "Speed-up techniques for solving large-scale bTSP with the two-phase Pareto local search," in *Proc. 10th Annu. Conf. Genetic Evol. Comput. (GECCO)*, Atlanta, GA, USA, Jul. 2008, pp. 761–762.
[44] M. M. Drugan and D. Thierens, "Stochastic Pareto local search: Pareto neighbourhood exploration and perturbation strategies," *J. Heuristics*, vol. 18, no. 5, pp. 727–766, 2012.
[45] X. Cai, H. Sun, Q. Zhang, and Y. Huang, "A grid weighted sum Pareto local search for combinatorial multi and many-objective optimization," *IEEE Trans. Cybern.*, vol. 49, no. 9, pp. 3586–3598, Sep. 2019.
[46] L. Paquete, M. Chiarandini, and T. Stützle, *Pareto Local Optimum Sets in the Biobjective Traveling Salesman Problem: An Experimental Study*. Berlin, Germany: Springer, 2003.
[47] L. Paquete and T. Stützle, "A study of stochastic local search algorithms for the biobjective QAP with correlated flow matrices," *Eur. J. Oper. Res.*, vol. 169, no. 3, pp. 943–959, 2006.
[48] L. Ke, Q. Zhang, and R. Battiti, "Hybridization of decomposition and local search for multiobjective optimization," *IEEE Trans. Cybern.*, vol. 44, no. 10, pp. 1808–1820, Oct. 2014.
[49] J. Dubois-Lacoste, M. López-Ibáñez, and T. Stützle, "Anytime Pareto local search," *Eur. J. Oper. Res.*, vol. 243, no. 2, pp. 369–385, 2015.
[50] E. Zitzler and L. Thiele, "Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach," *IEEE Trans. Evol. Comput.*, vol. 3, no. 4, pp. 257–271, Nov. 1999.

QING ZHOU received the Ph.D. degree from Beihang University, in 2013. He is currently a Senior Engineer with the China Aeronautical Radio Electronics Research Institute. His research interests include avionic system, distributed computing, and modeling and simulation of complex systems.

JINYAN WANG received the Ph.D. degree from Shanghai Jiaotong University, in 2006. He is currently a Research Fellow with the China Aeronautical Radio Electronics Research Institute. His research interests include avionics system, distributed computing, and modeling and simulation of complex systems.

GUOQUAN ZHANG, photograph and biography not available at the time of publication.

KEQING GUO is currently pursuing the master's degree with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics. His research interests include modeling of avionic system, evolutionary computation, and multiobjective optimization.

XINYE CAI received the B.Eng. degree from the Electronic and Information Engineering Department, Huazhong Univeristy of Science and Technology, China, in 2004, the master's degree from the Electronic Department, University of York, U.K., in 2006, and the Ph.D. degree from the Electrical and Computer Engineering Department, Kansas State University, in 2009. He is currently an Associate Professor with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics. His main research interests include computational intelligence, data mining and their applications in avionics, scheduling, and logistics. He has published more than 40 papers in various journals and conferences, including IEEE Transactions on Evolutionary Computation, the IEEE Transactions on Cybernetics and Information Sciences. Dr. Cai was the winner of CEC2017 Many-objective Optimization Competition. He is an Associate Editor of the *Swarm and Evolutionary Computation Journal*.

LISONG WANG received the Ph.D. degree from the Nanjing University of Aeronautics and Astronautics, in 2010. He is currently an Associate Professor with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, China. His research interests include wireless sensor network, data management in distributed environment, and formal methods.

YUHUA HUANG received the B.Sc. degree in communication engineering from the Harbin Institute of Technology, China, in 1996, the M.Sc. degree in communication and information system from Xinjiang University, China, in 2002, and the Ph.D. degree in signal and information processing from Southeast University, China, in 2006. He is currently an Associate Professor with the College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, China. His current research interests include evolutionary computation, optimization, and data mining with their applications.