TC-MFEA: Task Clone-Based Multifactorial Evolutionary Algorithm for Constrained Reliability Redundancy Allocation Problem

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***Abstract*— The Reliability Redundancy Allocation Problem (RRAP) is a challenging NP-hard optimization problem aimed at maximizing system reliability under resource constraints. While evolutionary algorithms perform well for single-task RRAP, evolutionary multitask optimization (EMTO) has recently shown promise in solving multiple RRAPs simultaneously. However, the constrained and nonlinear nature of RRAP often leads to premature convergence, necessitating effective constraint-handling strategies. To address this, we propose a task-cloning-based EMTO framework using the multi-factorial evolutionary algorithm (TC-MFEA). It formulates a primary constrained RRAP alongside an auxiliary unconstrained task generated via task cloning and treats them as joint optimization. It enables exploration and knowledge transfer, which improves solution quality for the primary task. The proposed method is validated on both series and bridge system RRAPs. Further, Taguchi method is used for the parameter tuning, and the experimental results demonstrate that TC-MFEA-RRAP outperforms existing EMTO approaches in achieving higher system reliability.**

Keywords—Evolutionary Multi-task Optimization, MFEA, Constrained Optimization, System Reliability Optimization, Series System, Complex (Bridge) System.

I. INTRODUCTION

System reliability is the probability that a system operates without failure under specified conditions for a given period [1], with higher values indicating lower failure risk. Maximizing reliability is critical in applications such as telecommunications [2], electrical power systems, pharmaceutical manufacturing, mechanical systems, and cyber-physical systems [3] - [7].

There are two main approaches exist for improving system reliability: (a) reliability allocation, which increases component reliability but also raises system cost, and (b) redundancy allocation (RAP), which enhances reliability by adding redundant components at the expense of increased cost, weight, and volume [8]. The joint consideration of these approaches, known as the reliability redundancy allocation problem (RRAP) [9], aims to maximize overall system reliability by optimally selecting component reliabilities and redundancy levels while satisfying resource constraints (i.e. cost, weight, and volume).

RRAP is a computationally challenging NP-hard problem [10]. Traditional methods, such as dynamic programming, branch-and-bound, and mixed-integer nonlinear programming [11], [12], often struggle to obtain satisfactory solutions, motivating the use of metaheuristic approaches [9]. RRAP has been widely studied as a single-objective problem using algorithms such as GA [13], PSO [14], ACO [15], and ABC [16] etc. It has also been formulated as a multi-objective problem, considering reliability along with cost or weight, and solved using methods like NSGA-II, MOPSO, and MOEA [17] - [19]. Additionally, many-objective formulations involving reliability, cost, weight, and volume have been explored [20] along with hybrid evolutionary approaches to further enhance solution quality [21] - [24].

Recently, Chowdury et al. [25] - [27] proposed several EMTO-based frameworks for solving multiple RRAPs, demonstrating superior computational efficiency over single-task optimizers. However, due to the inherently constrained nature of RRAP, effective constraint-handling remains critical for improving system reliability. To address this, in this paper we propose a task-cloning-based EMTO framework using the multi-factorial evolutionary algorithm (MFEA), termed TC-MFEA-RRAP. The approach formulates a primary constrained RRAP (series system) alongside an auxiliary unconstrained task generated by removing all constraints. Both tasks are jointly optimized within the MFEA framework, where the auxiliary task enhances exploration and facilitates knowledge transfer, leading to improved solution quality for the primary task. The effectiveness of the proposed method is further validated on a complex bridge system RRAP. Parameter tuning is performed using the L9 Taguchi method, and performance is compared with existing EMTO-based approaches in terms of best system reliability. Results demonstrate that TC-MFEA-RRAP consistently achieves superior reliability performance.

The remainder of the paper is organized as follows: Section II presents the RRAP formulation, Section III describes the proposed methodology, Section IV details the experimental setup and results, and Section V concludes the paper with limitations and future directions.

II. PROBLEM FORMULATION

This section presents the problem formulation, while the associated notations and their definitions are summarized in Table I. The study focuses on widely recognized and extensively investigated reliability optimization problems reported in the literature [8]. The mathematical expression of the reliability model is given as follows:

$$Maximize\ \mathrm{F} = \mathrm{R_s}(\mathrm{r}, \mathrm{n}) \quad (1)$$

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Table I. Symbols and their definitions.

Symbol	Definition	Symbol	Definition
$\boldsymbol{R_S(r,n)}$	Overall reliability of the system.	r_i	i^{th} sub-system's component reliability.
$\boldsymbol{Q_i}$	i^{th} sub-system's failure probability	n_i	i^{th} sub-system's redundant components.
$\boldsymbol{R_i}$	i^{th} sub-system's reliability.	$v_{i,}$	i^{th} sub-system's volume
$\boldsymbol{V}$	Maximum limit for volume constraint	$w_{i,}$	i^{th} sub-system's weight
$\boldsymbol{C}$	Maximum limit for cost constraint	α_i	i^{th} sub-system's shaping factor
$\boldsymbol{W}$	Maximum limit for weight constraint	β_i	i^{th} sub-system's scaling factor
$\boldsymbol{k}$	Total constraints	g_j	j^{th} resource constraint
$\boldsymbol{m}$	Number of sub-systems.	b_j	j^{th} constraint's upper limit.

Subject to,

$$g_j(r,n) \le b_j; j = 1,2,3 \ldots \ldots \ldots k$$

Here, R_s is the overall system reliability and its calculation is based on the parameters: $r\ and\ n$, representing components reliability and number of redundant components corresponding to each sub system, respectively. K represents the total number of constraints and g_j represents the (j^{th}) resource constraint and its associated upper limit are denoted by (g_j) and (b_j), respectively. The reliability function provided in Eq. (1) is determined by the system configuration. For example, when a system consists of m number of sub-systems and they follow series structure, then the overall system reliability is computed as:

$$R_s(r,n) = \prod_{i=1}^{m} R_i(r_i,n_i) = \prod_{i=1}^{m}[1 - Q_i^{n_i}] = \prod_{i=1}^{m}[1-(1-r_i)^{n_i}] \quad (2)$$

Here, (i) is representing the (i^{th}) subsystem, while its corresponding system reliability is R_i and failure probability is Q_i. The reliability of the component corresponding to i^{th} sub-system is represented by r_i, while corresponding number of redundant components is represented by n_i. In this work, two popular reliability optimization problems are investigated, namely, the series system and the complex (bridge) system. Their mathematical formulations are presented below:

A. Case study-1: Series System

The system structure considered in this case study is illustrated in Fig. 1(a). and the corresponding RRAP is formulated as follows:

$$Maximize\ R_S(r,n) = \prod_{i=1}^{m}\ [1-(1-r_i)^{n_i}] \quad (3)$$

Subject to,

$$g_1(n) = \sum_{i=1}^{m} v_i n_i^2\ \le V$$

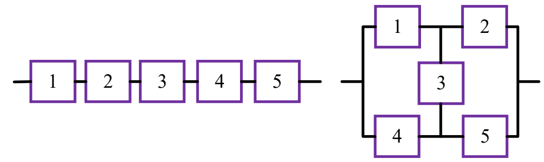
$$g_2(r,n) = \sum_{i=1}^{m} \alpha_i(-\frac{1000}{\ln(r_i)})^{\beta_i}[n_i + \exp(\frac{n_i}{4})]\ \le C$$

$$g_3(n) = \sum_{i=1}^{m} w_i * n_i * \exp(0.25 n_i) \le W$$

$$0.5 \le r_i \le 1, r_i \in [0,1] \subset \mathbb{R}^+;\ 1 \le n_i \le 5, n_i \in Z^+; i = 1,2, \ldots m$$

B. Case study-2: Complex Bridge System

The system structure considered in this case study is illustrated in Fig. 1(b) and the corresponding RRAP is formulated as follows:



(a) Series System (b) Complex Bridge System

Fig. 1. System structure of both the RRAP case studies.

$$Maximize\ \ R_s(r,n) = R_1R_2 + R_3R_4 + R_1R_4R_5 + R_2R_3R_5 - R_1R_2R_3R_4 - R_1R_2R_3R_5 - R_1R_2R_4R_5 - R_1R_3R_4R_5 - R_2R_3R_4R_5 + 2R_1R_2R_3R_4R_5 \quad (4)$$

Subject to,

$$g_1(n) = \sum_{i=1}^{m} v_i n_i^2 \le V$$

$$g_2(r,n) = \sum_{i=1}^{m} \alpha_i(-\frac{1000}{ln(r_i)})^{\beta_i}[n_i + \exp(\frac{n_i}{4})]\ \le C$$

$$g_3(n) = \sum_{i=1}^{m} w_i * n_i * exp(0.25 n_i) \le W$$

$$0.5 \le r_i \le 1, r_i \in [0,1] \subset \mathbb{R}^+;\ 1 \le n_i \le 5, n_i \in Z^+; i = 1,2, \ldots m$$

In both the cases, the objective is to maximize the overall system reliability $R_s(\mathrm{r},\mathrm{n})$. The symbol m denote the total number of subsystems. In this study, both case studies comprise five subsystems, and therefore $m = 5$. The reliability of the i^{th} subsystem, R_i, is a function of r_i and n_i, where $r_i \in [0,1]$ is a continuous decision variable and n_i is an integer decision variable taking values from 1 to 5. Whereas, i^{th} sub-system's volume and costs are represented by v_i and c_i, respectively. The resource constraint functions $g_1(*)$, $g_2(*)$, and $g_3(*)$ represent the total consumption of volume, cost, and weight resources, respectively. The corresponding upper bounds on volume, cost, and weight are denoted by V, C, and W.

C. Constraint Handling Technique

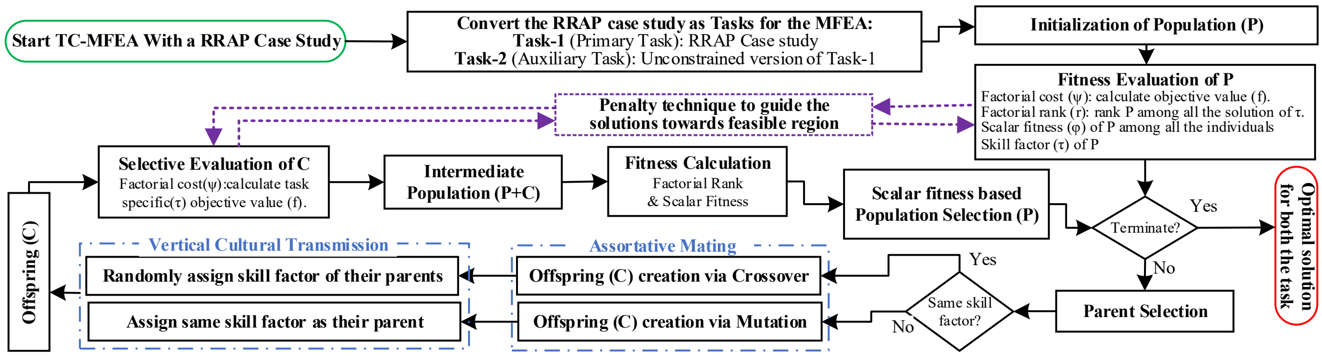
RRAP being a constrained optimization problem [28], [29], requires effective constraint handling technique. In this study, a penalty-based approach is adopted [30], [31], where violations of resource constraints are incorporated into the objective function through penalty terms proportional to the magnitude of violation. The reformulated system reliability objective is expressed as:

$$R_{total}(x) = \begin{cases} -R_s(x) + \psi(x), & if\ g_y(x) > b_y \\ -R_s(x), & otherwise \end{cases} \quad (5)$$

Here, $R_s(x)$ denotes the overall system reliability, $g_y(x)$ is the y^{th} resource constraint, b_y is its upper bound and $\psi(x)$ represents the total penalty applied for constraint violations. The penalty term is defined as:

$$\psi(x) = \sum_{y=1}^{M} \phi_y * \left(\max\left(0, g_y(x) - b_y\right)\right)^2 \quad (6)$$

Where, M is the total number of constraints and ϕ_y is the penalty coefficient for the y^{th} constraint. Here, all constraints are treated equally with $\phi_y = 1$. The decision vector $x = (r,n)$ includes both component reliabilities and redundancy levels. For computational simplicity, the problem is formulated as a minimization problem. The maximum system reliability R_s is obtained by removing the negative sign after optimization.



III. Solution Approach

Evolutionary algorithms (EAs) are population-based metaheuristics widely used for solving complex engineering optimization problems, including genetic algorithms (GA), particle swarm optimization (PSO), and differential evolution (DE). Recently, evolutionary transfer optimization (ETO) has gained attention for enabling knowledge transfer between tasks [32], with evolutionary multitask optimization (EMTO) emerging as an effective framework for solving multiple problems simultaneously. The multi-factorial evolutionary algorithm (MFEA), proposed by Gupta et al. [33], is a pioneering EMTO method that has been successfully applied across various domains [34] - [37] and extended to multi-objective and many-objective optimization problems [38] - [40]. EMTO has also been adapted for constrained optimization by reformulating problems into multiple tasks, such as combining constrained and unconstrained variants [41], using multiple constrained task variants [42], and integrating decoupled constraint-handling strategies [43].

Motivated by these approaches, we propose a task-cloning-based MFEA (TC-MFEA) for solving constrained RRAPs. The method constructs an auxiliary unconstrained task by removing all constraints from the primary problem and jointly optimizes both tasks within the MFEA framework. The auxiliary task enhances exploration and facilitates knowledge transfer, thereby improving the solution quality of the primary task. The detailed procedure of TC-MFEA for RRAPs is presented in the following subsection, while standard MFEA details can be found in [33].

A. Working of Task Cloning Based Multi-factorial Evolutionary Algorithm (TC-MFEA) for RRAPs

This subsection describes the working principle of the TC-MFEA for solving constrained RRAPs. The approach optimizes a constrained RRAP (e.g., case study-1) to maximize system reliability while satisfying resource constraints such as weight, volume, and cost. As shown in Fig. 2, the TC-MFEA framework consists of key stages: task formulation, population initialization, fitness evaluation and parent selection, offspring generation and population update, and termination based on predefined criteria.

1) Stage-1: Converting the RRAPs as Tasks for MFEA

The TC-MFEA mainly starts with converting the considered case study as suitable tasks for MFEA. As we have a single constrained RRAP case study to solve at a time. It will be converted to two different tasks namely primary task (Task-1) and an auxiliary task (Task-2). The Task-1 will hold the actual constrained RRAPs problem which needs to be maximized and the Task-2 will be the unconstrained version of primary task and termed as auxiliary task. These two tasks will be treated as two different tasks of MFEA to solve them simultaneously. These way of solving two tasks within MFEA may have the benefit of solving the primary tasks with the help of auxiliary task through knowledge transfer.

2) Stage-2: Population Initialization

Before initializing the population P, a unified chromosome set is generated based on the predefined population size and the maximum task dimension. In this study, both tasks share the same dimensionality of 10, where five variables correspond to component reliabilities (r_i) and the remaining five represent the number of redundant components(n_i).

Initially, all chromosomes are encoded as real-valued vectors in the range [0,1], as illustrated in Fig. 3. Each chromosome is associated with factorial cost, factorial rank, scalar fitness, and skill factor [33]. Task-specific population decoding is performed according to the nature of the decision variables. Since r_i is continuous and n_i is integer-valued, both continuous and integer decoding schemes are applied. Although each chromosome can be decoded for all tasks, it is primarily effective for a single task determined by its skill factor. Accordingly, chromosomes are converted into task-specific solutions and evaluated only for their associated task.

3) Stage -3: Fitness Evaluation and Parent Selection

Fitness evaluation in TC-MFEA is performed in two stages. Initially, all individuals are evaluated on both tasks to compute factorial costs. Task-1 (constrained RRAP) uses a penalty-based constraint-handling mechanism, while Task-2 is treated as unconstrained to enable broader exploration. Based on the factorial costs (objective function value), both factorial ranks and scalar fitness are computed, and each individual is assigned a skill factor corresponding to its better-performing task.

Unified Search Space / Chromosome									
0.8489	0.8703	0.8362	0.7088	0.7830	0.2382	0.0382	0.3523	0.3443	0.4347
d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}
r_i					n_i				

Fig. 3. Sample of a unified solution/chromosome representing decision variables for the RRAP.

During evolution, selective fitness evaluation is employed, where individuals are evaluated only on their associated task, reducing computational cost. Parent selection is then performed using tournament selection to generate offspring.

4) Stage-4: Offspring Creation (C) and New Population Selection (P)

Offspring *(C)* are generated via assortative mating and vertical cultural transmission. In assortative mating, parents with the same skill factor undergo crossover to produce offspring, while parents with different skill factors may also mate if they satisfy the random mating probability *(rmp)*; otherwise, polynomial mutation is applied. In this study, simulated binary crossover (SBX) is used.

During vertical cultural transmission, offspring inherit skill factors based on the mating process. Offspring from parents with identical skill factors retain the same factor, whereas those from cross-task mating inherit a skill factor randomly from one parent. This mechanism facilitates knowledge transfer across tasks. Notably, although Task-1 (constrained RRAP) suffers from limited exploration due to penalty-based constraint handling, interaction with Task-2 (unconstrained RRAP) enables exploration of promising regions, thereby improving solution quality.

Following skill-factor assignment, offspring undergo selective fitness evaluation *(Stage-3)* to update factorial costs. The offspring are then merged with the parent population, and the next generation is selected based on scalar fitness, which ensures the survival of fitter individuals.

5) Stage-5: Termination Criteria

The optimization process iterates through *Stage-3* until the predefined termination condition is satisfied. In TC-MFEA, termination is based on reaching the maximum number of generations. Although the final population contains optimal solutions for both tasks, but only the solution corresponding to Task-1 is considered, since it represents the target constrained RRAP for the case study.

IV. Experimental Results and Comparison Analysis

For the evaluation, two RRAP case studies: series and complex (bridge) systems (Section II) are considered. All simulations are conducted in MATLAB 2024b on a system with 24 GB RAM, a 4 GB GPU, and an Intel Core i5-7300HQ CPU at 2.50 GHz.

A. Input Data

The input data for considered RRAPs such as series system (CS-1) and complex bridge systems (CS-2) are provided in the Table II. Each table of input data includes the shaping (α_i) & scaling factors (β_i), volume and weight values corresponding to each component. It also includes the upper limit of resource constraints namely volume, cost and weight of overall system.

Table II. Input data for case study-1 and 2

i	$10^5\alpha_i$	β_i	v_i	w_i	V	C	W
1	2.330	1.5	1	7			
2	1.450	1.5	2	8			
3	0.541	1.5	3	8	110	175	200
4	8.050	1.5	4	6			
5	1.950	1.5	2	9			

B. Parameter Settings

The parameter tuning is performed using the Taguchi design of experiments, an efficient method based on orthogonal arrays for identifying optimal parameter settings with a minimal number of experiments [44]. In the proposed TC-MFEA, the key parameters considered are population size, crossover index (mu), and random mating probability (rmp). Each parameter is evaluated at three levels: *population* [50, 100, 150], *mu* [5, 10, 15], and *rmp* [0.3, 0.6, 0.8], representing low, medium, and high similarity, respectively. Based on these factors, an L-9 orthogonal array is adopted (Table III). For each parameter setting, five independent runs are conducted, and the average system reliability is computed. The setting yielding the highest average reliability is selected as optimal. Accordingly, experiments 5 and 7 are identified as the best configurations for CS-1 (series system) and CS-2 (bridge system), respectively. These optimal settings are subsequently used to perform 10 independent runs for final performance evaluation of the proposed TC-MFEA.

Table III. L-9 orthogonal array for Taguchi-based experimental design and corresponding best parameter settings.

TC-MFEA	Parameters			Case Study	
Experiments	**Population**	**mu**	**rmp**	**CS-1**	**CS-2**
Exp-1	50	5	0.3	0.92406	0.99981
Exp-2	50	10	0.6	0.91707	0.99976
Exp-3	50	15	0.8	0.91106	0.99971
Exp-4	100	5	0.6	0.92332	0.99984
Exp-5	100	10	0.8	**0.92522**	0.99973
Exp-6	100	15	0.3	0.91462	0.99971
Exp-7	150	5	0.8	0.92497	**0.99984**
Exp-8	150	10	0.3	0.92211	0.99974
Exp-9	150	15	0.6	0.91717	0.99973

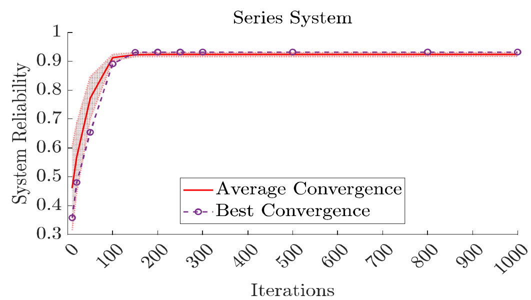
C. Experimental Results

This section evaluates the performance of the proposed TC-MFEA in terms of convergence behavior and solution quality for both case studies. The performance is assessed using average system reliability with standard deviation and best-achieved reliability across iterations, along with comparisons against EMTO-based methods reported in the literature.

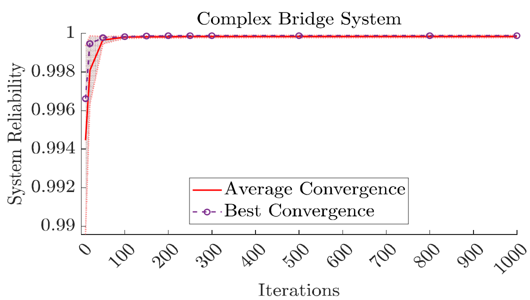
Table IV summarizes the average, standard deviation, and best reliability values. The convergence behavior is analyzed at selected iterations (10, 20, 50, 100, 150, 200, 300, 500, 800, and 1000). Fig. 4 illustrates the average and best reliability curves along with standard deviation. For the series system (Fig. 4(a)), average reliability stabilizes around 100 iterations, while best reliability converges near 150 iterations. For the bridge system (Fig. 4(b)), both metrics converge around 100 iterations, indicating rapid convergence and low variability.

Table IV. Average, standard deviation and best convergence values of case study-1 and case study-2

Case Study	Iterations	10	20	50	100	150	200	250	300	500	800	1000
Series System	Average ± Std	0.460009 ±1.45E-01	0.565379 ±1.20E-01	0.773250 ±7.26E-02	0.912514 ±1.13E-02	0.922888 ±6.86E-03	0.923228 ±6.86E-03	0.923264 ±6.86E-03	0.923271 ±6.87E-03	0.923292 ±6.88E-03	0.923307 ±6.88E-03	0.923316 ±6.88E-03
	Best	0.358024	0.480271	0.654087	0.890745	0.930733	0.931508	0.931509	0.931572	0.931583	0.931670	0.931670
Bridge System	Average ± Std	0.994471 ±4.89E-03	0.998103 ±1.78E-03	0.999655 ±1.91E-04	0.999803 ±5.79E-05	0.999821 ±6.21E-05	0.999829 ±6.75E-05	0.999837 ±6.18E-05	0.999839 ±6.16E-05	0.999840 ±6.19E-05	0.999841 ±6.17E-05	0.999841 ±6.18E-05
	Best	0.996619	0.999477	0.999779	0.999835	0.999871	0.999884	0.999887	0.999887	0.999889	0.999889	0.999889



(a)



(b)

Fig. 4. Convergence of average (shaded std) and best system reliability using TC-MFEA for (a) series and (b) complex systems over iterations.

Table V. Comparative results of case study-1 (Series system)

Method	Proposed Approach (TC-MFEA)	MFEA-II [26]	MFEA [26]
R_s	**0.931670**	0.931542	0.931662
r_1	0.7810	0.7847	0.7816
r_2	0.8706	0.8684	0.8730
r_3	0.9021	0.9055	0.9021
r_4	0.7124	0.7121	0.7100
r_5	0.7875	0.7827	0.7869
n_1	3	3	3
n_2	2	2	2
n_3	2	2	2
n_4	3	3	3
n_5	3	3	3
V	83.00	83.00	83.00
W	192.48	192.48	192.48
C	175.00	175.00	175.00

Table VI. Comparative results of case study-2 (Complex bridge system)

Method	Proposed Approach (TC-MFEA)	MFEA-II [26]	MFEA [26]	MFEA [25]
R_s	**0.999889**	0.999863	0.999888	0.999851
r_1	0.8191	0.8313	0.8123	0.8256
r_2	0.8687	0.8736	0.8632	0.8636
r_3	0.8531	0.9027	0.8682	0.8935
r_4	0.7094	0.6807	0.7190	0.7001
r_5	0.7580	0.6164	0.7380	0.7699
n_1	2	3	3	2
n_2	2	3	3	3
n_3	3	2	3	3
n_4	3	3	3	3
n_5	1	2	1	2
V	92.00	83.00	92.00	93.00
W	195.74	189.43	195.74	192.48
C	175.00	175.00	175.00	175.00

Tables V and VI compare the best solutions obtained by TC-MFEA with existing EMTO approaches, including MFEA and MFEA-II. All methods satisfy resource constraints, however, TC-MFEA consistently achieves higher system reliability (0.931670 for the series system and 0.999889 for the bridge system). This improvement is attributed to the task-cloning strategy, which enhances exploration and knowledge transfer. Overall, the results demonstrate the superiority and robustness of TC-MFEA for solving constrained RRAPs.

V. Conclusion and Future Work

This paper proposes a novel EMTO-based framework, termed task-cloning-based multi-factorial evolutionary algorithm (TC-MFEA), for solving constrained RRAPs. The approach reformulates a constrained RRAP into two tasks: a primary constrained task and an auxiliary unconstrained counterpart. The auxiliary task enhances exploration and enables effective knowledge transfer, thereby improving solution quality while satisfying all constraints. The effectiveness of TC-MFEA is validated on two benchmark RRAPs (series and complex bridge systems) using a penalty-based constraint-handling mechanism and Taguchi-based parameter tuning. The experimental results in terms of average and best system reliability, demonstrates that TC-MFEA consistently outperforms existing EMTO-based approaches.

Despite these promising results, the current framework is limited to single constrained RRAP instances and relatively small-scale problems. Future work will focus on extending TC-MFEA to handle multiple constrained RRAPs simultaneously and to address large-scale problems, further evaluating its scalability and robustness.

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