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Enhanced NSGA-II Algorithm for Solving Real-world Multi-objective Optimization Problems

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Abstract: Multi-objective optimization problems are crucial in real-world scenarios, where multiple solutions exist rather than a single one. Traditional methods like PERT/CPM often struggle to address such problems effectively. Meta-heuristic techniques, such as genetic algorithms and non-dominated sorting genetic algorithms (NSGA-II), are well-suited for finding true Pareto-optimal solutions. This paper introduces an enhanced NSGA-II algorithm, which utilizes Sobol sequences for initial population generation, ensuring uniform search space coverage and faster convergence. The proposed algorithm is validated using benchmark problems from the ZDT test suite and compared with state-of-the-art algorithms. Additionally, real-world optimization problems in project management, particularly the time-cost trade-off (TCT) problem, are solved using the enhanced NSGA-II. The performance evaluation includes key metrics such as standard deviation, providing a comprehensive assessment of the algorithm's efficiency. Experimental results confirm that the proposed method outperforms traditional NSGA-II and other meta-heuristic algorithms in maintaining a well-distributed Pareto front while ensuring computational efficiency.

Index Terms: Meta-heuristics, Multi-objective Optimization Problems, Non-dominated Sorting Genetic Algorithm-II, Evolutionary Optimization, Time-cost Tradeoff, Sobol Sequences.

1. Introduction

Over the past years, evolutionary multi-objective optimization (EMO) has gained prominence as a practical and influential area of research. Evolutionary optimization algorithms use a population-based approach, where multiple solutions participate in each iteration to evolve a new population of solutions [1]. Among various multi-objective optimization problems (MOOPs), the time-cost trade-off (TCT) problem stands out as a critical problem for enhancing project efficiency by balancing the objectives of minimizing project duration and controlling costs [2]. Traditionally, project managers have relied on heuristic methods or linear programming techniques to tackle TCT challenges [3]. However, these conventional approaches often struggle to address the complexity and dynamic nature of real-world problems, resulting in sub-optimal solutions [3]. Meta-heuristic algorithms, including evolutionary and swarm-based methods, have emerged as powerful tools to overcome these limitations [4–6]. By leveraging mechanisms such as exploration, exploitation, and adaptive learning, meta-heuristics can efficiently navigate the vast and complex search spaces associated with TCT problems. Their ability to handle complexities in multi-objective optimization problems makes them particularly suited for solving real-world optimization challenges, offering robust and near-optimal solutions that outperform traditional techniques.

In this research, we improved NSGA-II algorithm to solve multi-objective optimization problems in continuous search spaces. Therefore, the proposed algorithm named as enhanced NSGA-II has been employed in our research. The proposed algorithm uses Sobol sequences to initialize the population, offering superior space-filling properties, faster convergence, and deterministic behavior, particularly in high-dimensional spaces. The enhanced NSGA-II algorithm performed the following important tasks:

- It is tested and validated on ZDT benchmark problems, demonstrating its effectiveness on standard test functions.
- The performance of the algorithm is compared with existing meta-heuristic algorithms, showing significant improvements in certain metrics.
- To further evaluate the effectiveness of the enhanced NSGA-II algorithm, real-world multi-objective optimization problems are also solved, and obtained results are compared with other established algorithms.

2. Related Works

Numerous methods for addressing the time-cost trade-off (TCT) problem are discussed in [7–12]. Pathak et al. [13] utilized a multi-objective evolutionary algorithm to manage TCT challenges in project scheduling. Agdas et al. [14] demonstrated that genetic algorithms (GAs) consistently solve large-scale benchmark networks with high accuracy, proving their effectiveness for large-scale construction TCT problems. Kumar et al. [15] employed the NSGA-II algorithm to solve a time-cost trade-off model for Indian highway construction projects. A practical optimization model is developed to minimize project duration and cost, enhancing decision-making for efficient project management in complex construction environments. Chassiakos et al. [16] investigates time-cost trade-offs at varying project scales using NSGA-II for multi- objective optimization. Dhawan et al. [17] proposed a TCT model using the simulated annealing (SA) approach, validated through a case study. The results demonstrate that SA effectively establishes the time-cost relationship, outperforms genetic algorithms in achieving minimum cost for desired project durations, and offers a practical decision-making tool for scheduling and profit optimization. Sharma et al. [18] introduced an NSGA-II-based time-cost-quality trade-off optimization model, assuming that each project activity offers distinct alternatives with varying time, cost, and quality impacts. Their research also employed pairwise comparison-based analytical hierarchy process (AHP) techniques to determine the relative importance of activities and quality measures. Pathak et al. [19] developed a method providing project managers with a valuable tool for conducting sensitivity analyses of time-cost trade-off profiles under diverse real-world scenarios. Albayrak [20] emphasized that competitive conditions intensify the interdependence between time and cost, necessitating a balance between these conflicting components under varying project constraints. Their work treated the TCT problem as a multi-objective problem and proposed a novel hybrid algorithm (NHA) to resolve it. Genetic algorithm-based techniques are also applied in other domains. Ankita and Sahana [21] enhanced GA performance by introducing significant improvements to its initialization step, discussing critical aspects of their proposed approach. Hamta et al. [22] presented a goal programming model for the time-cost-quality trade-off problem. In their approach, each project is characterized by critical time, cost, and quality goals, with project managers striving to achieve these objectives at minimal cost and highest quality to ensure project success.

Most existing studies have focused on optimizing continuous spaces and addressing linear, non-linear, and discrete multi-objective optimization problems. However, none have explored using Sobol sequences for population initialization, While Liang et al. [23] applied this approach to single-objective optimization, this study extends its application to multi-objective optimization problems (MOOPs). These advancements make enhanced NSGA-II a novel approach by integrating Sobol sequence-based initialization into a multi-objective evolutionary algorithm, improving solution quality, stability, and search efficiency compared to traditional NSGA-II and other meta-heuristics.

The paper is organized as follows: initially, the enhanced NSGA-II algorithm is introduced, followed by a comprehensive literature review in Section 2. The problem which has been taken into the consideration defined in Section 3. The methodology of the proposed algorithm is presented in Section 4. Section 5 validates the benchmark problems using the enhanced NSGA-II algorithm. The results, comparing various algorithms, are discussed in Section 6. Experimental results for real-world test problems are presented in Section 7, and the conclusions of paper are summarized in Section 8.

3. Problem Description

The study offers an efficient optimization model to handle TCT problems in real life, which are often referred to as MOOPs [19]. In this context, the terms “normal time ($\mathrm{NT_i}$)” and “normal cost ($\mathrm{NC_i}$)” refer to the maximum duration and minimum costs, respectively, required to finish a project activity. Conversely, “crash time ($\mathrm{CT_i}$)” signifies the shortest possible duration to complete a project activity, along with the related “crash cost ($\mathrm{CC_i}$)”.

The model aims to reduce project activity costs ($\mathrm{C_\theta}$) and durations ($\mathrm{T_\theta}$) for any relevant constraint requirements.

$$\text{minimize } T_\theta = \sum_{i=1}^{n} t_i \tag{1}$$

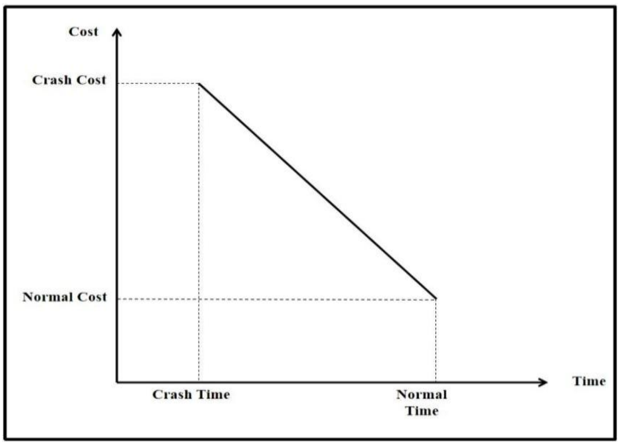

Fig.1. Linear Time-cost tradeoff relationship of the project activity

The duration of each activity (t_i) must satisfy the constraint:

$$CT_i \leq t_i \leq NT_i \tag{2}$$

$$\text{and minimize } C_\theta = \sum_{i=1}^{n} c_i \tag{3}$$

where, the cost of each activity (c_i), defined as:

$$c_i = m_i t_i + k_i \tag{4}$$

The cost of each activity must satisfy the constraint:

$$NC_i \leq c_i \leq CC_i \tag{5}$$

The relationship between cost and time is defined using the slope (m_i) and intercept (ki):

$$m_i = \frac{CC_i - NC_i}{NT_i - CT_i} \tag{6}$$

$$k_i = CC_i - NC_i \tag{7}$$

Fig.1. illustrates the linear model utilized in this paper to determine the relationship between time and cost [19]. This TCT problem can be solved using the proposed algorithm (shown in Section 4). The enhanced NSGA-II algorithm allows for more flexible modeling of project parameters and can optimize conflicting objectives such as minimizing time while controlling costs, to find optimal or near optimal solutions.

4. Methodology of enhanced NSGA-II algorithm

This section presents all the important steps involved in the proposed algorithm.

4.1. Population Initialization

Consider a population with N individuals, where each individual $x_i = i = 1, 2, \ldots, N$ is represented as a vector of decision variables, i.e., $x_i = [x_{i1}, x_{i2}, \ldots, x_{ij}]$. In this algorithm, we have utilized the Sobol sequence to generate the initial population, where the Sobol sequence values $S_{ij} \in [0, 1]$ are scaled to fit within each decision variable's bounds using the Equation (8):

$$x_{i,j} = x_{i,,j}^{min} + S_{i,j} \times x_{i,j}^{max} - x_{i,j}^{min} \tag{8}$$

This ensures a uniform and efficient population distribution across the search space, leading to faster convergence compared to random sequences. The low-discrepancy property of Sobol sequences allows faster convergence with error decreasing at a rate of $O(1/N)$, whereas random sequences have a slower convergence rate of $O(1/\sqrt{N})$. Random points may cluster or leave gaps, requiring more samples to adequately cover the space. Therefore, due to their structured distribution, Sobol sequences provide better coverage of the space, as compared to random sequences as shown in Fig.2. After that, the fitness functions f_m, where m represents the number of objectives, are evaluated for each individual to guide the optimization process.

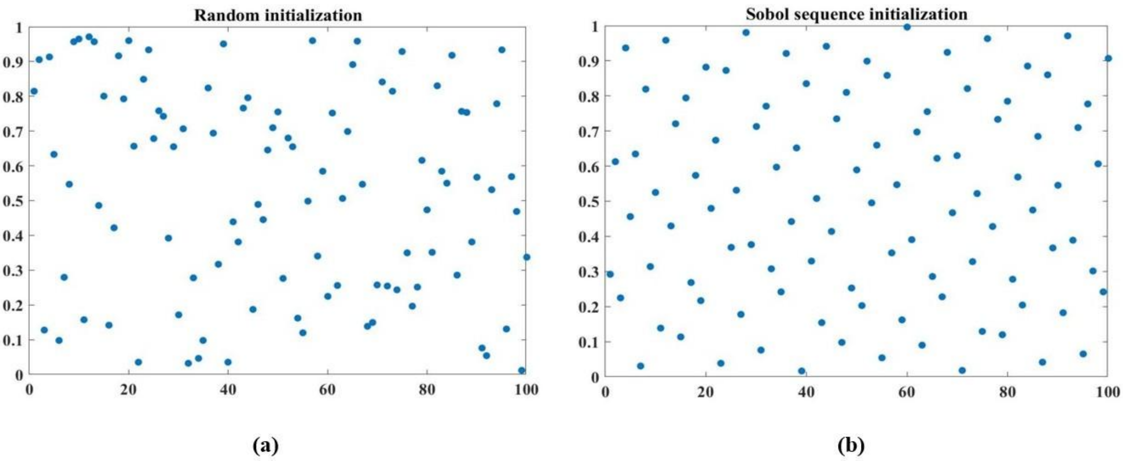

Fig.2. Comparison of initial population using random initialization (a) and Sobol sequence initialization (b)

4.2. Non-dominated Sorting

The algorithm assigns a fitness rank to each solution based on its level of non-dominance (rank 1 for the best solutions, rank 2 for the next, and so on) [24, 25]. Solutions are iteratively grouped into non-dominated fronts. Solutions in the first front are not dominated by any others, and subsequent fronts are determined by removing the higher-ranked solutions. This process continues until all solutions are assigned to a front.

4.3. Selection

Chromosomes are selected to form a mating pool using binary tournament selection, which prioritizes solutions with lower ranks. Within the same rank, the crowding distance is used to maintain diversity, preferring solutions in less crowded regions of the Pareto front [24, 25].

4.4. Genetic Operators

Simulated Binary Crossover (SBX) is used to combine two parent chromosomes, generating new offspring solutions and polynomial mutation introduces diversity by modifying offspring solutions, allowing exploration of new regions in the search space [26].

4.5. Intermediate Population

The parent and offspring populations are combined to form an intermediate population, which has a size one and half times the original population. This larger population allows for more robust comparison and selection in the next steps.

4.6. Non-dominated Sorting of Intermediate Population

The intermediate population is sorted again using the non-dominated sorting algorithm to determine ranks for all solutions.

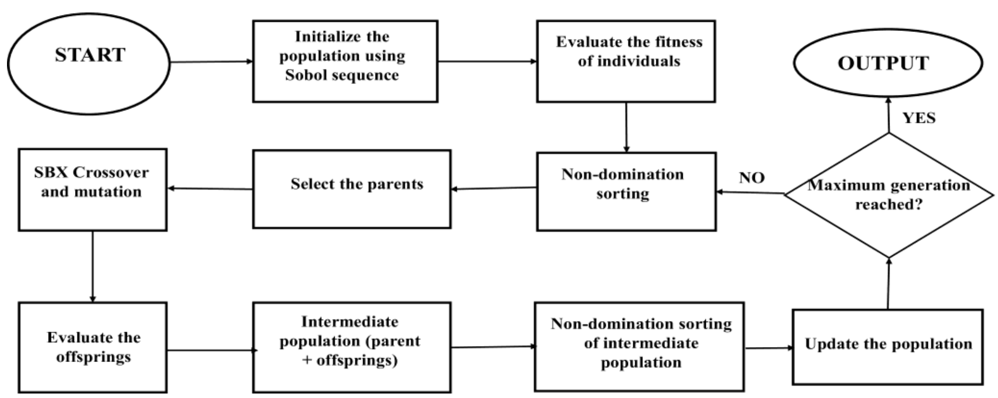

Fig.3. The working methodology of enhanced NSGA-II

4.7. Update the Population

The best solutions are selected from the sorted intermediate population based on rank and crowding distance. The population is then reduced to its original size by filling each front in ascending order until the desired population size is reached. For the final front, individuals with the largest crowding distance are preferred to ensure diversity. This process iteratively refines the population, converging towards the Pareto front while maintaining a diverse set of high-quality solutions [24, 25].

For further clarity, the working methodology of the proposed algorithm is illustrated in Fig.3.

5. Validation on Benchmark Problems

To evaluate the performance of the proposed enhanced NSGA-II algorithm, a comprehensive set of benchmarks problems from the ZDT test suite [27] is employed. These benchmark problems enable for a robust comparison, showcasing the algorithm's strengths and potential limitations in tackling complex optimization challenges.

For solving these benchmark problems, the important initial parameters of the enhanced NSGA-II algorithm are as follows: initial population $N = 100$, crossover probability $p_c = 0.9$, mutation probability $p_m = 0.5$. The algorithm terminates when either ten consecutive iterations show no change in the tradeoff points or after 15,000 generations (g_{max}), a threshold determined through an extensive experimentation.

5.1. ZDT1 Benchmark Problem

The ZDT1 problem features a convex Pareto-optimal front. The objective functions $f_1(x)$ and $f_2(x)$ which are to be minimized subject to constraint $g(x)$, are defined as follows:

$$ZDT1: \begin{cases} f_1(u) & = & u_1 \\ f_2(u) & = & g(u)\left[1 - \sqrt{\frac{u_1}{g(u)}}\right] \\ g(u) & = & 1 + 9 \times \sum_{i=2}^{n} \frac{u_i}{n-1} \end{cases} \tag{9}$$

In this problem, thirty decision variables are used i.e. $n = 30$ and each variable x_i is bounded between 0 and 1. The Pareto-optimal front occurs when $g = 1.0$. This benchmark problem is solved using the enhanced NSGA-II algorithm, and the results are shown in Fig.4. It is evident that the results obtained from the enhanced NSGA-II algorithm are evenly dispersed across the solution space and closely align with the Pareto-optimal front. This highlights the enhanced NSGA-II algorithm's capacity to converge on the Pareto-optimal front while identifying diverse solutions to complicated problems.

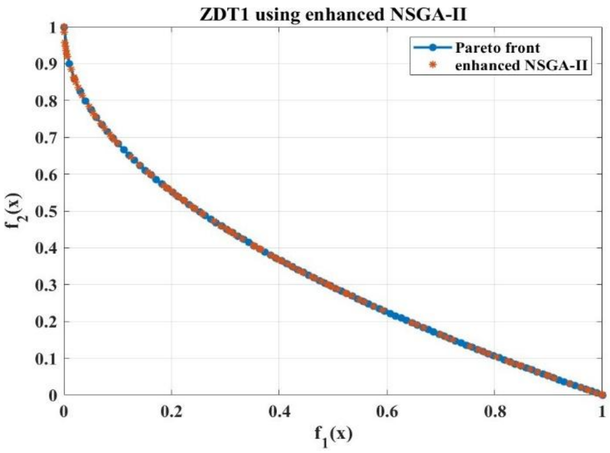

Fig.4. ZDT1 using enhanced NSGA-II

5.2. ZDT2 Benchmark Problem

The ZDT2 function features a non-convex Pareto-optimal front. The objective functions $f_1(x)$ and $f_2(x)$ which are to be minimized, subject to constraint $g(x)$, are defined as:

$$ZDT2: \begin{cases} f_1(u) & = & u_1 \\ f_2(u) & = & g(u)\left[1 - \left(\frac{u_1}{g(u)}\right)^2\right] \\ g(u) & = & 1 + 9 \times \sum_{i=2}^{n} \frac{u_i}{n-1} \end{cases} \tag{10}$$

In this formulation, thirty decision variables x_i are utilized ($n = 30$), with each variable taking values from 0 to 1. The Pareto-optimal front is achieved when $g = 1.0$.

The results obtained using the enhanced NSGA-II algorithm, as illustrated in Fig.5., demonstrate that the solutions are evenly distributed across the solution space and closely match the Pareto-optimal front. This confirms the enhanced NSGA-II algorithm's effectiveness in identifying diverse solutions while converging towards the optimal front.

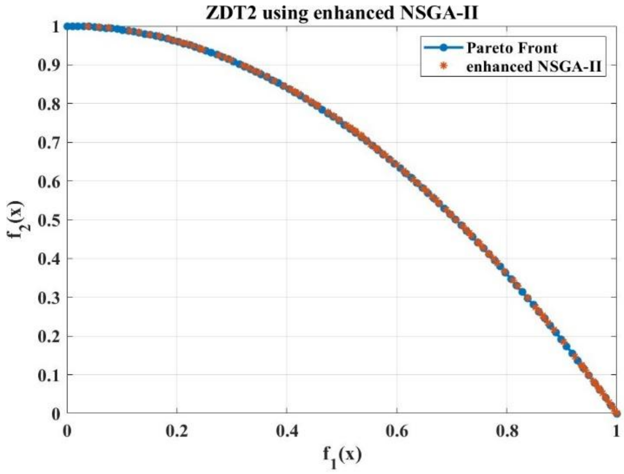

Fig.5. ZDT2 using enhanced NSGA-II

5.3. ZDT3 benchmark Problem

The ZDT3 problem introduces a challenging, discontinuous Pareto front with multiple disconnected regions. The objective functions and the constraint $g(x)$ are defined as:

$$ZDT3: \begin{cases} f_1(u) &= u_1 \\ f_2(u) &= g(u)\left[1 - \sqrt{\frac{f_1}{g(u)}} - \frac{f_1}{g(u)}\sin\left(10\pi f_1\right)\right] \\ g(u) &= 1 + 9 \times \sum_{i=2}^{n} \frac{u_i}{n-1} \end{cases} \tag{11}$$

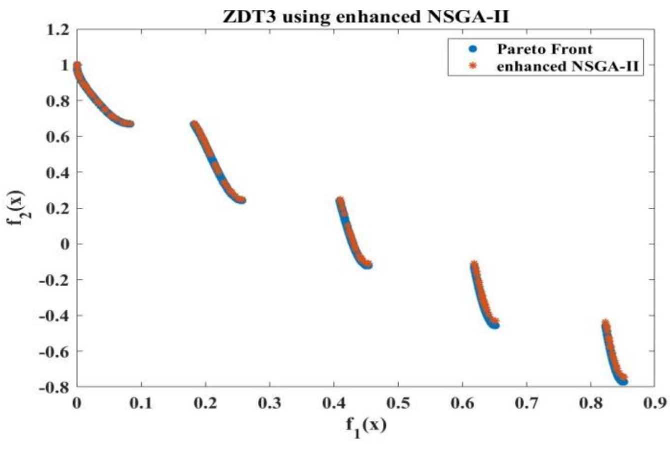

Fig.6. ZDT3 using enhanced NSGA-II

5.4. ZDT6 Benchmark Problem

The ZDT6 problem presents a non-uniform search space, where the Pareto-optimal solutions are sparsely distributed near the global front. The objective functions and the constraint $g(x)$ are given by:

$$ZDT6: \begin{cases} f_1(u) &= 1 - e^{-(4u_1)} \times sin^6(6\pi u_1) \\ f_2(u) &= g(u)\left[1 - \left(\frac{f_1}{g(u)}\right)^2\right] \\ g(u) &= 1 + 9 \times \left(\sum_{i=2}^{n} \frac{u_i}{n-1}\right)^{\frac{1}{4}} \end{cases} \tag{12}$$

In this formulation of the ZDT6 function, ten decision variables are utilized ($n = 10$), and the design variables are constrained to the range of 0 to 1. The global Pareto-optimal front is achieved when $g = 1.0$.

Fig.7. shows the enhanced NSGA-II algorithm's performance on ZDT6, where the results again reveal a well-dispersed set of solutions that align closely with the Pareto-optimal front. This further highlights the enhanced NSGA-II algorithm's capability to handle non-uniform search spaces while maintaining diversity and convergence towards the optimal front.

6. Comparative Analysis of Enhanced NSGA-II Algorithm with Existing Algorithms

To assess the effectiveness of the proposed algorithm, its performance is compared against several optimization techniques, including the improved Multi-Objective Genetic Algorithm (iMOGA) [28], Multi-Objective Genetic Algorithm (MOGA) [9], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [27], on the ZDT1 and ZDT2 benchmark problems.

The experimental results are illustrated in Fig.8. and Fig.9, with corresponding statistical analysis provided in Table 1. and Table 2., respectively.

As visible in Fig.8. and highlighted in Table 1., the standard deviations for the enhanced NSGA-II algorithm are slightly higher than those of NSGA-II and MOGA, yet they remain comparable to iMOGA. This indicates that the enhanced NSGA-II algorithm effectively maintains a diverse set of solutions, thereby avoiding premature convergence while ensuring thorough exploration of the solution space. Therefore, when considering the diversity metrics, the enhanced NSGA-II algorithm reflects a healthy balance between exploration and exploitation, which contributes to its overall strong performance. As shown in Fig.9. and Table 2., the enhanced NSGA-II algorithm demonstrates competitive performance or at least comparable to the other optimization algorithms.

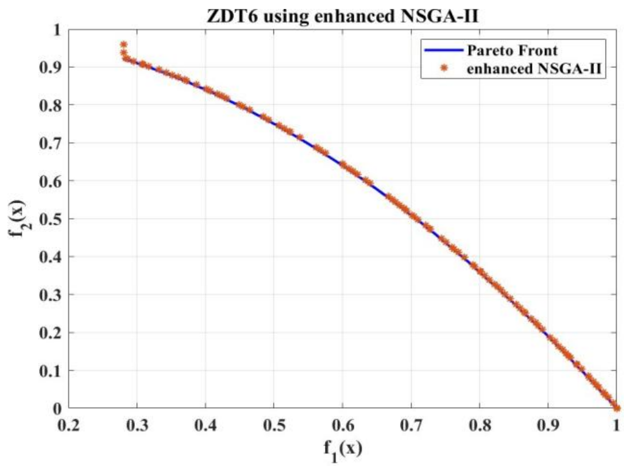

Fig.7. ZDT6 using enhanced NSGA-II

Table 1. Statistical analysis of various algorithms validated through ZDT1 problem

Algorithm	Objectives	Min	Max	Mean	Median	Mode	Std
enhanced NSGA-II	$f_1(x)$	0	1	0.4353	0.3969	0	0.3073
	$f_2(x)$	2.058e-08	1	0.3999	0.37	2.058e-08	0.2756
NSGA-II	$f_1(x)$	0	1	0.4018	0.3549	0	0.2993
	$f_2(x)$	1.03e-09	1	0.4284	0.4043	1.03e-09	0.2754
iMOGA	$f_1(x)$	0	1	0.4204	0.3892	0	0.3098
	$f_2(x)$	0.0003411	1.001	0.4153	0.3771	0.0003411	0.2795
MOGA	$f_1(x)$	0	1	0.5	0.5	0	0.293
	$f_2(x)$	0	1	0.3352	0.2929	0	0.2421

In summary, the enhanced NSGA-II algorithm successfully covering the solution space and preserving solution diversity, both of which are essential for effective multi-objective optimization.

7. Experimental Results on Real World Problems

In this section, the proposed algorithm is applied to real-world problems to demonstrate its capability in finding optimal or near-optimal solutions. The real-world project networks depicted in Fig.10., Fig.11., Fig.12, from [19], [29], and [19] have been appropriately modified to establish a linear and continuous relationship between the time and cost of the activities.

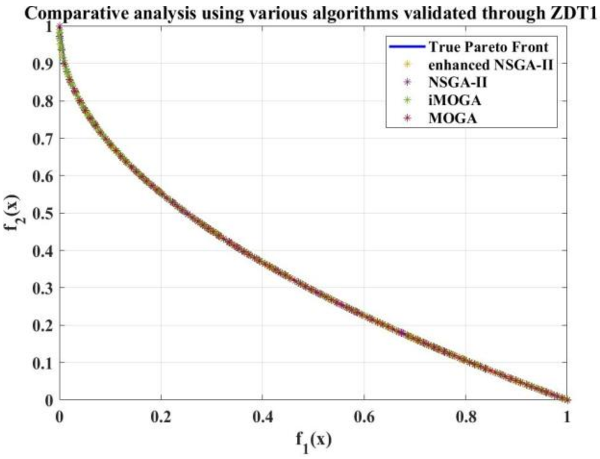

Fig.8. Comparative analysis using various algorithms validated through ZDT1

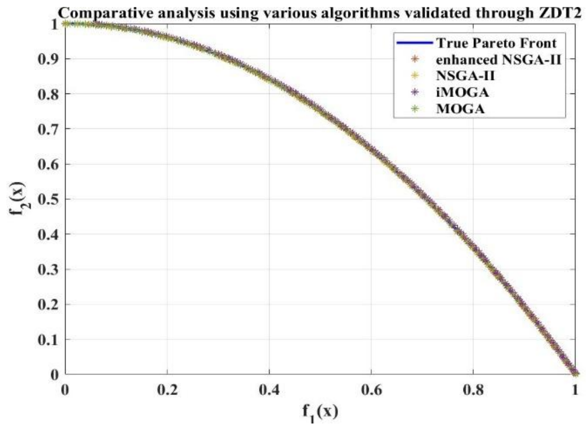

Fig.9. Comparative analysis using various algorithms validated through ZDT2

The alternatives for these test problems are presented in Table 3., Table 4., and Table 5. respectively. To address these real-world problems, the enhanced NSGA-II algorithm is implemented with the following key parameters: initial population $N = 200$, crossover probability $p_c = 0.9$, mutation probability $p_m = 0.9$, and a maximum generation limit $(g_{max}) = 2000$.

Table 2. Statistical analysis of various algorithms validated through ZDT2 problem

Algorithm	Objectives	Min	Max	Mean	Median	Mode	Std
enhanced NSGA-II	$f_1(x)$	0	1	0.6138	0.6353	0	0.2701
	$f_2(x)$	2.534e-06	1	0.5511	0.5964	2.534e-06	0.3076
NSGA-II	$f_1(x)$	0	1	0.5734	0.6187	0	0.2882
	$f_2(x)$	1.437e-06	1	0.589	0.6172	1.437e-06	0.3097
iMOGA	$f_1(x)$	0	1	0.5847	0.6182	0	0.2854
	$f_2(x)$	0.003096	1.002	0.5808	0.6215	0.003096	0.3155
MOGA	$f_1(x)$	0	1	0.5	0.5	0	0.293
	$f_2(x)$	0	1	0.665	0.75	0	0.3028

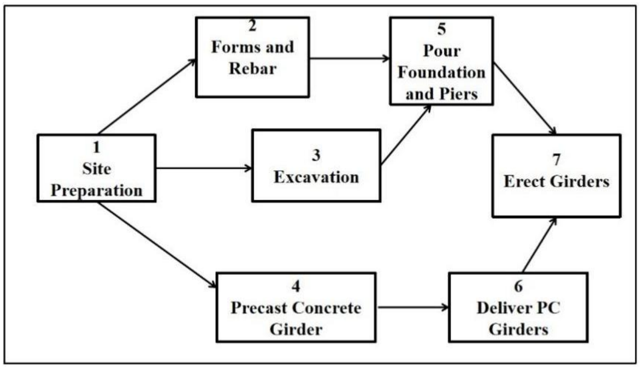

Fig.10. Network of first test problem

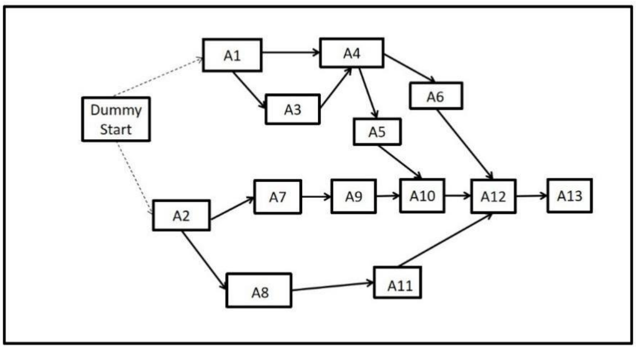

Fig.11. Network of second test problem

The results obtained for the first, second and third real-world test problems using the enhanced NSGA-II algorithm are illustrated in Fig.13., Fig.14., and Fig.15. respectively. A detailed statistical analysis of these test problems is provided in Table 6., Table 7., and Table 8. The experimental findings demonstrate the enhanced NSGA-II algorithm's strong capability in effectively solving complex real-world optimization problems.

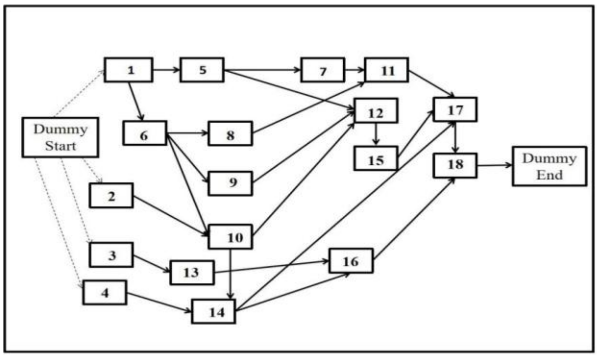

Fig.12. Network of third test problem

Table 3. Alternatives of first test problem

Activity No.	CT	NT	CC	NC
1	14	24	2400	1500
2	15	25	3000	1000
3	15	33	4500	3200
4	12	20	45000	30000
5	22	30	20000	10000
6	14	24	40000	18000
7	09	18	30000	20000

Table 4. Alternatives of second test problem

Activity No.	CT	NT	CC	NC
A1	14	10	1000	1600
A2	18	15	4000	4540
A3	19	19	1200	1200
A4	15	13	200	440
A5	8	08	600	600
A6	19	16	2100	2490
A7	22	20	4000	4600
A8	24	24	1200	1200
A9	27	24	5000	5450
A10	20	16	2000	2200
A11	22	18	1400	1900
A12	18	15	700	1150
A13	20	18	1000	1200

Table 5. Alternatives of third test problem

Activities	CT	NT	CC	NC
1	14	24	2400	1500
2	15	25	3000	1000
3	15	33	4500	3200
4	12	20	45000	30000
5	22	30	20000	10000
6	14	24	40000	18000
7	09	18	30000	20000
8	14	24	220	120
9	15	25	300	100
10	15	33	450	320
11	12	20	450	300
12	22	30	2000	1000
13	14	24	4000	1800
14	09	18	3000	2200
15	16	16	3500	3500
16	20	30	3000	1000
17	14	24	4000	1800
18	09	18	3000	2200

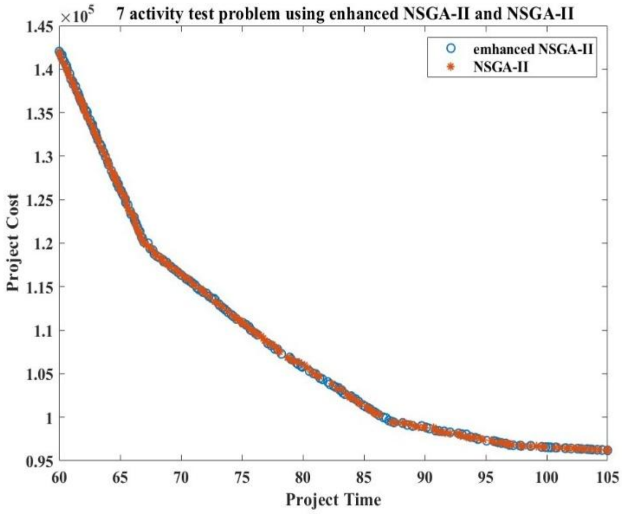

Fig.13. 7 activity test problem using enhanced NSGA-II

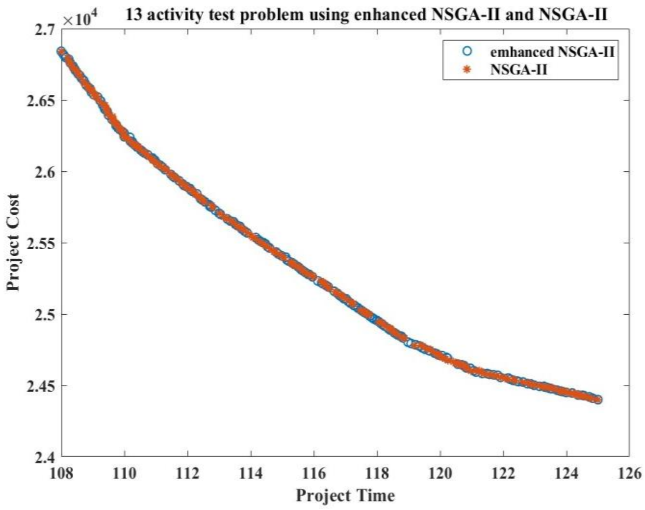

Fig.14. 13 activity test problem using enhanced NSGA-II

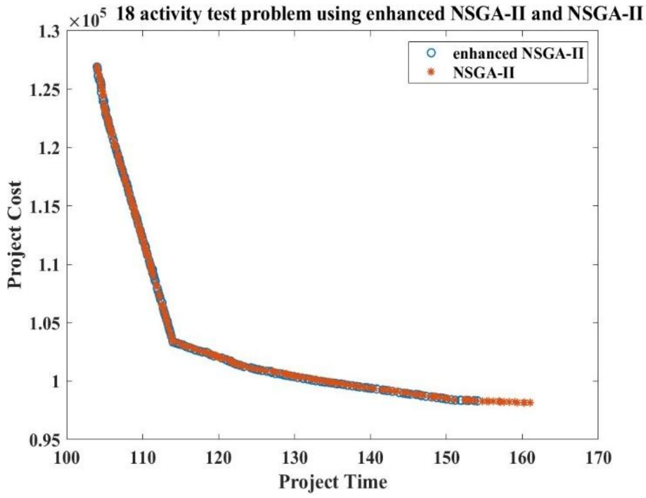

Fig.15. 18 activity test problem using enhanced NSGA-II

Table 6. Statistical analysis of 7 activity test problem

Algorithm	Objectives	Min	Max	Mean	Median	Mode	Std
enhanced NSGA-II	Project Time	60	105	77.37	73.99	105	13.43
	Project Cost	9.62e+04	1.42e+05	1.135e+05	1.119e+05	9.62e+04	1.427e+04
NSGA-II	Project Time	60	105	77.12	74.53	105	13.34
	Project Cost	9.62e+04	1.419e+05	1.137e+05	1.143e+05	9.62e+04	1.412e+04

Table 7. Statistical analysis of 13 activity test problem

Algorithm	Objectives	Min	Max	Mean	Median	Mode	Std
enhanced NSGA-II	Project Time	108	125	115.6	115.6	125	4.973
	Project Cost	2.44e+04	2.684e+04	2.543e+04	2.532e+04	2.44e+04	739.4
NSGA-II	Project Time	108	125	115.6	115.3	108	5.077
	Project Cost	2.44e+04	2.684e+04	2.543e+04	2.536e+04	2.44e+04	738.7

Table 8. Statistical analysis of 18 activity test problem

Algorithm	Objectives	Min	Max	Mean	Median	Mode	Std
enhanced NSGA-II	Project Time	104	154.1	119.8	113.4	104	14.62
	Project Cost	9.832e+04	1.269e+05	1.084e+5	1.048e+05	9.832e+04	9073
NSGA-II	Project Time	104	161	122.1	114	104	16.8
	Project Cost	9.816e+04	1.27e+05	1.079e+05	1.034e+05	9.816e+04	9087

8. Conclusions

This study highlights the efficacy of the enhanced NSGA-II algorithm in addressing multi-objective optimization problems by leveraging Sobol sequences for population initialization. The algorithm's effectiveness was validated using benchmark problems and real-world applications, showcasing its superior convergence, robustness, and solution diversity compared to existing techniques. While the results demonstrate strong potential, future work should explore the algorithm's scalability for large-scale and multi-construction projects, as well as its adaptability to incorporate additional objectives like quality and risk under uncertainty. This advancement represents a promising direction for practical optimization in complex project environments.

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The first author conducted the MATLAB coding, program development, document authoring, and manuscript formatting.

The second author assisted with manuscript editing, formatting, and supervision, while also executing the MATLAB code.

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References

[1] K. Deb, "Multi-objective Optimisation Using Evolutionary Algorithms: An Introduction," in: Wang, L., Ng, A., Deb, K. (eds) *Multi-objective Evolutionary Optimisation for Product Design and Manufacturing*, Springer, London, 2011. DOI: 10.1007/978-0-85729-652-8- 1.

[2] A. S. Patil, A. K. Agarwal, K. Sharma, and M. K. Trivedi, "Time-cost trade-off optimization model for retrofitting planning projects using MOGA," *Asian Journal of Civil Engineering*, 2024. DOI: 10.1007/s42107-024-01014-y.

[3] P. K. Mandal, "A review of classical methods and Nature-Inspired Algorithms (NIAs) for optimization problems," *Results in Control and Optimization*, vol. 100315, 2023.

[4] A. Kaveh, "Applications of Metaheuristic Optimization Algorithms in Civil Engineering," Springer, 2016. DOI: 10.1007/978-3-319-48012-1.

[5] S. Sharma and V. Kumar, "A comprehensive review on multi-objective optimization techniques: Past, present and future," *Archives of Computational Methods in Engineering*, vol. 29, no. 7, pp. 5605–5633, 2022.

[6] G. Karakaya, "Editorial for 'Recent Advances and Applications of Multi-objective Optimization'," *EURO Journal on Decision Processes*, Article ID 100049, 2024.

[7] G. Ulusoy and Ö. Hazır, "The Time/Cost Trade-off Problems," in *An Introduction to Project Modeling and Planning*, pp. 141–165, 2021.

[8] M. Shahriari, "Multi-objective optimization of discrete time–cost tradeoff problem in project networks using non- dominated sorting genetic algorithm," *Journal of Industrial Engineering International*, vol. 12, pp. 159–169, 2016.

[9] C. W. Feng, L. Liu, and S. A. Burns, "Using Genetic Algorithms to Solve Construction Time-Cost Trade-Off Problems," *Journal of Computing in Civil Engineering*, vol. 11, pp. 184–189, 1997.

[10] P. De, E. J. Dunne, J. B. Ghosh, and C. E. Wells, "The discrete time-cost tradeoff problem revisited," *European Journal of Operational Research*, vol. 81, pp. 225–238, 1995.

[11] D. E. Goldberg, "Genetic algorithms in search optimization and machine learning," Addison-Wesley, 1989.

[12] E. Zitzler and L. Thiele, "Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach," *IEEE Transactions on Evolutionary Computation*, vol. 3, pp. 257–271, 1999.

[13] B. K. Pathak, S. Srivastava, and K. Srivastava, "Neural network embedded multiobjective genetic algorithm to solve non-linear time-cost tradeoff problems of project scheduling," *Journal of Scientific and Industrial Research*, vol. 67, pp. 124–131, 2008.

[14] D. Agdas, D. J. Warne, J. Osio-Norgaard, and F. J. Masters, "Utility of Genetic Algorithms for Solving Large-Scale Construction Time-Cost Trade-Off Problems," *Journal of Computing in Civil Engineering*, vol. 32, 2018.

[15] K. M. Kumar, D. Agrawal, V. K. Vishwakarma, and M. A. Eirgash, "Development of time-cost trade-off optimization model for Indian highway construction projects using non-dominated sorting genetic algorithm-II methodology," *Asian Journal of Civil Engineering*, vol. 25, no. 8, pp. 5975–5988, 2024.

[16] A. P. Chassiakos and P. K. Tsikas, "Time-cost trade-off optimization at different project sizes," in *Proceedings of the Eleventh International Conference on Engineering Computational Technology*, vol. 2, Paper 14.2, Civil-Comp Press, Edinburgh, UK, 2022. DOI: 10.4203/ccc.2.14.2.

[17] A. Dhawan, K. Sharma, and M. K. Trivedi, "Simulated Annealing-Based Time–Cost Trade-Off Model for Construction," presented at ICSISCET-2020, 2020.

[18] K. Sharma, S. Gwalior, M. Trivedi, and S. Gwalior, "AHP and NSGA-II based Time-Cost-Quality Trade-Off Optimization model for Construction," presented at ICSISCET-2020, 2020.

[19] B. K. Pathak and S. Srivastava, "Integrated Fuzzy-HMH for project uncertainties in time-cost tradeoff problem,"*Applied Soft Computing Journal*, vol. 21, pp. 320–329, 2014.

[20] G. Albayrak, "Novel Hybrid Method in Time–Cost Trade-Off for Resource-Constrained Construction Projects," *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, vol. 44, pp. 1295–1307, 2020.

[21] Ankita and S. Kumar Sahana, "Evolutionary based hybrid GA for solving multi-objective grid scheduling problem,"*Microsystems Technology*, vol. 26, pp. 1405–1416, 2020.

[22] N. Hamta, M. Ehsanifar, and J. Sarikhani, "Presenting a goal programming model in the time-cost-quality trade-off," *International Journal of Construction Management*, vol. 21, pp. 1–11, 2021.

[23] Z. Liang and Z. Wang, "Enhancing population diversity based gaining-sharing knowledge based algorithm for global optimization and engineering design problems," *Expert Systems with Applications*, Article ID 123958, 2024.

[24] K. Deb, "Multi-objective genetic algorithms: Problem difficulties and construction of test problems," *Evolutionary Computation*, vol. 7, pp. 205–230, 1999.

[25] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II,"*IEEE Transactions on Evolutionary Computation*, vol. 6, pp. 182–197, 2002.
[26] K. Dev, and R. B. Agrawal, 'Simulated binary crossover for continuous search space," *Complex systems*, vol. 9, no. 2, pp. 115-148, 1995.
[27] K. Deb, "Multi-objective optimization using evolutionary algorithms," Wiley, New York, 2001.
[28] S. Sharma, B. K. Pathak, and R. Kumar, "Adopting an Improved Genetic Algorithm for Multi-Objective Service Composition Optimization in Smart Agriculture," *Austrian Journal of Statistics*, vol. 53, no. 5, pp. 11–25, 2024.
[29] T. Göçken, "Solution of fuzzy multi-objective project crashing problem," *Neural Computing and Applications*, vol. 23, pp. 2167–2175, 2013.

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