Thesis for the Degree of Master of Science

Evolutionary Multi/Many-objective Approaches for Next Release Optimization Problem

School of Electronics Engineering

Major in Signal Processing

The Graduate School

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I. INTRODUCTION

Recent days the IT industry is experiencing a boom in terms of software development, applications and web services due to the proliferation of the computational technology as well as widespread availability of digital technologies. In order to provide quality services as well as customer satisfactions, software companies are committing their resources to provide up to date versions of their dedicated software platform to the customers with most desirable features. This feature selection is mostly driven by the customer reviews as well as the commercial aspects of the software system in terms of Return on Investment, development time and committed resources. Software companies usually build, develop, and maintain software systems that are large, complete, and very much needed by the community. For this reason, software companies often face the dilemma of deciding what improvements or requirements should be applied in further development or Next Release. The compelling features that a company always aims while deciding the Next Release must include

1. Features aims to improve software architecture and user interface (UI)
2. Features requested by the customer community.

Allocation of time, cost of feature improvement and human resource allocation for the next release. Above points can be termed as an optimization problem, first introduced by Bagnall et al and named as the Next Release Problem (NRP) [1]. Typically, the NRP can be regarded as an example of the problem of finding a subset of future elections [2]. As to assist in the consideration and determination of the release of the next development by considering the cost and the benefit of each feature.

The important thing in software company requirements is determining the assignment of requirements in the next release. Hence the customers always want to buy effective products according to what they need, while companies want to choose certain conditions optimally to maximize commercial profits. Due to the complexity of the demands that customers want and the product's eligibility requirements, sometimes decisions regarding software releases often conflict to maximize project profits. In fact, in maximizing the benefits of software projects, there is an ideal approach that can be a way out that is by applying all the requirements to satisfy every potential customer. However, it is undeniable the limitations of software costs such as budget or development time, because only some of these requirements can be chosen in the next release. Then concluded from the perspective of the software company, the goal in the next release is to choose the optimal requirements to maximize customer satisfaction.

Optimization is a method to get the best results under given circumstances. The ultimate goal of all these methods are to minimize the effort or maximize the desired benefits. Because the required effort or desired benefits can be expressed as a function of the decision variable, optimization can be defined as the process of finding conditions that give a minimum or maximum value of a function [3]. There is no single method that can be used to solve all optimization problems. Many optimization methods have been developed to solve different types of optimization. Depending on the number of objective functions that are minimized, optimization problems can be classified as single-objective and multi-objective programming problems.

In the practical of NRP, first, the companies must be related to conflicting objectives, such as cost and customer satisfaction. A single objective formulation has the disadvantage that the optimization of one objective can be achieved at the expense of other objectives, which results in the search for bias in certain parts of the solution space. At present, multi-objective next release problem (MONRP), each of the objectives must be optimized as a separate objective and sometimes might be conflicting with each other.

For example, a two-objective MONRP which balances the pressure between the requirements of the consumer and the device level [4], and considers quality and price as two factors in the multi-objective next release problem in terms of the number of specifications and the number of customers [5]. Overview of existing research and mentioned MOEAs are promising methods to address the optimization of requirements [6]. Subsequential, various classical domination-based multi-objective evolutionary approaches (MOEAs), such as PEAs, SPEA2, and NSGA-II were contrasted in [7-9]. Invasive weeds optimization is integrated into a domination-based multi-objective optimization system to tackle the MONRP. The results show that it outperforms other domination-based approaches [9].

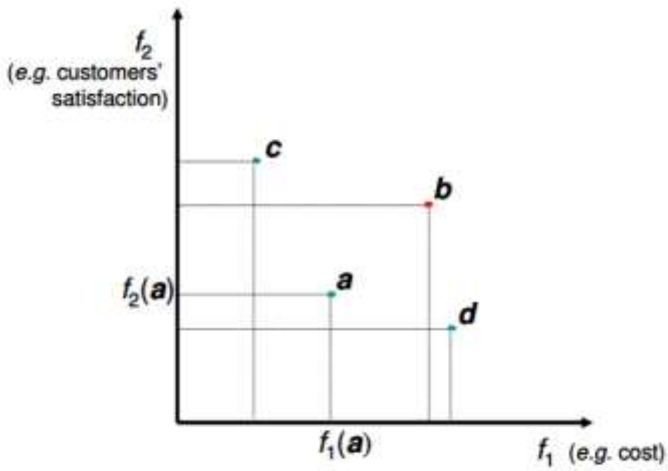

Fig. 1.1 (a) An example of solutions for the MONRP, where a dominates b; and a, c, and d are non-dominated solutions

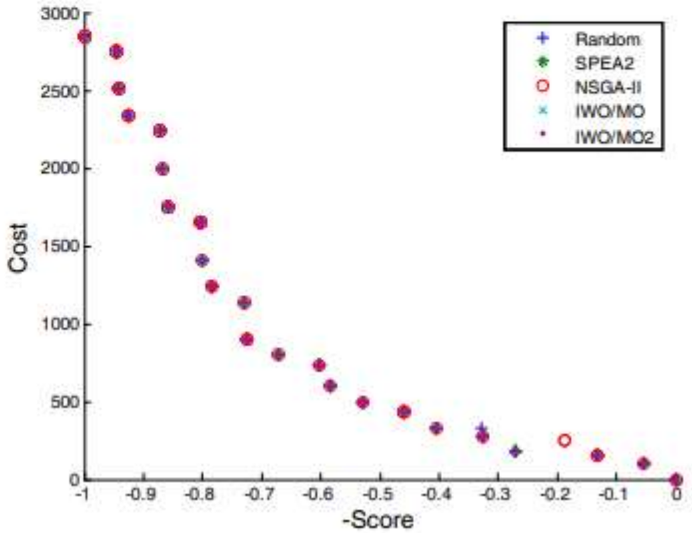

Fig. 1.1 (b) Comparison of the Random Search for the Motorola Data Set [9]

In principle, MONRP resides in the domain of combinatorial multi-objective development. Since MONRP is highly complex [1], exact algorithms are inappropriate when the demands are significant for the solution of the problem. Several earlier publications have found metaheuristic problems of this kind, such as MOEA, to be solved. Nonetheless, it was not fully explored how MOEAs were best used in the sense of MONRP. All the MOEAs used for MONRP are based on the Pareto domination framework, to our best knowledge.

In this thesis, we approached the NRP model with five additional objectives, namely the Multi/Many-objective NRP. We proposed an evolutionary Multi/Many-objective approaches for Next Release Optimization Problem with three state-of-the-art evolutionary optimization algorithms: NSGA-II, I_{SDE}, and IBEA. We conceived the study to investigate how to evaluate five objectives by our approaches, including the maximum of customer profits, the minimum requirements cost, the fairness of requirements selection, and so forth.

In this work, four evaluation metric are considered which includes the optimization performance, the importance of outcomes, metric quality division, and the comparison between the benchmark methods. This work provides an overall way of supporting the choice of many objectives.

II. Hierarchical Approach for Optimization Many-Objective

2.1. Introduction

Multi-conflict optimization problems, known as multi-objective optimization problems (MOPs), gained immense recognition due to their various applications in the real-world problems [10-12]. To efficiently solve the MOPs, various approaches were proposed in the literature, among them, multi-objective evolutionary algorithms have proved to be efficient due to the ability to generate the required Pareto optimal solution set in one run [13-15]. When dealing with MOPs, MOEAs has to consider two significant indicators, convergence and distribution where convergence is the distance from PF_{known} to PF_{true} (true PF), and distribution refers to the population distribution in the PF. Convergence and distribution have been shown to clash and convergence is expected to be affected if we find a good distribution quality [10-14].

In recent years, Many-objective optimization problems (MaOPs), which are the special case of MOPs with more than three objectives, are under consideration due to the difficulties possessed by MaOPs. Most of the MOEAs encounter difficulties while handling MaOPs [10-12], as providing a better trade-off between the convergence and diversity with an increasing number of objectives is a challenging task. To achieve faster convergence with better diversity, MOEAs adopted various selection techniques, out of which Pareto-dominance techniques are popular which gives more priority to the solutions with better Pareto rank while handling MOPs, Pareto dominance-based MOEAs (PDMOEAs) [12-17] exhibits better performance but while solving MaOPs their performance deteriorates as the objectives increases. The main reason for the deterioration in the performance of PDMOEAs is that as the objectives increases, the effect of Pareto dominance gradually vanishes. In other words, as the objectives increase the quantity of non-dominated solutions increases in the population.

In PDMOEAs, along with Pareto-dominance, various secondary selection metrics were employed to cope with the difficulties while solving MaOPs [12-17]. In other words, if the Pareto-dominance approach is unable to prioritize the solutions solely, then PDMOEAs completely rely on the secondary selection metrics. In the classical PDMOEAs such as NSGA-II [12] and SPEA2 [16], the additional selection metrics focus more on the diversity, which results in a diversified Pareto optimal set, which is far from the true Pareto front. Along with the Pareto-dominance based approaches, other approaches were also proposed in the literature such as Decomposition-based approaches [18], Indicator-based approaches [19, 20], Reference set based methods [15], Preference-based approaches [21].

Decomposition-based approaches are the cue of preference-based approaches that drive the population toward the region of interest (ROI), researchers have proposed to perform searches to several well-deployed ROIs, to cover the entire PF* for MaOPs. MOEA/D is the first research in this field [18]. MOEA/D divides the MOP into several sub-problems and assigns a weight vector to each population member and optimized its corresponding sub-problems through a scalarizing function. Numerous MOEA/D versions, such as the MOEA/D-DE [22], and MOEA/D-M2M [23] were created to resolve MaOPs.

Indicator-based approaches, MaOP is transformed into an optimizing indicator problem by determining solutions using an output metric, such as an indicator for hyper-volume [24] or epsilon [25]. The high measurement value of the exact HC contribution when the number of goals reaches five thresholds is being criticized in HV-based approaches [19, 26, 27]. Using HypE, which is an algorithm based on Monte Carlo sampling, Bader and

Zitzler [28] have thus implemented the HV contribution to make HV choice workable [29].

Preference-based approaches, as most MOEAs in Pareto-based to address problems with a large number of objectives, researchers have developed new ordering relationships that allow comparisons of solutions for the larger sized objective space. There have been a significant number of studies in this regard, such as expansion preference relation [30], k-optimality relation [31], average ranking [32], maximum ranking [32], and favor relation [33]. The main weaknesses of preference order-based strategies are that some preferred connections prioritize solutions in the middle portion of the PF* only, while others emphasize good performance solutions for some goals, while they do have poor overall results.

Recently, to enhance the convergence properties of the PDMOEAs, an approximate efficient nondominated sorting (AENS) procedure is proposed in [34] using only three objective correlations to determine the relationship of superiority between the candidate solutions. In other words, the AENS approach irrespective of several objectives considers only three objective comparisons. The experimental results presented in [34] have proved that the AENS approach improves the convergence but results in the degradation of the diversity performance. On the other hand, a shift-based density estimation [35] is proposed to improve the performance of the PDMOEAs. Hence, in this work, we focus on incorporating the AENS approach and shift-based density estimation into the PDMOEAs along with the Pareto-dominance. In other words, in this work, we propose a novel hierarchical approach that combines Pareto-dominance with the AENS approach and shift-based density estimation in the mating and environmental selection to preserve the elite solutions for the next generations. In the proposed approach at first, the Pareto-dominance procedure is employed and then for the solutions in each non-domination level, the AENS approach is adopted. Then, the shift-based density estimation is calculated with the help of Pareto-dominance.

2.2. Basic Definition of Multi-objective Optimization Problems (MOPs)

A constant, multi-objective optimization problem (MOPs), which is restricted to the container, can be defined as:

$$\text{Minimize: } F(x) = (f_1(x), f_2(x), \dots, f_M(x))^T$$
$$\text{s.t. } a_i \leq x_i \leq b_i, \forall_i \in \{1, \dots, n\} \quad (2.1)$$

The vector function: $F: X \rightarrow \mathbb{R}^M$ is composed by $M \geq 2$ scalar objective functions $f_i: X \rightarrow \mathbb{R}$ $(i = 1, \dots, M)$, refers to the feasible set that is implications defined by the problem's box restrictions, i.e., $X = \sum_{i=1}^{n}[a_i, b_i]$.

There is no canonical order on $\mathbb{R}^M$ in multi-objective optimization problems and therefore we need weaker definitions for ordering vectors in $\mathbb{R}^M$ to be compared. The meanings are as follows:

2.2.1. Pareto Dominance Relation

A z^1 solution dominates the z^2, denoted in $z^1 < z^2$, if and only if:

$$\forall_i \in \{1, \dots, M\}: \; z_i^1 \leq z_i^2 \text{ and } \exists_i \in \{1, \dots, M\}: \; z_i^1 < z_i^2 \quad (2.2)$$

Two vectors, z^1 and z^2, are said to be shared non-dominated, with $z^1 \nless z^2$ and $z^2 \nless z^1$. For $x^1, x^2 \in X$, being the corresponding non-dominant vectors $x^1 < x^2 \leftrightarrow F(x^1) < F(x^2)$.

2.2.2. Pareto Optimality

Pareto optimal is ideal for a solution $x^* \in X$ complete when there is no other solution $x \in X$ such that $F(x) < F(x^*)$.

2.2.3. Pareto Set

This defines the Pareto optimal set (PS) as $PS = \{x \in X \mid \nexists y \in X : F(y) < F(x)\}$.

2.2.4. Pareto Front

Pareto front (PF) is set to $PF = \{z = \left(f_1(x), \dots, f_M(x)\right)^T \mid x \in PS\}$, which the choice of a Pareto optimal set (PS).

2.3. Proposed Method

In this field, a detailed explanation of the proposed hierarchical approach is presented. In the proposed hierarchical approach, we utilize the advantages provided by the AENS approach and shift-based density estimation to improve the performance of PDMOEAs in handling the MaOPs. The proposed approach aims at balancing both convergence and diversity.

2.3.1. General Framework of the Proposed Method

The framework of the proposed hierarchical approach is similar to the existing NSGA-II with slight differences in the mating and environmental selections. In the proposed hierarchical approach, at first, the parent population P_1 of size N is random initialized and evaluated. After Initialization, the mating section procedure is adopted to generate offspring and the parents are selected based on the sorted order of the Pareto-dominance, AENS and shift-based density estimation. After the mating selection, the obtained the parent population and Pareto-dominance integrate offspring population, AENS approach and shift-based density procedures are employed. Then environmental selection procedure is adopted to preserve the elite solutions for the next generations. The framework of the proposed method is depicted in figure 2.1.

2.3.2. Mating Selection and Environmental Selection

The main motive of the mating selection is to generate promising offspring solutions that have the ability to explore the whole search space. In the mating selection of the proposed approach, after the Pareto-dominance, for solutions in each nondominated fronts, the AENS approach is adopted. In other words, each solution will be assigned with Pareto rank based on Pareto-dominance and sub-Pareto rank based on the AENS approach. Then for each solution, shift-based density estimation is obtained with the help of the Pareto-dominance. Then each solution is sorted based on Pareto rank and sub-Pareto rank in ascending order and shift-based density estimation in descending order. Then for each solution, a rank is assigned based on the sorted order. After obtaining the rank, randomly two individuals are selected. Both the solutions will be compared based on the rank and the solution with less rank is selected for the offspring generation. If both the solutions A and B have rank, then one solution is chosen is random. The procedure of the mating selection is depicted in figure 2.2.

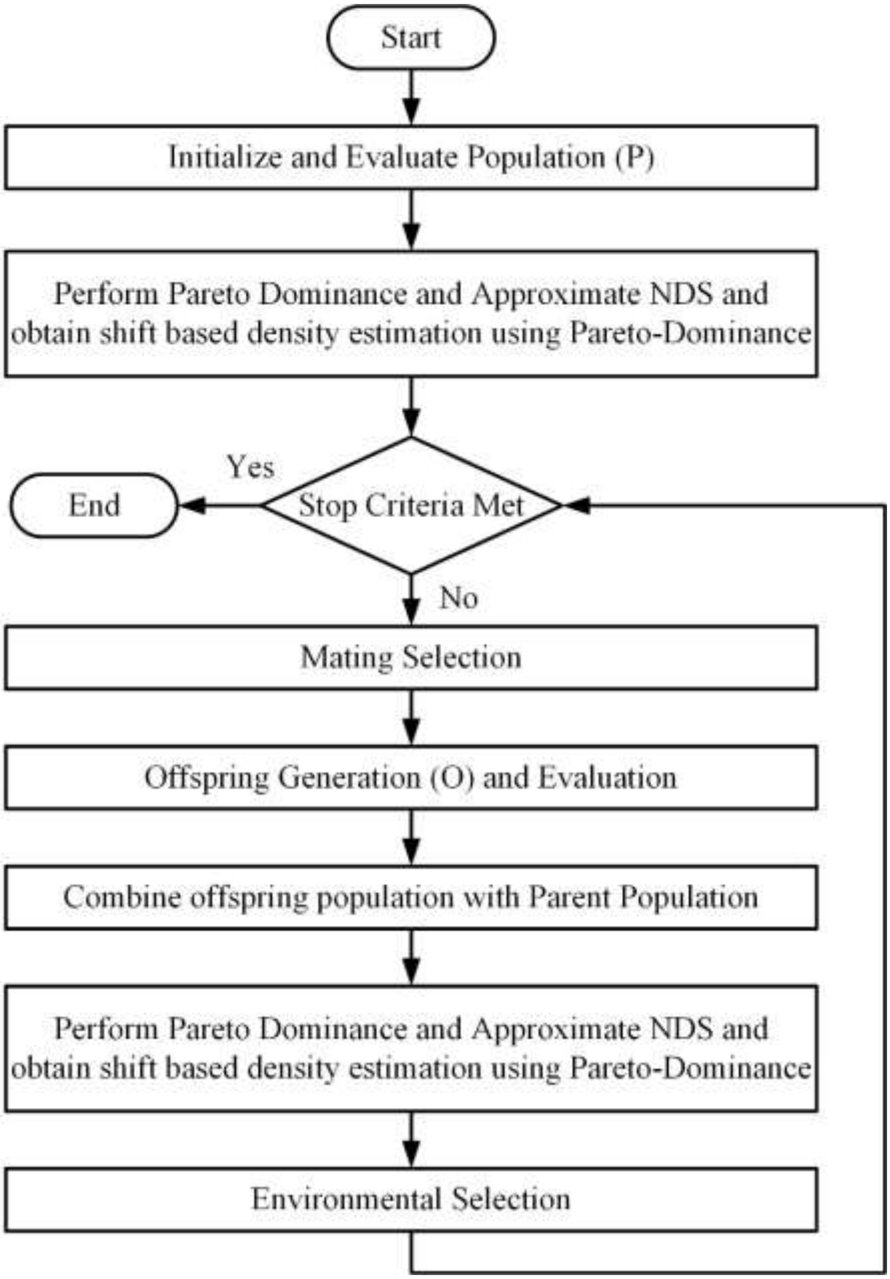

Fig. 2.1. Flowchart of Proposed Method

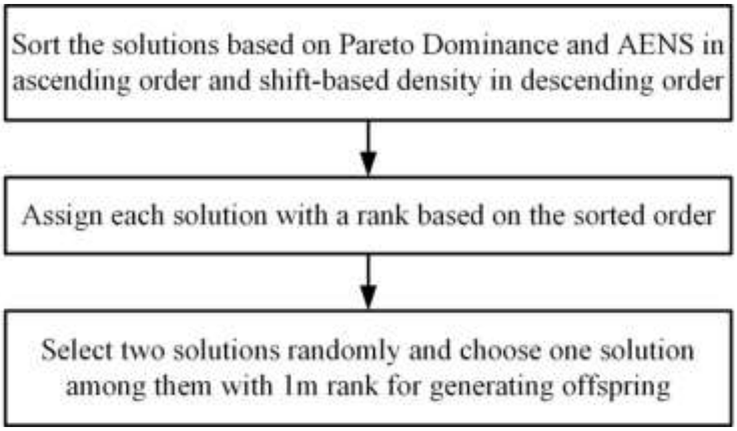

Fig. 2.2. Flowchart of Mating Selection

The main aim of the environmental selection is to preserve the elite solution, which drives the algorithm towards the convergence. In the environmental selection, the Pareto-dominance procedure is adopted on the combined parent and offspring population. Then similar to the mating selection, sub-Pareto rank and shift-based density for each solution are obtained. As mentioned in the mating selection, the solutions are sorted based on the Pareto rank and sub-Pareto rank in ascending order and shift-based density estimation in descending order and the best N solutions are chosen in the sorted order. The procedure of environmental selection is depicted in figure 2.3.

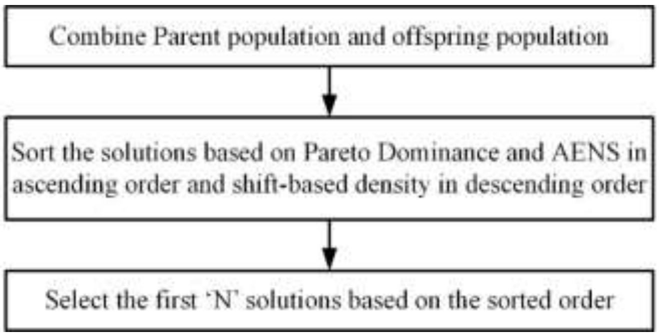

Fig. 2.3. Flowchart of Environmental Selection

2.4. Result and Discussion

In this section, we have presented the results of the experiments to analyze the performance of the proposed approach by comparing it with the state-of-art algorithms. We have conducted experiments on two popular benchmark test suites DTLZ [36] and WFG [37]. The DTLZ test suite consists of seven problems DTLZ1 to DTLZ7 and the WFG test suite contains nine problems WFG1 to WFG9. To demonstrate the effectiveness of the proposed hierarchical approach, we have compared our method with state-of-art algorithms such as NSGA-II [12], SPEA2 [16], KnEA [14], and NSGA-III [15]. We have employed the parameter settings for the benchmark problems and number of generation and Population sizes as presented in. Each algorithm is simulated for 30 times and the final obtained populations are saved for the comparisons. To compare the performance of the proposed approach with the state-of-art algorithms, we have employed the hypervolume (HV) indicator [38]. The hypervolume indicator considers both convergence and diversity.

We have conducted Wilcoxon's rank-sum test to obtain the statistical significance and presented the mean and standard deviation results of Hypervolume results in table 2.1 and 2.2. The algorithm with the best results is presented in the bold and shaded with grey color. From the hypervolume results presented in table 2.1 and 2.2, we can observe that the proposed method outperforms the NSGA-II algorithm and performs competitively when compared with the SPEA2, KnEA, and NSGA-III. The proposed hierarchical approach out of 64 test instances performs better, equal and worse than NSGA-II in 36, 6 and 22 instances respectively.

From the experimental results, we can also observe that the proposed method when compared with SPEA2, performs better in 29 cases, competitive in 2 cases and worse in 33 cases. KnEA algorithm performs better in 30 cases and worse in 22 cases with equal performance in 12 cases in comparison with the proposed approach. The proposed hierarchical approach performs better in 21 instances, equal performance in 15 cases and worse in 28 cases with the NSGA-III algorithm.

Table 2.1. Mean and Standard Deviation of Hypervolume results for DTLZ problems

Problem	M	NSGA-II			SPEA2			KnEA			NSGAIII			Hierarchical	
DTLZ1	4	0.7913	0.2412	(+)	0.9103	0.0010	(–)	0.6415	0.1294	(+)	**0.9120**	**0.0005**	(–)	0.8589	0.0214
	6	0.1346	0.2611	(+)	0.8193	0.2822	(+)	0.5194	0.1018	(+)	**0.9783**	**0.0060**	(–)	0.9108	0.0404
	8	0.0177	0.0968	(+)	0	0	(+)	0.3265	0.1058	(+)	**0.9729**	**0.1049**	(–)	0.8772	0.1075
	10	0	0	(+)	0	0	(+)	0.6841	0.2941	(+)	0.9566	0.1610	(+)	**0.9640**	**0.0594**
DTLZ2	4	0.4956	0.0091	(+)	0.5702	0.0048	(–)	0.5738	0.0043	(–)	**0.6012**	**0.0009**	(–)	0.5119	0.0170
	6	0.4502	0.1828	(+)	0.7749	0.1213	(+)	0.9861	0.0005	(–)	**0.9874**	**0.0028**	(–)	0.9617	0.0142
	8	0.6287	0.0687	(+)	0.6445	0.0218	(+)	**0.9999**	**0.0000**	(=)	0.9998	0.0003	(=)	0.9986	0.0013
	10	0.8819	0.0267	(+)	0.9122	0.0039	(+)	**1.0000**	**0.0000**	(=)	**1.0000**	**0.0000**	(=)	**1.0000**	**0.0000**
DTLZ3	4	0.5173	0.0117	(–)	0.5944	0.0037	(–)	0.4323	0.0784	(+)	**0.6048**	**0.0031**	(–)	0.4870	0.0241
	6	0.8714	0.1256	(+)	0.7589	0.2487	(+)	0.9970	0.0021	(+)	0.9998	0.0008	(+)	**0.9998**	**0.0004**
	8	0.5564	0.1259	(+)	0.0344	0.0774	(+)	0.8970	0.2723	(+)	**1.0000**	**0**	(=)	**1.0000**	**0**
	10	0.4770	0.1052	(+)	0.2391	0.0707	(+)	**1.0000**	**0.0000**	(=)	**1.0000**	**0**	(=)	**1.0000**	**0**
DTLZ4	4	0.5217	0.0091	(=)	0.5497	0.0494	(–)	**0.5940**	**0.0052**	(–)	0.4995	0.1110	(+)	0.5009	0.1058
	6	0.7608	0.1209	(+)	0.9171	0.0519	(+)	**0.9980**	**0.0001**	(=)	0.9920	0.0062	(=)	0.9909	0.0088
	8	0.8969	0.0361	(+)	0.8763	0.0149	(+)	**1.0000**	**0.0000**	(–)	0.9999	0.0001	(=)	0.9999	0.0001
	10	0.9524	0.0135	(+)	0.9296	0.0065	(+)	**1.0000**	**0.0000**	(=)	**1.0000**	**0.0000**	(=)	**1.0000**	**0.0000**
DTLZ5	4	**0.7797**	**0.0010**	(–)	0.7641	0.0082	(–)	0.7676	0.0051	(–)	0.7721	0.0021	(–)	0.6402	0.1523
	6	0.8370	0.0068	(–)	0.6706	0.1093	(+)	**0.8656**	**0.0040**	(–)	0.8365	0.0068	(–)	0.7210	0.1273
	8	0.8209	0.0141	(–)	0.4208	0.1636	(+)	**0.8751**	**0.0039**	(–)	0.8512	0.0080	(–)	0.7320	0.0970
	10	0.8335	0.0166	(–)	0.4491	0.1325	(+)	**0.8795**	**0.0031**	(–)	0.8786	0.0061	(–)	0.7442	0.1092
DTLZ6	4	0.8993	0.0501	(–)	0.9139	0.0244	(–)	**0.9281**	**0.0081**	(–)	0.9349	0.0008	(–)	0.7890	0.2109
	6	0.5453	0.0484	(+)	0.2882	0.0467	(+)	**0.9864**	**0.0030**	(–)	**0.9853**	**0.0030**	(–)	0.8901	0.0585
	8	0.5262	0.0465	(+)	0.4263	0.0219	(+)	**0.9885**	**0.0023**	(–)	**0.9877**	**0.0039**	(–)	0.9298	0.0520
	10	0.5880	0.0467	(+)	0.4732	0.0243	(+)	**0.9898**	**0.0012**	(–)	0.9876	0.0031	(–)	0.9144	0.0515
DTLZ7	4	0.1581	0.0060	(+)	0.1844	0.0059	(–)	**0.1924**	**0.0094**	(–)	0.1885	0.0023	(–)	0.1660	0.0072
	6	0.0397	0.0121	(+)	0.1153	0.0113	(+)	**0.1745**	**0.0109**	(–)	0.1424	0.0083	(=)	0.1347	0.0123
	8	0.0563	0.0170	(+)	0.2345	0.1474	(+)	0.5154	0.0262	(+)	0.3428	0.1175	(+)	**0.5536**	**0.0053**
	10	0.1238	0.0280	(+)	0.3328	0.2144	(+)	0.3373	0.2226	(+)	0.6307	0.1579	(+)	**0.8309**	**0.0141**
+/=/-		21/1/6			21/0/7			9/5/14			5/9/14				

Table 2.2. Mean and Standard Deviation of Hypervolume results for WFG problems

Problem	M	NSGA-II			SPEA2			KnEA			NSGAIII			Hierarchical	
WFG1	4	0.9716	0.0027	(=)	**0.9822**	**0.0004**	(–)	0.9695	0.0042	(=)	0.9567	0.0548	(+)	0.9650	0.0136
	6	0.9955	0.0005	(–)	**0.9970**	**0.0003**	(–)	0.9863	0.0025	(=)	0.9230	0.0756	(+)	0.9851	0.0045
	8	0.9986	0.0002	(–)	**0.9989**	**0.0001**	(–)	0.9878	0.0027	(=)	0.8813	0.0861	(+)	0.9917	0.0047
	10	0.9992	0.0001	(–)	**0.9993**	**0.0000**	(–)	0.9928	0.0026	(=)	0.8531	0.1084	(+)	0.9966	0.0013
WFG2	4	0.5578	0.0200	(=)	**0.5847**	**0.0269**	(=)	0.5460	0.0231	(+)	0.5541	0.0618	(+)	**0.5611**	**0.0264**
	6	0.5157	0.0300	(–)	**0.5850**	**0.0257**	(–)	0.4955	0.0240	(–)	0.5267	0.0633	(–)	0.2976	0.1568
	8	0.5045	0.0244	(–)	**0.6333**	**0.0049**	(–)	0.4709	0.0349	(=)	0.5951	0.0124	(–)	0.4826	0.0758
	10	0.5247	0.0203	(–)	**0.6339**	**0.0040**	(–)	0.5519	0.0387	(–)	0.5776	0.0140	(–)	0.4203	0.1115
WFG3	4	**0.2581**	**0.0024**	(=)	**0.2598**	**0.0023**	(=)	**0.2597**	**0.0035**	(=)	0.1909	0.0562	(+)	**0.2521**	**0.0045**
	6	**0.1697**	**0.0073**	(–)	0.1680	0.0072	(–)	0.1473	0.0119	(+)	0.0739	0.0258	(+)	0.1545	0.0056
	8	**0.1468**	**0.0057**	(–)	**0.1457**	**0.0054**	(–)	0.1064	0.0102	(–)	0.0468	0.0215	(+)	0.0749	0.0195
	10	**0.1325**	**0.0045**	(–)	0.1292	0.0062	(–)	0.0892	0.0114	(–)	0.0037	0.0039	(+)	0.0405	0.0244
WFG4	4	0.3102	0.0117	(+)	0.3472	0.0071	(–)	**0.3778**	**0.0049**	(–)	0.3372	0.0472	(=)	0.3399	0.0073
	6	0.2286	0.0122	(+)	0.2822	0.0127	(+)	**0.3484**	**0.0144**	(=)	0.2298	0.0829	(+)	**0.3471**	**0.0120**
	8	0.3391	0.0197	(+)	0.4114	0.0140	(+)	0.4223	0.0192	(+)	0.4479	0.0510	(+)	**0.4867**	**0.0188**
	10	0.3271	0.0142	(+)	0.4102	0.0147	(+)	0.4488	0.0239	(+)	0.3803	0.1385	(+)	**0.5299**	**0.0208**
WFG5	4	0.2328	0.0081	(+)	**0.2686**	**0.0029**	(–)	0.2619	0.0043	(–)	0.2647	0.0034	(–)	0.2555	0.0055
	6	0.1830	0.0125	(+)	0.2330	0.0077	(–)	0.1547	0.0191	(+)	**0.2438**	**0.0094**	(–)	0.2216	0.0171
	8	0.1879	0.0175	(–)	**0.3011**	**0.0068**	(–)	0.1896	0.0184	(–)	0.2666	0.0275	(–)	0.1379	0.0412
	10	0.1875	0.0140	(–)	0.2708	0.0110	(–)	0.1737	0.0224	(–)	**0.2767**	**0.0201**	(–)	0.1082	0.0268
WFG6	4	0.2129	0.0206	(+)	0.2663	0.0118	(+)	0.2200	0.0213	(+)	0.2710	0.0265	(=)	**0.2748**	**0.0109**
	6	0.1365	0.0365	(+)	0.1801	0.0307	(–)	0.0877	0.0290	(+)	**0.2203**	**0.0251**	(–)	0.1413	0.0404
	8	0.1243	0.0254	(+)	0.2018	0.0203	(–)	0.1083	0.0207	(+)	**0.2181**	**0.0533**	(–)	0.1415	0.0376
	10	0.1263	0.0284	(–)	0.1792	0.0160	(–)	0.0877	0.0201	(+)	**0.1966**	**0.0345**	(–)	0.1173	0.0329
WFG7	4	0.4375	0.0106	(–)	0.4794	0.0040	(–)	**0.4884**	**0.0038**	(–)	0.4296	0.0774	(=)	0.4246	0.0160
	6	0.4673	0.0087	(=)	0.5327	0.0047	(–)	**0.5424**	**0.0057**	(–)	0.4381	0.0844	(+)	0.4648	0.0156
	8	0.5138	0.0089	(–)	0.5765	0.0037	(–)	**0.5789**	**0.0108**	(–)	0.2919	0.1725	(+)	0.4789	0.0203
	10	0.5454	0.0099	(–)	**0.6118**	**0.0037**	(–)	0.5461	0.0372	(–)	0.3196	0.1031	(+)	0.5329	0.0223
WFG8	4	0.0997	0.0248	(+)	0.1338	0.0238	(+)	0.0285	0.0204	(+)	**0.1943**	**0.0201**	(=)	**0.1961**	**0.0184**
	6	0.0645	0.0239	(+)	0.0588	0.0157	(+)	0.0111	0.0072	(+)	0.1164	0.0175	(+)	**0.1559**	**0.0121**
	8	0.0500	0.0173	(+)	0.0980	0.0132	(+)	0.0480	0.0092	(+)	**0.1689**	**0.0158**	(=)	**0.1654**	**0.0157**
	10	0.0410	0.0141	(+)	0.0771	0.0185	(+)	0.0380	0.0070	(+)	**0.1504**	**0.0202**	(=)	**0.1570**	**0.0129**
WFG9	4	0.4061	0.0234	(+)	0.4783	0.0297	(–)	**0.5094**	**0.0243**	(–)	0.4766	0.0288	(–)	0.4433	0.0214
	6	0.3861	0.0194	(–)	0.5121	0.0409	(–)	**0.5797**	**0.0327**	(–)	0.5247	0.0366	(–)	0.3785	0.0514
	8	0.4528	0.0220	(=)	0.6056	0.0379	(–)	0.6233	0.0578	(–)	**0.6679**	**0.1267**	(–)	0.4570	0.0906
	10	0.5212	0.0199	(+)	0.6792	0.0322	(–)	0.6317	0.0917	(–)	**0.6947**	**0.0738**	(–)	0.6106	0.0854
+/=/-		15/5/16			8/2/26			13//7/16			16/6/14				

III. Multi-Objective Next Release Problems

3.1. Next Release Problems

The Next Release Problem (NRP) is an optimization problem for the trade-off between feature selection, resource allocation and minimization of cost for future release of software systems which helps find the best option to meet customer needs as well as commercial profit for the company. The first NRP design was proposed by Bagnall et al [1]. The quality of several heuristic items such as hill climbing and genetic algorithms has been tested. An estimated multi-level backbone algorithm was developed to achieve the maximal gain on a restricted budget [39]. J. Ren [40] developed the NRP as a new multi-target model: simultaneously optimize consumer income and reduce the costs of requirements. Researchers have suggested many approaches and models to solve the multi-objective NRP decision, including fairness analysis [41], robust analysis [42], interactive optimization [43], and hardness exploration [44].

All current multi-objective NRP are aimed at two objectives, namely profits cost [7], or profits and fairness [41]. The Pareto frontier [12] is a general method of resolving the multi-objective NRP, which means the collection of optimal solutions currently offered. Users select requirements for balancing two overlapping objectives for their next release based on such a multi-objective NRP. However, an organization must at the same time deal with three or more deadlines to assess the scope of the specifications. For example, consumer total income, minimum costs for requirements and the equal range of requirements should be taken together to assess an optimum decision. In the meantime, it may be impossible to identify the Pareto frontiers for more than two goals [45]. There is no preliminary study to help the NRP requirements decision with a large number of decision goals.

In this work, The design NRP has five objectives and three state-of-the-art evolutionary optimizer algorithms are proposed: NSGA-II, I_{SDE}, and IBEA. A development study aims to analyze how to evaluate the minimum requirements for the fair selection of demands for five objectives of the multi/many-objective including the maximum profit of the company.

3.2. Principle for Objective Functions

The next release problem should not meet each customer requirement. Many requirements can be met and the other condition has to be omitted. The equality to assess if customers are being treated fairly is suggested for this purpose:

1. *Principle of fair distribution of resources*

   The fair distribution of resources rule states that every consumer must obtain the entire resource equally. The calculation of the distributed capital, which is the total cost of the next release, in this case, is a consequence of this theory. If each customer has the same amount of fulfilled cost demands, the equal distribution of resources rule is achieved.

2. *Principle of fair customer satisfaction*

   Suppose that the criteria of two individual customers are both $1,000, but one has reported for only $1,000, he has fulfilled 100%, the other for $10,000, and only 10%. They're obviously not in the same place. They were not treated fairly under the equal rule of customer satisfaction, which states that every customer must be fairly satisfied.

The first principle seeks to ensure that each person is equal to the absolute, and the second principle seeks to ensure that each individual is equal to their satisfied demand. If all the customer wants the same number, these two values will be expressed in an ideal scenario with a different equation. For if two groups have the same denominator, the requirement to be equitable is similar to the requirement that the two fractions be equal in terms of their worth.

Nevertheless, for the same sum of the specification, we cannot anticipate every customer statement. Such two concepts thus constitute a conflicting objective. When a company, for instance, tries to meet its client equally under the second principle, each client has the same percentage of fulfilled requirements, so the first principle has to be unreasonable because a particular client demands different requirements.

In the next segment, which is built for multiplicative objectively constructive problems, some analytical formulas will be shown from these issues.

3.3. Problem Statement

It is assumed that for an existing software system, there is a set of customers,

$$U = \{u_1, u_2, \dots, u_m\}$$

whose requirements are to be considered in the development of the next release. The set of possible software requirements is denoted by:

$$R = \{r_1, r_2, \dots, r_n\}$$

It is assumed that all the requirements are independent. In order to satisfy each requirement, some resources need to be allocated. The resources needed to implement a particular requirement can be transformed into cost terms and considered to be the associated cost to fulfill the requirement. The resultant cost vector for the set of requirements $r_i (1 \leq i \leq n)$ is denoted by:

$$C = \{c_1, c_2, \dots, c_n\}$$

where c_i displays the value used to introduce $r_i \in R$ alternatives.

3.4. Evolutionary Operators of MONRP

In our approach we are following the general framework of evolutionary algorithm which are focus on the variation operator. In the variation operator, there are mutation and crossover operation that are very important on evolutionary algorithm.

3.4.1. The Crossover Operation

Crossover is a system in which more than one (usually two) parent solutions are taken from and children are created. Figure 3.1 shows a template in which two parents are separated from the third bit and two children are engendered. Crossover methods can be more complex than they can, by splitting the parents into more than two parts and providing a cap of bits, but the principle remains the same.

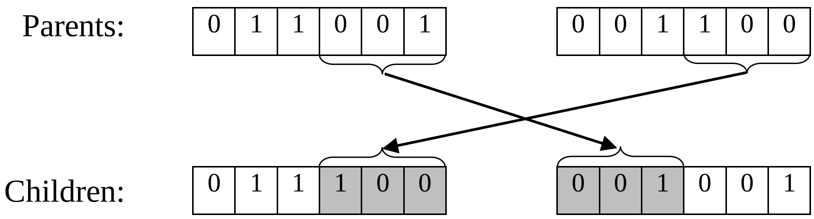

Fig. 3.1. Illustration of Crossover Operation

For purpose of this work, we used existing crossover such as single-point crossover, two-point crossover, binomial crossover, and multi-parent crossover.

3.4.1.1. Single-Point Crossover

A single-point crossover on both parents organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. Single crossover point selected at random and chromosomes are cut at the crossover point. Tail part of each chromosome spliced with head part of the other chromosome. Figure 3.2 shows the single-point crossover (SPC) process.

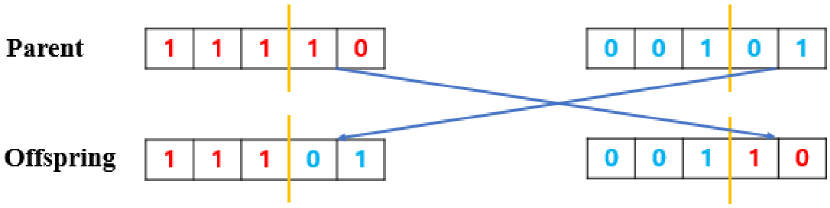

Fig. 3.2. Single-Point Crossover

3.4.1.2. Two-Point Crossover

In two-point crossover (TPC), randomly two crossover points are chosen. Avoids that genes at the head and genes at the tail of a chromosomes, the contents between these points are exchanged between two mated parents. Figure 3.3 shows the two-point crossover (TPC) process.

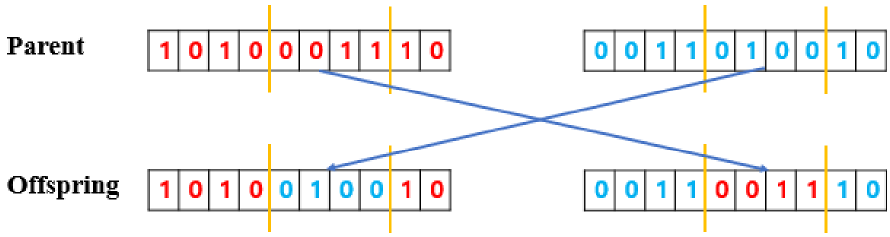

Fig. 3.3. Two-Point Crossover

3.4.1.3. Binomial Crossover

In the case of binomial crossover, a component of the offspring is taken with probability CR from the mutant vector, ***y***, and with probability 1-CR from the current element of the population, ***x***.

$$z'_{i,j} = \begin{cases} y'_{i,j} & if\ (rand\ (0,1) \leq CR | j = j_r) \\ x'_{i,j} & otherwise \end{cases} \qquad 3.1$$

The condition "$rand\ (0,1) \leq CR | j = j_r$" of the ***if*** statement ensures the fact that at least one component is taken from the mutant vector.

3.4.1.4. Multi-Parent Crossover

A multi-parent crossover operator is designed to generate offsprings from numerous parents. In Multi-parent crossover (MPX), crossover chosen n random crossover point and split along points. Glue parts alternating between parents, and generalization of 1 point.

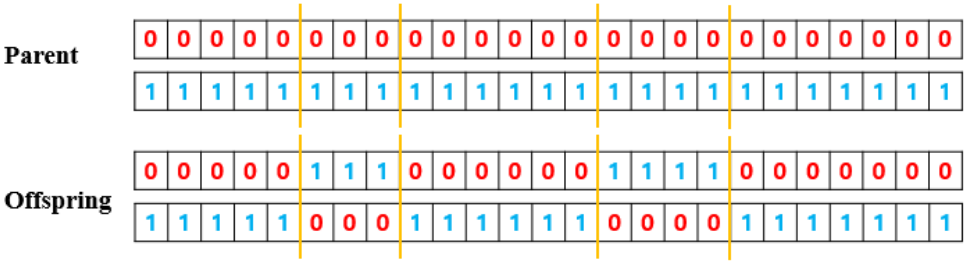

Fig. 3.4. Multi-Parent Crossover

3.4.2. The Mutation Operation

Each genetic algorithm has a mutation operator to increase its diversity within the population. As Figure 3.5 shows, there are different mechanisms for a mutation: the alteration, the exchange, the insertion, and removal. The likelihood of mutation needs to be selected well in order to progress slowly. 0.001, 0.01 or $\frac{1}{length}$ should be used in publications.

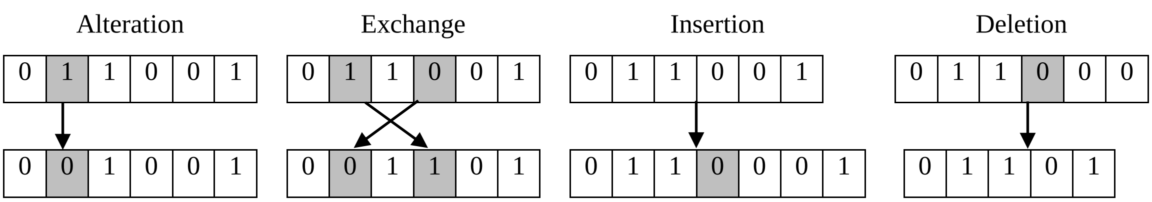

Fig. 3.5. Illustration of Mutations on binary examples

The mutation operator can be applied to either function or terminal nodes. This operator can modify one or many nodes. Given a selected individual, the mutation operator first randomly selects a node in the tree representation of the individual. Then, if the selected node is a terminal (source or target metamodel element), it is replaced by another terminal (another metamodel element).

In this work, we used bitwise mutation as existing mutation and radius mutation as our proposed mutation.

3.4.2.1. The Bitwise Mutation

The crossover operator is mainly responsible for the search aspect of genetic algorithms, even though the mutation operator is also used for this purpose. The bitwise mutation operator which changes 1 to 0 and attempted to mutate every bit (alter the bit to its complement) with a probability of p_m independently to the outcome of mutation to other bits.

The need for mutation is to keep diversity in the population. The bitwise mutation procedure of a random number for every bit. After a bit is mutated, the location of the next mutated bit is determined by an exponential distribution, that mean of the distribution is assumed to be $\mu = \frac{1}{p_m}$. The procedure is: First, create a random number $r \in [0,1]$. Estimate the next bit to be mutated by skipping $\eta = -p_m \ln(1 - r)$ bits from the current bit.

3.4.2.2. Radius Mutation

Radius mutation is our proposed mutation. In the radius mutation, randomly one solution is selected from population and radius R is determined. All the solutions within the radius of the selected solutions are chosen and one solution in the chosen solutions is selected as the second parent by using two solutions child population is generated.

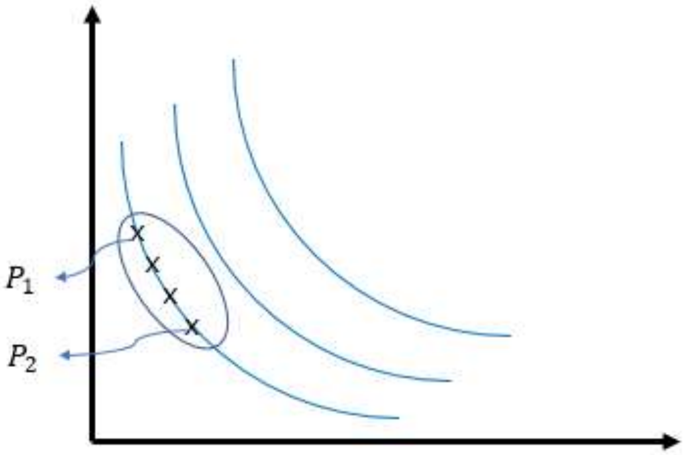

Fig. 3.6 (a) Solution for the radius mutation, where the selection randomly chosen from the population and radius R

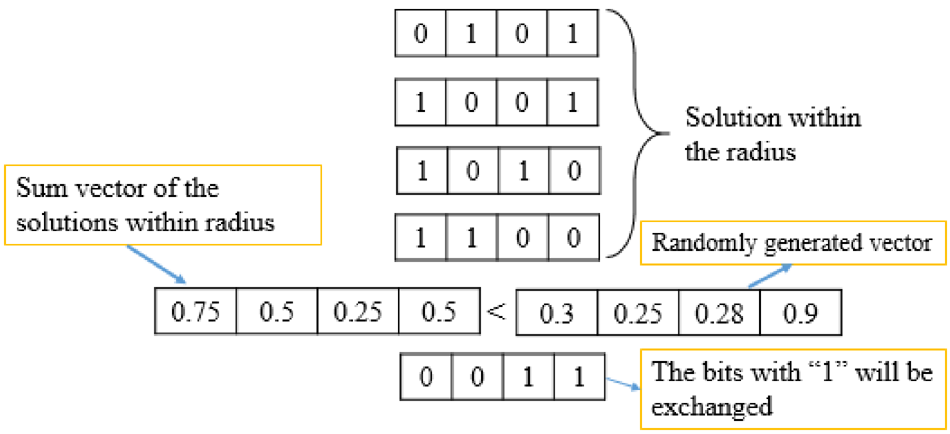

Fig. 3.6 (b) Solution within the radius

3.5. Implementation of the Experimental Setup and Experimental Analysis

We presents the implementation of an experimental setup for the crossover and mutation that we applied on our approaches and experimental analysis for the generations.

3.5.1. Objective Formulation

The concept of equality is taken into account in the execution of this plan to examine the tension between them. In the sense of evaluating the entire Pareto optimal frontier, which is a valuable source for decision-makers to assess what needs to be selected at different budget scales, the total cost of the following launch is considered to zero.

The level of customer satisfaction depends on the requirements achieved in the next software release. The main objective of the early phase of the NRP is the amount of consumer revenue.

3.5.1.1. The Minimum of Requirements Costs

It is estimated that the total cost of the specifications will be minimum. The cost of implementation is a pre-defined budget in the first original model. The costs of the requirements are:

$$minimize\ f_1(X) = \sum_{r_j \in R(X)} c_j \tag{3.2}$$

3.5.1.2. The Maximum of Customer Profits

The company's profits were originally intended to offer the NRP model [1], the degree of its maximum expected satisfaction is defined by:

$$maximize\ f_2(X) = \sum_{s_i \in X} w_i \tag{3.3}$$

The problem is to select a subset of the customer requirements which results in the maximum value for the company.

From a company's point of view, an optimal solution is to satisfy all customer requirements. The first study to test the scope of customer requirements [41].

3.5.1.3. The Coverage of Requirements for Customers

The scope of the satisfied requirements for all customers is reduced to a minimum. Defined $\sigma(v)$ be the standard deviation of a set of values specified is {v}, i.e., $\sigma(v) = \sqrt{\sum(v - \bar{v})^2}$, where $\bar{v}$ is the average of elements in {v}. In cases where $R(s_i)$ is the satisfied customer requirements s_i, i.e., $R(s_i) = \cup_{r_j \in R(X), q_{i,j}=1} \{r_j\}$. Notice that, under the $R(s_i)$ definition, not all customer requirements are fulfilled, part of the requirements required for a customer can be counted. For example, if a customer needs five requirements, the next release could include three out of five requirements for other customers. The objective described by:

$$minimize\ f_3(X) = \sigma(|R(s_i)|) \tag{3.4}$$

where |.| is the cardinality of a set.

3.5.1.4. Customer Fairness Function

The relationship between the requirements fulfilled and the expectations are essential to customers. Consumer fairness through the division of the amount of fulfilled requirements by maximum requests. Let $A(s_i)$ be the maximum requested requirements and $A(s_i) = \cup_{q_{i,j}=1} \{r_j\}$. The objective described by:

$$minimize\ f_4(X) = \sigma\left(\frac{|R(s_i)|}{|A(s_i)|}\right) \tag{3.5}$$

3.5.1.5. The Fairness of Resource Allocation

When choosing the requirements, the fairness of the allocation of resources is addressed, i.e. how much is spent when creating customer requirements [41]. The objective described by:

$$minimize\ f_5(X) = \sigma\left(\sum_{r_j \in R(s_i)} c_j\right) \tag{3.6}$$

The NRP set consists of the realistic instances problems which are given by table 3.1 [39, 46, 47].

Table 3.1. NRP Dataset

Instance	Problems							
	e1	**e2**	**e3**	**e4**	**g1**	**g2**	**g3**	**g4**
Requirements	3502	4254	2844	3186	2690	2650	2512	2246
Customers	536	491	456	399	445	315	423	294
Requirement cost	1-7	1-7	1-7	1-7	1-7	1-7	1-7	1-7
Customer profit	10-50	10-50	10-50	10-50	10-50	10-50	10-50	10-50
Requests by customer	4-20	5-30	4-15	5-20	4-20	5-30	4-15	5-20

3.5.2. Design Issues of Multi/Many-objective Optimization Problem Algorithms (MOPs) for MONRP

MONRP is a multi-objective combination optimization problem that seeks to find Pareto optimal solutions in a discreet and finite solution space. We have chosen three algorithms when developing MOPs for MONRP, which decide the fitness of each solution and the widest use of these algorithms. Such algorithms can be divided approximately into five categories: genetic algorithms, decomposition, indicator, reference-points, and ε-dominance.

3.5.2.1. NSGA-II Algorithm

In recent years there have been many multi-objective evolutionary algorithms. The NSGA-II consists of two main parts: a fast non-dominated sorting solution and the preservation of the diversity of the solution. Higher-ranking solutions survive and are chosen for reproduction. A secondary classification criterion known as the crowding distance is used to further distinguish between solutions for those solutions that are non-dominated by one another (i.e. with the same classification). This method favors approaches with larger crowding intervals. The NSGA-II standard incorporates a binary tournament choice to define the parental pool and uses the Simulated Binary Crossover (SBX) and the Polynomial (PM) to create children from parents [12]. The tacit policy of elitism guarantees that the best solutions ever to be discovered in the history of quest remain for the public. This allows a new population to be generated via the quick non-dominated sorting approach from the combination of parents and their offspring. NSGA-II also offers a restriction strategy for dealing effectively with restricted issues, which supports binary and true coding representations.

NSGA-II has different parameters that can affect its software performance differently. The most common ones studied were population size (PS), the number of feature evaluations (NFE_s), the probability of SBX (P_c), and the probability of PM (P_m). The maximum software budget applied to a given problem is calculated jointly by PS and NFE_s. This means that the NFE_s ratio to the PS is the same as the NSGA-II series. Note that a greater number of generations usually ensure better NSGA-II convergence. However, as the optimization continues, the convergence rate will decrease significantly and only small changes with an additional software budget can be made. It is also important to pay special attention to PS, as a small value can lead to a crowded population, namely, rather than a diverse set, with a number of similar solutions. This normally leads to an inefficient transfer of new information in the population's gene pool. P_c and P_m control the likelihood of crossover and mutation processes occurring at each chromosome. A broader approach is to maintain high P_c (e.g., 0.9) and a low P_m values (e.g. reverse decision variables numbers ($NDVs$), $1/NDVs$) in the value of P_c. The crossover frequency plays an essential role in optimizing as the predominant search operator. The mutation rate primarily helps to avoid concentrating the population in the local optima.

3.5.2.2. Indicator Shift-Based Density Estimation ($\boldsymbol{I_{SDE}}$)

When the density of a single p is determined, SDE transfer the positions of another individual in the population by comparing the convergence of these people to p for each objective. More precisely, if an individual performs as much as $better^3$ than p for an objective, it will be moved to the same location as p for that objective; it remains unchanged as otherwise. The density of one individual p can be formally be expressed in a population P of N individuals [48]:

$$Density(\,P) = SF\{dist(p, q_1), dist(p, q_2), \dots, dist(p, q_{N-1})\} \qquad (3.7)$$

Where N indicates the size of P, $dist(p,\, q_i)$ corresponds to the degree of similitude between the p and q individuals, q_i is an entity shifted q_i ($q_i \epsilon P$ and $q_i \neq p$) alternatively. The function SF{ } feature tests in p and the following degrees of similarity between P and other subjects defined by follows:

$$q'_{i(j)} = \begin{cases} p_{(j)}, & if\ q_{i(j)} < p_{i(j)} \\ q_{i(j)}, & otherwise \end{cases}, j \in (1,2, \dots, m) \qquad (3.8)$$

The number of objectives indicates $p_{(j)}$, $q_{i(j)}$, and $q'_{i(j)}$ denote the j^{th} and the number of objectives is defined by p, q_i, and q'_i, respectively, and m denotes the number of objectives. Therefore, in SDE, the individual positions are modified in the target space to reflect their convergence with regard to p in P. Thus, the shift-based density can be expressed in the following words:

$$SDE(p, P) = SF\{dist(p, q'_1), dist(p, q'_2), \dots, dist(p, q'_{N-1})\} \quad (3.9)$$

It has become clear from (2.4) and (2.5) that SDE pushes people in crowded regions with low convergence and assign high-density rates to them. Furthermore, the probability that these solutions will be removed increases in Pareto-based EMO algorithms. In other words, two non-dominated solutions are differentiated in terms of convergence and heterogeneity if SDE is employed as a secondary criterion. The implementation of SDE significantly improved the performance of EMO algorithms from Pareto [48] as well as the diversity measure, was able to promote convergence.

On the basis of SDE, an indicator known as I_{SDE} was proposed [49] as a computationally efficient one. The individual I_{SDE} indicator value depends on the position of all individuals and their convergence. Therefore, all other individuals in the population are changed in order to determine the I_{SDE} of an individual. The predictor is evaluated by for a single p in P:

$$I_{SDE}(p) = p \in P^{min}{}_{p \neq q}\{dist(p, q'_1), dist(p, q'_2), \dots, dist(p, q'_{N-1})\} \quad (3.10)$$

Where the SF{ } is used to be minimum. Therefore, the I_{SDE} measure is useful for promoting diversity of solutions in the population during evolution. Even if the solution considers the convergence data, the selection pressure needed to direct the search to the optimal Pareto front can not alone be imparted.

3.5.2.3. Indicator-Based Evolutionary Algorithm (IBEA)

Multi-objective solution approaches focused on metrics have recently increased use, mainly due to the clear incorporation of the user choices and the adaptation of the search for solutions according to subjective performance measures [24]. They also believed to have no strategies for preserving diversity. Experimental studies have shown that the hypervolume predictor, in general, has shown better efficiency in multi-target Evolutionary Algorithms (MOEAs). The hypervolume indicator is the parameter used for the algorithm.

Zitzler et al. first named the 'size of the space covered' and also called the S-metric [19]. If a number of solutions dominate another set, the value of the hypervolume indicator is greater than that of the latter and vice versa, making it consistent with Pareto. That is why it is gradually being implemented in algorithms dependent on indicators. The hypervolume indicator $I_{H_v}(A)$ in the solution set $A \subseteq R$ can be alternatives defined as the space hypervolume dominated by set A and surrounded by a point $r = (r_1, \dots, r_k)$, Let R be the decision of:

$$I_{H_v}(S) = Leb(\cup_{x \in S} \, [f_1(x), r_1] \times [f_2(x), r_2] \times \dots \times [f_n(x), r_n]) \qquad (3.11)$$

Where $[f_1(x), r_1] \times [f_2(x), r_2] \times \dots \times [f_n(x), r_n]$ is the k dimensional hyper cuboid is made up of all points occupied by x but not the point of reference [19].

3.5.3. Experimental Setup

All approaches have been taken for a total of 250 generations, with 5 objectives, 100 populations and 30 runs to all of the algorithms. For all algorithms, each was set 5 different operators, such as 1). Single point crossover bitwise mutation, 2). Single point crossover radius mutation, 3). Two point crossover radius mutation, 4). Binomial crossover radius mutation, 5). Multi point crossover radius mutation.

3.5.4. Experimental Analysis

This work has executed 30 runs with 250 generations for each run, in every algorithm and every instance of the problem. Because we deal with stochastic algorithms, a statistical analysis of the results obtained needs to be carried out in order to compare them with some confidence.

3.5.4.1. Hypervolume Results from Multi-objective

This results showing three state-of-the-art algorithms which we applied on our approach with two objective functions. Table 3.2, 3.3, and 3.4 contain when the evaluation was performed respectively, with the mean and standard deviation of Hypervolume.

Table 3.2. Mean ($\bar{x}$) and standard deviation (σ) of the NSGA-II HV quality indicator results with two objective functions

Problems	NSGAII SPCBMW		NSGAII-SPCradiusmut		NSGAII-TPCradiusmut		NSGAII-BNCradiusmut		NSGAII-MrPCradiusmut	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No.of objectives = 2										
NRP-e1	0.2103	0.0141	0.2998	0.0422	0.3001	0.0511	0.2801	0.0499	**0.3111**	**0.0371**
NRP-e2	0.1674	0.0104	0.2713	0.0403	0.2873	0.0420	0.2561	0.0584	**0.2992**	**0.0479**
NRP-e3	0.2169	0.0141	0.2886	0.0435	0.2908	0.0484	0.2722	0.0416	**0.3054**	**0.0374**
NRP-e4	0.2034	0.0133	0.2831	0.0500	0.2636	0.0409	0.2774	0.0431	**0.3135**	**0.0453**
NRP-g1	0.2263	0.0157	0.2884	0.0388	0.2981	0.0402	0.2639	0.0448	**0.3036**	**0.0412**
NRP-g2	0.2392	0.0155	0.2954	0.0348	**0.3074**	**0.0436**	0.2891	0.0434	**0.3097**	**0.0352**
NRP-g3	0.2299	0.0150	0.2887	0.0484	0.2762	0.0470	0.2639	0.0443	**0.2923**	**0.0333**
NRP-g4	0.2461	0.0116	0.2740	0.0410	0.2838	0.0577	0.2758	0.0536	**0.2966**	**0.0376**

Table 3.3. Mean ($\overline{x}$) and standard deviation (σ) of the I_{SDE} HV quality indicator results with two objective functions

Problems	ISDE+-SPCBMW		ISDE+-SPCradiusmut		ISDE+-TPCradiusmut		ISDE+-BNCradiusmut		ISDE+-MrPCradiusmut	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No.of objectives = 2										
NRP-e1	0.2016	0.0110	**0.5126**	**0.0166**	**0.5136**	**0.0165**	0.4690	0.0171	**0.5163**	**0.0177**
NRP-e2	0.1708	0.0103	**0.5138**	**0.0147**	**0.5064**	**0.0151**	0.4704	0.0234	**0.5086**	**0.0154**
NRP-e3	0.2070	0.0131	**0.5122**	**0.0168**	**0.5091**	**0.0197**	0.4615	0.0167	**0.5088**	**0.0150**
NRP-e4	0.2133	0.0131	**0.5166**	**0.0169**	**0.5150**	**0.0158**	0.4766	0.0131	**0.5089**	**0.0167**
NRP-g1	0.2052	0.0157	**0.5096**	**0.0163**	**0.5090**	**0.0162**	0.4713	0.0203	**0.5067**	**0.0194**
NRP-g2	0.2245	0.0163	**0.5171**	**0.0133**	**0.5136**	**0.0137**	0.4751	0.0235	**0.5108**	**0.0187**
NRP-g3	0.2133	0.0130	**0.5128**	**0.0146**	**0.5103**	**0.0165**	0.4694	0.0211	**0.5108**	**0.0173**
NRP-g4	0.2149	0.0175	**0.5101**	**0.0147**	**0.5076**	**0.0165**	0.4659	0.0187	**0.5016**	**0.0170**

Table 3.4. Mean ($\overline{x}$) and standard deviation (σ) of the IBEA HV quality indicator results with two objective functions

Problems	IBEA-SPCBMW		IBEA+-SPCradiusmut		IBEA+-TPCradiusmut		IBEA+-BNCradiusmut		IBEA+-MrPCradiusmut	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No.of objectives = 5										
NRP-e1	0.0800	0.0098	0.0956	0.0050	0.1034	0.0024	0.0914	0.0113	**0.1198**	**0.0272**
NRP-e2	0.0792	0.0034	0.0896	0.0095	0.0818	0.0108	0.0812	0.0051	**0.1174**	**0.0487**
NRP-e3	0.0700	0.0090	0.1164	0.0109	**0.1120**	**0.0087**	0.0924	0.0040	**0.1114**	**0.0150**
NRP-e4	0.0562	0.0058	**0.1002**	**0.0079**	**0.1006**	**0.0139**	0.0838	0.0055	**0.1000**	**0.0070**
NRP-g1	0.0570	0.0072	0.1604	0.0171	**0.1844**	**0.0045**	0.1388	0.0278	0.1674	0.0261
NRP-g2	0.0798	0.0052	**0.1346**	**0.0095**	0.1206	0.0167	0.1096	0.0096	0.1140	0.0137
NRP-g3	0.0644	0.0135	0.1026	0.0171	**0.1104**	**0.0155**	0.0936	0.0146	0.1042	0.0095
NRP-g4	0.0812	0.0031	**0.1296**	**0.0079**	**0.1214**	**0.0101**	0.1138	0.0064	**0.1252**	**0.0061**

From the hypervolume quality indicator results with two objective functions that shown in Table 3.2, 3.3, and 3.4 above, we can see from the five comparison operators that our approach which is radius mutation is work perfectly by giving the best results. From the table above, we can see that I_{SDE} is the best among other algorithms.

3.5.4.2. Hypervolume Results from Many-objective

In the many-objective, we applied the same state-of-the-art algorithms which we applied on our approach with five objective functions. Table 3.5, 3.6, and 3.7 contain when the evaluation was performed respectively, with the mean and standard deviation of Hypervolume.

Table 3.5. Mean ($\overline{x}$) and standard deviation (σ) of the NSGA-II HV quality indicator results with five objective functions

Problems	NSGAII-SPCBMW		NSGAII-SPCradiusmut		NSGAII-TPCradiusmut		NSGAII-BNCradiusmut		NSGAII-MrPCradiusmut	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No. of Objectives = 5										
NRP-e1	0.0618	0.0082	**0.0758**	**0.0134**	**0.0704**	**0.0137**	0.0660	0.0110	**0.0750**	**0.0121**
NRP-e2	0.0710	0.0078	**0.0832**	**0.0071**	**0.0820**	**0.0060**	0.0694	0.0140	**0.0854**	**0.0059**
NRP-e3	0.0598	0.0049	0.0680	0.0114	**0.0782**	**0.0079**	0.0672	0.0049	**0.0700**	**0.0154**
NRP-e4	0.0652	0.0093	**0.0748**	**0.0092**	**0.0764**	**0.0062**	**0.0786**	**0.0205**	**0.0726**	**0.0094**
NRP-g1	0.0620	0.0141	**0.0734**	**0.0101**	0.0690	0.0053	0.0594	0.0124	0.0696	0.0079
NRP-g2	0.0778	0.0105	**0.0816**	**0.0092**	**0.0836**	**0.0061**	0.0752	0.0142	**0.0866**	**0.0083**
NRP-g3	0.0624	0.0091	**0.0784**	**0.0075**	0.0622	0.0062	0.0684	0.0061	**0.0718**	**0.0068**
NRP-g4	0.0712	0.0033	0.0756	0.0135	**0.0828**	**0.0197**	0.0704	0.0130	0.0764	0.0099

Table 3.6. Mean ($\overline{x}$) and standard deviation (σ) of the $I_{SDE}+_{-}$ HV quality indicator results with five objective functions

Problems	ISDE+-SPCBMW		ISDE+-SPCradiusmut		ISDE+-TPCradiusmut		ISDE+-BNCradiusmut		ISDE+-MrPCradiusmut	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No. of Objectives = 5										
NRP-e1	0.0552	0.0085	**0.1128**	**0.0050**	**0.1036**	**0.0144**	0.0778	0.0100	0.0900	0.0107
NRP-e2	0.0598	0.0066	**0.1180**	**0.0119**	**0.1176**	**0.0072**	0.0946	0.0118	0.1060	0.0154

NRP-e3	0.0478	0.0034	**0.1086**	**0.0083**	**0.1032**	**0.0073**	0.0794	0.0083	0.0958	0.0144
NRP-e4	0.0558	0.0070	0.0986	0.0095	**0.1070**	**0.0157**	0.0870	0.0122	0.0976	0.0096
NRP-g1	0.0586	0.0047	0.0976	0.0059	**0.1094**	**0.0093**	0.0860	0.0098	0.0986	0.0068
NRP-g2	0.0638	0.0100	**0.1172**	**0.0143**	**0.1150**	**0.0126**	0.0850	0.0050	0.1048	0.0096
NRP-g3	0.0690	0.0114	**0.1222**	**0.0081**	0.1166	0.0054	0.0886	0.0119	0.1022	0.0183
NRP-g4	0.0754	0.0080	**0.1180**	**0.0129**	**0.1152**	**0.0055**	0.0980	0.0095	**0.1188**	**0.0157**

Table 3.7. Mean ($\overline{x}$) and standard deviation (σ) of the IBEA HV quality indicator results with five objective functions

Problems	**IBEA-SPCBMW**		**IBEA+-SPCradiusmut**		**IBEA+-TPCradiusmut**		**IBEA+-BNCradiusmut**		**IBEA+-MrPCradiusmut**	
	mean	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**	**mean**	**std.dev**
No.of objectives = 5										
NRP-e1	0.0789	0.0103	**0.4212**	**0.0123**	**0.4172**	**0.0121**	**0.4030**	**0.0138**	**0.4150**	**0.0160**
NRP-e2	0.0608	0.0091	**0.4280**	**0.0161**	**0.4184**	**0.0148**	**0.4036**	**0.0157**	**0.4258**	**0.0158**
NRP-e3	0.1172	0.0104	**0.4270**	**0.0126**	**0.4281**	**0.0128**	**0.4160**	**0.0201**	**0.4298**	**0.0181**
NRP-e4	0.1213	0.0105	**0.4274**	**0.0165**	**0.4396**	**0.0150**	**0.4176**	**0.0165**	**0.4301**	**0.0115**
NRP-g1	0.1445	0.0135	**0.4432**	**0.0134**	**0.4364**	**0.0179**	**0.4358**	**0.0196**	**0.4384**	**0.0137**
NRP-g2	0.1307	0.0098	**0.4390**	**0.0173**	**0.4307**	**0.0123**	**0.4211**	**0.0150**	**0.4329**	**0.0162**
NRP-g3	0.1452	0.0117	**0.4376**	**0.0154**	**0.4454**	**0.0136**	**0.4261**	**0.0170**	**0.4360**	**0.0150**
NRP-g4	0.1713	0.0151	**0.4464**	**0.0145**	**0.4449**	**0.0157**	**0.4323**	**0.0137**	**0.4482**	**0.0107**

From the hypervolume quality indicator results with five objective functions that shown in Table 3.5, 3.6, and 3.7 above, we can see from the five comparison operators that our approach which is radius mutation is work perfectly by giving the best results. From the table above, we can see that IBEA giving high value which is the best among other algorithms.

IV. Conclusion

In this analysis, we analyzed the Next Release Problem with the aim of evaluating the output and solutions of four distinct multi-objective algorithms both in the test cases and in the actual case of the problem. We tested three algorithms: NSGA-II, I_{SDE}, and IBEA in order to solve multi-objective and many-objective of MONRP. Two performance metrics of the hyper-volume are used in this analogy.

In the propose work of a novel hierarchical approach for Pareto-dominance MOEAs for handling the MaOPs, we adopt a hierarchical approach to select and preserve the best solutions in the mating and environmental selection respectively. The solutions in the population are sorted in the order of Pareto rank (Pareto-dominance in ascending order), sub-Pareto rank (AENS in ascending order) and shift-density estimation (in descending order) and the best solutions are chosen in mating and environmental selection. The experimental findings show that the solution proposed is competitive with state-of-the-art algorithms. The performance of the proposed method is reducing in the WFG problems due to more focus on the convergence and the diversity performance is being affected. In the future, we would like to adopt different selection metrics instead of the shift-based estimation to analyze the performance of the PDMOEAs.

In terms of convergence towards the global optimal solution from the results of the hyper-volume table, IBEA and I_{SDE} were the best solutions to compare. The conventional algorithm produced the best results and performed fewer tests. As regards the distribution of hyper-volume table results for solutions included in algorithms, in our contrast, IBEA was the most excellent algorithm.

About the number of solutions obtained, compared from the 5 operators, Single Point Crossover with radius random mutation, Two-point crossover with radius random mutation and Multi parents crossover with radius random mutation are the best among other operators. However in IBEA, Binomial crossover with radius random mutation results also almost high to the three best operators.

Certain problem formulations that take account of different sets of goals and specifications, and the development of techniques that enable software engineers to take decisions, are also important to study. In addition, this could lead to the need to find more efficient solutions. It is also interesting to examine the scope of such strategies when demand and/or consumer numbers increase. A method that allows the systemic development of instances with desired functions will be required to reach this goal; we intend to develop a problem generator for MONRP instances in this regard.

References

[1] A. J. Bagnall, V. J. Rayward-Smith, and I. M. Whittley, "The next release problem," *Information and software technology,* vol. 43, pp. 883-890, 2001.

[2] K. Lakhotia, M. Harman, and P. McMinn, "A multi-objective approach to search-based test data generation," in *Proceedings of the 9th annual conference on Genetic and evolutionary computation*, pp. 1098-1105, 2007.

[3] D. Savic, "Single-objective vs. multiobjective optimisation for integrated decision support," in *International Congress on Environmental Modelling and Software*, pp. 7-12, 2002.

[4] M. O. Saliu and G. Ruhe, "Bi-objective release planning for evolving software systems," in *Proceedings of the the 6th joint meeting of the European software engineering conference and the ACM SIGSOFT symposium on The foundations of software engineering*, pp. 105-114, 2007.

[5] Z. Zhang, "Immune optimization algorithm for constrained nonlinear multiobjective optimization problems," *Applied Soft Computing,* vol. 7, pp. 840-857, 2007.

[6] Q. Zhang, A. Zhou, and Y. Jin, "RM-MEDA: A regularity model-based multiobjective estimation of distribution algorithm," *IEEE Transactions on Evolutionary Computation,* vol. 12, pp. 41-63, 2008.

[7] J. J. Durillo, Y. Zhang, E. Alba, M. Harman, and A. J. Nebro, "A study of the bi-objective next release problem," *Empirical Software Engineering,* vol. 16, pp. 29-60, 2011.

[8] Y. Zhang, M. Harman, A. Finkelstein, and S. A. Mansouri, "Comparing the performance of metaheuristics for the analysis of

multi-stakeholder tradeoffs in requirements optimisation," *Information and software technology,* vol. 53, pp. 761-773, 2011.

[9] X. Cai, O. Wei, and Z. Huang, "Evolutionary approaches for multi-objective next release problem," *Computing and Informatics,* vol. 31, pp. 847-875, 2012.

[10] A. Zhou, B.-Y. Qu, H. Li, S.-Z. Zhao, P. N. Suganthan, and Q. Zhang, "Multiobjective evolutionary algorithms: A survey of the state of the art," *Swarm and Evolutionary Computation,* vol. 1, pp. 32-49, 2011.

[11] B. Li, J. Li, K. Tang, and X. Yao, "Many-objective evolutionary algorithms: A survey," *ACM Computing Surveys (CSUR),* vol. 48, p. 13-47, 2015.

[12] 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.

[13] V. Palakonda and R. Mallipeddi, "Pareto dominance-based algorithms with ranking methods for many-objective optimization," *IEEE Access,* vol. 5, pp. 11043-11053, 2017.

[14] X. Zhang, Y. Tian, and Y. Jin, "A knee point-driven evolutionary algorithm for many-objective optimization," *IEEE Transactions on Evolutionary Computation,* vol. 19, pp. 761-776, 2015.

[15] K. Deb and H. Jain, "An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: Solving problems with box constraints," *IEEE Trans. Evolutionary Computation,* vol. 18, pp. 577-601, 2014.

[16] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the strength Pareto evolutionary algorithm," *TIK-report,* vol. 103, pp. 1-22, 2001.

[17] V. Palakonda, S. Ghorbanpour, and R. Mallipeddi, "Pareto

Dominance-based MOEA with Multiple Ranking methods for Many-objective Optimization," in *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 958-964, 2018.

[18] Q. Zhang and H. Li, "MOEA/D: A multiobjective evolutionary algorithm based on decomposition," *IEEE Transactions on evolutionary computation,* vol. 11, pp. 712-731, 2007.

[19] E. Zitzler and S. Künzli, "Indicator-based selection in multiobjective search," in *International Conference on Parallel Problem Solving from Nature,* pp. 832-842, 2004.

[20] T. Pamulapati, R. Mallipeddi, and P. N. Suganthan, "ISDE+—An Indicator for Multi and Many-Objective Optimization," *IEEE Transactions on Evolutionary Computation,* vol. 23, pp. 346-352, 2018.

[21] F. di Pierro, S.-T. Khu, and D. A. Savic, "An investigation on preference order ranking scheme for multiobjective evolutionary optimization," *IEEE Transactions on Evolutionary Computation,* vol. 11, pp. 17-45, 2007.

[22] H. Li and Q. Zhang, "Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II," *IEEE transactions on evolutionary computation,* vol. 13, pp. 284-302, 2008.

[23] H.-L. Liu, F. Gu, and Q. Zhang, "Decomposition of a multiobjective optimization problem into a number of simple multiobjective subproblems," *IEEE Transactions on Evolutionary Computation,* vol. 18, pp. 450-455, 2013.

[24] 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.

[25] E. Zitzler, L. Thiele, M. Laumanns, C. M. Fonseca, and V. G. Da

Fonseca, "Performance assessment of multiobjective optimizers: An analysis and review," *IEEE Transactions on evolutionary computation*, vol. 7, pp. 117-132, 2003.

[26] N. Beume, B. Naujoks, and M. Emmerich, "SMS-EMOA: Multiobjective selection based on dominated hypervolume," *European Journal of Operational Research*, vol. 181, pp. 1653-1669, 2007.

[27] R. H. Gómez and C. A. C. Coello, "MOMBI: A new metaheuristic for many-objective optimization based on the R2 indicator," in *2013 IEEE Congress on Evolutionary Computation*, pp. 2488-2495, 2013.

[28] J. Bader and E. Zitzler, "HypE: An algorithm for fast hypervolume-based many-objective optimization," *Evolutionary computation*, vol. 19, pp. 45-76, 2011.

[29] S. Jiang, J. Zhang, Y.-S. Ong, A. N. Zhang, and P. S. Tan, "A simple and fast hypervolume indicator-based multiobjective evolutionary algorithm," *IEEE Transactions on Cybernetics*, vol. 45, pp. 2202-2213, 2014.

[30] H. Sato, H. E. Aguirre, and K. Tanaka, "Controlling dominance area of solutions and its impact on the performance of MOEAs," in *International conference on evolutionary multi-criterion optimization*, pp. 5-20, 2007.

[31] M. Farina and P. Amato, "A fuzzy definition of" optimality" for many-criteria optimization problems," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 34, pp. 315-326, 2004.

[32] P. J. Bentley and J. P. Wakefield, "Finding acceptable solutions in the pareto-optimal range using multiobjective genetic algorithms," in *Soft computing in engineering design and manufacturing*, ed: Springer, pp.

231-240, 1998.

[33] N. Drechsler, R. Drechsler, and B. Becker, "Multi-objective optimization in evolutionary algorithms using satisfiability classes," in *International Conference on Computational Intelligence*, pp. 108-117, 1999.

[34] X. Zhang, Y. Tian, and Y. Jin, "Approximate non-dominated sorting for evolutionary many-objective optimization," *Information Sciences,* vol. 369, pp. 14-33, 2016.

[35] M. Li, S. Yang, and X. Liu, "Shift-based density estimation for Pareto-based algorithms in many-objective optimization," *IEEE Transactions on Evolutionary Computation,* vol. 18, pp. 348-365, 2014.

[36] K. Deb, L. Thiele, M. Laumanns, and E. Zitzler, "Scalable test problems for evolutionary multiobjective optimization," in *Evolutionary multiobjective optimization*, ed: Springer, pp. 105-145, 2005.

[37] S. Huband, P. Hingston, L. Barone, and L. While, "A review of multiobjective test problems and a scalable test problem toolkit," *IEEE Transactions on Evolutionary Computation,* vol. 10, pp. 477-506, 2006.

[38] L. While, P. Hingston, L. Barone, and S. Huband, "A faster algorithm for calculating hypervolume," *IEEE transactions on evolutionary computation,* vol. 10, pp. 29-38, 2006.

[39] H. Jiang, J. Xuan, and Z. Ren, "Approximate backbone based multilevel algorithm for next release problem," in *Proceedings of the 12th annual conference on Genetic and evolutionary computation*, pp. 1333-1340, 2010.

[40] J. Ren, "Sensitivity analysis in multi-objective next release problem

and fairness analysis in software requirements engineering," *Master's thesis, DCS/PSE, King's College London, London,* 2007.

[41] A. Finkelstein, M. Harman, S. A. Mansouri, J. Ren, and Y. Zhang, "A search based approach to fairness analysis in requirement assignments to aid negotiation, mediation and decision making," *Requirements engineering,* vol. 14, pp. 231-245, 2009.

[42] M. Harman, J. Krinke, I. Medina-Bulo, F. Palomo-Lozano, J. Ren, and S. Yoo, "Exact scalable sensitivity analysis for the next release problem," *ACM Transactions on Software Engineering and Methodology (TOSEM),* vol. 23, p. 19, 2014.

[43] A. A. Araújo, M. Paixao, I. Yeltsin, A. Dantas, and J. Souza, "An architecture based on interactive optimization and machine learning applied to the next release problem," *Automated Software Engineering,* vol. 24, pp. 623-671, 2017.

[44] Z. Ren, H. Jiang, J. Xuan, S. Zhang, and Z. Luo, "Feature based problem hardness understanding for requirements engineering," *Science China Information Sciences,* vol. 60, p. 032105, 2017.

[45] H. Seada and K. Deb, "A unified evolutionary optimization procedure for single, multiple, and many objectives," *IEEE Transactions on Evolutionary Computation,* vol. 20, pp. 358-369, 2015.

[46] J. Geng, S. Ying, X. Jia, T. Zhang, X. Liu, L. Guo*, et al.*, "Supporting Many-Objective Software Requirements Decision: An Exploratory Study on the Next Release Problem," *IEEE Access,* vol. 6, pp. 60547-60558, 2018.

[47] J. Xuan, H. Jiang, Z. Ren, and Z. Luo, "Solving the large scale next release problem with a backbone-based multilevel algorithm," *IEEE Transactions on Software Engineering,* vol. 38, pp. 1195-1212, 2012.

[48] M. Li, S. Yang, and X. Liu, "Shift-based density estimation for

Pareto-based algorithms in many-objective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 18, pp. 348-365, 2013.

[49] B. Li, K. Tang, J. Li, and X. Yao, "Stochastic ranking algorithm for many-objective optimization based on multiple indicators," *IEEE Transactions on Evolutionary Computation*, vol. 20, pp. 924-938, 2016.

Abstract

Evolutionary Multi/Many-objective Approaches for Next Release Optimization Problem

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In the following update, deciding the assignment of specifications is a major problem in the software company requirements. Software companies typically build and manage large and complex software systems marketed to various clients. One common problem facing organizations is that they determine which changes or specifications in the next release of the software, the Next Release Problem (NRP), is to be introduced.

In practical terms, NRPs should tackle many contradictory priorities, i.e. price and satisfaction of customers. Single objective strategies have the disadvantage of achieving the optimization of one goal at the detriment of another, leading to the skewed pursuit of a particular section of the solution. More recently it has become increasingly popular with multi-target NRP formulation. In the multi-objective next release problem (MONRP), each of the objectives is to be optimized as a separate goal, and they may be conflicting with each other.

In this thesis, we have presented the NRP models with five additional goals, namely the multi-objective NRP. For Next Release Optimization

Problems, we have introduced evolutionary multi-objective methods using the five objectives with most sophisticated evolutionary optimization algorithms NSGA-II, I_{SDE}, and IBEA. The research was conceived to look at how to identify five objectives of Multi / Many NRP, including total customer profits, minimum requirements cost, and fairness of requirements selection, etc. This study focuses on four questions of analysis, including optimization efficiency, the significance of performance, the distribution of metric values and the correlation between metrics.

다음 릴리스 최적화 문제를 위한 혁신적인 다중 / 다중 객관적인 접근 방식

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(초록)

'Next release'에서 요구 사항 할당을 결정하는 것은 소프트웨어 회사에서 중요한 문제이다. 소프트웨어 회사는 일반적으로 다양한 고객에게 판매 되는 크고 복잡한 소프트웨어 시스템을 개발하고 유지 관리한다. 회사가 직면한 일반적인 문제 중 하나는 NRP (Next Release Problem)라고 하는 소프트웨어의 다음 버전('next release')에서 어떤 개선 또는 요구 사항을 구현해야 하는지 결정하는 것이다.

NRP 의 실질적인 측면에서, 회사는 여러 가지 상충되는 목표, 예를 들어 비용이나 고객 만족을 처리해야 한다. 단일 목적 제형 (Single objective formulations)은 다른 목적을 희생시키면서 하나의 목적의 최적화가 달성 될 수 있다는 단점이 있으며, 이는 해결 공간의 특정 부분의 편향된 탐색으로 이어진다. 최근에는 NRP 의 다목적 제제가

점점 인기를 얻고 있다. MONRP (Multi-Objective Next Release Problem)에서 각 목표는 별도의 목표로 최적화 되어야 하며, 서로 상충될 수 있다.

이 논문에서 우리는 NRP 모델에 다섯가지 추가 목표, 즉 다목적 NRP 를 제시했다. Next Release 최적화 문제를 위해, 우리는 가장 정교한 진화 최적화 알고리즘인 NSGA-II, I_{SDE}, 및 IBEA 와 함께 다섯가지 목표를 사용하여 진화적인 다목적방법을 도입했다. 이 연구는 총 고객 이익, 최소 요구비용 및 요구사항 선택의 공정성 등을 포함하여 Multi / Many NRP 의 다섯가지 목표를 식별하는 방법을 조사하기 위해 고안되었다. 이 연구는 최적화 효율성, 성능의 중요성, 메트릭 값의 분포 및 메트릭 사이의 상관 관계를 포함하여 네가지 분석 문제에 중점을 둔다.