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Multi-Objective Evolutionary Algorithm Based Approach for Solving Rfid Reader Placement Problem Using Weight-Vector Approach with Opposition-Based Learning Method

Spurti Sachin Shinde, K. Devika, S. Thangavelu, G. Jeyakumar

Abstract*: For smart building applications, identifying and tracking the objects and people in and around a building is an inevitable problem. There exist many approaches for solving this problem. Nowadays, the RFID network based approaches have become most popular for its speed and accuracy. However, placing the RFID readers at optimal places in a building to cover all the areas in order to identify and track the objects and people is a cumbersome task. This paper proposes a model in which the RFID reader placement problem is formulated as a multi-objective optimization problem and also proposes an algorithmic framework to solve the same. The proposed algorithmic frame work consists of a multi-objective Differential Evolution algorithm which adds weights to each of the objective and also follows the opposition-based learning approach for initializing the populations. The results obtained in solving the RFID reader placement problem with proposed algorithmic framework is studied and reported in details for individual objectives, combined objectives with different schemes and for two different population initialization techniques.

Index Terms*: Multi-Objective optimization, Evolutionary Algorithms, RFID Reader Placement, Opposition-Based Learning, Weight-Vector approaches.

I. INTRODUCTION

In many of the real world optimization problems there are more than one objective to be optimized. The classification of the optimization problems is done based on the number of objectives in the optimization problem. The optimization problems with one objective are the Single Objective Optimization Problems (*SOOP*). The problems with 2 or 3 objectives are Multi-Objective Optimization Problems (*MOOP*) and the problems with more than 3 objectives are Many-Objective Optimization Problems (*MaOOP*).The complexity of the optimization problems increases with the increase in number of objectives. There exist many algorithmic structures to solve *SOOP*, *MOOPs* and *MaOOPs*. The Evolutionary Algorithms (*EAs*) in the Evolutionary Computing (*EC*) filed of Computer Science are the potential tools for solving *SOOP*, *MOOPs* and *MaOOPs*. Numerous algorithmic structures using *EAs* are proposed in the literature to solve complex *MOOPs* and *MaOOPs*. They are named as *MOEAs* (Multi-Objective *EAs*) and *MaOEAs* (Many Objective *EAs*), respectively. The *MOEAs* follows different strategies to tackle multiple objectives in the *MOOPs*. Combining the objectives using well defined aggregate function with suitable weights to each objective is a most common strategy. Aggregate function helps in converting multi-objective problem into a single objective problem by using weight vectors. The weight vectors are generated randomly by the users.In *EA*,a population is a set of feasible solutions for a given optimization problem. There exist a wide variety of Population Initialization (*PI*) techniques for *EAs*. Each of the *PI* techniques has its own characteristics. Most commonly used *PI* technique is Random *PI* (*RPI*) technique. The other techniques are Pseudo Random Number Generators (*PRNGs*), Chaotic Number Generators (*CNGs*), Quasi Random Sequence (*QRS*), uniform Experimental Design (*UED*), Sobol Set (*SBL*), Good Lattice Point (*GLP*), Centroid Voronoi Tessellation (*CVT*) and Oppositional Based Learning (*OBL*). Among these *PI* techniques the *OBL* based technique has shown better results in many of the benchmarking and real time optimization problems. The *RFID* systems consist of tags and readers. *RFID* tags are attached to the objects and *RFID* readers are used to detect the objects with *RFID* tags. The *RFID* tags have a unique *ID* and information about the objects. The objects are tracked by using radio frequency electromagnetic field. The *RFID* tags are classified in to two classes viz. *Active* and *Passive* tags. Installation cost of the *RFID* system is very huge. So the placement of the *RFID* readers must be done in such a way that it leads maximum coverage with minimum number of readers. The *RFID* reader placement problem has two major objectives: coverage and cost. The coverage is to be maximized and the cost is to be minimized.

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***** Correspondence Author
Spurti Sachin Shinde, Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, Amrita VishwaVidyapeetham, India.
K. Devika, Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, Amrita VishwaVidyapeetham, India
S. Thangavelu, Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, Amrita VishwaVidyapeetham, India.
G. Jeyakumar, Department of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, Amrita VishwaVidyapeetham, India.

The cost is directly proportional to the number of readers placed. Apart from coverage and cost, the objectives like interference, accuracy and scalability are also considered for designing a better *RFID* system. Designing novel algorithmic frameworks using *MOEAs* to solve real time *MOOPs* is an upcoming research area. This paper is an attempt in this direction. This paper formulates the *RFID* reader placement problem as an *MOOP* and proposes an algorithmic framework to solve the same.

II. RELATED WORKS

Research works related to weight vectors based *MOEA*, Population Initialization of *EAs* and optimal *RFID* reader placement problems are briefly discussed in this section.

For solving *MOOPs* and *MaOOPs* the *MOEA* frame works follow different algorithmic structures. This paper has chosen only the works which use the weight vector based approaches. In [1], the authors proposed a dynamic weight design method for generating the weight vectors. Almost all *MOEAs* with aggregate function can use this proposed method. This work also illustrates the working of dynamic weight design method in solving seven difficult problems with uniform distribution. In [2],the authors presented a new method for weight vector generation and this new method is able to create equally spaced weight vectors. The proposed method is able to generate the weight vectors without any restriction to the size of the population and it enables to do adjustments in the aggregation. In [3], the authors proposed a new Multi-Objective Evolutionary Algorithm based on Decomposition (*MOEA/D*) with two modifications. One is weight vector generation based on geometrical analysis and the other is Adaptive Weight vector Adjustment (*AWA*). This method is implemented on two *MaOOPs* and it generates well diversified set of non-dominated solutions. In [4],the authors presented an adaptive method for weight vector generation that periodically updates the weight vectors. The authors also claim that the proposed method requires more computational resources than normal *MOEA/D*. Comparing to all other methods of solving *MOOPs* and *MaOOPs*, the weight vector based methods are simple to implement and proven to be best solution providers. Hence this study considers this approach for its experimental design. Though the *EAs* are robust tools for solving all types of optimization problems, their performance are largely depend on how good the initial population is. There are different approaches available in literature for population initialization, the details of the same is presented here. In [5], the authors have done a review on different *PI* techniques based on the working of different *PI* techniques on a set of benchmarking functions. Based up on the results they have ranked the *PI* techniques. The overall best performance is shown by *OBL* approach. In [6], the authors given a detailed description about various *PI* technique in *EA* and they have classified the *PI* techniques in to 3 broad categories based on randomness, compositionality and generality. The authors mentioned that proposing novel *PI* techniques has become an active research topic in the *EA* domain. In [7], the authors done a comparative study and reported the performance of random *PI* technique and *OBLPI* technique using convergence speed of Differential Evolution (*DE*) algorithm with 34 single objective benchmark functions. The comparative results shows that *OBL PI* technique is performing better than that of Random *PI* technique. Though there are numerous *PI* techniques, this work is restricted to include the *RI* and *OPLPI* techniques for its experimental purpose. The next part of this section summarizes various recent approaches proposed in the literature to solve the *RFID* reader placement problem as optimization problem. The authors, in [9], framed a two objective problem with number of readers and reader interrogation for *RFID* reader placement problem and proposed an algorithm to solve the same. This algorithm includes a load balancing strategy among the readers. In [10], a strategy to maximize the coverage by optimizing the antenna beam orientation using Genetic Algorithm (*GA*) is proposed. This algorithm also uses a radio propagation model to check the quality of the signal emitted from the reader. There are numerous work to develop application specific algorithms for reader placement problem [11][12].In [13], authors sets the elimination of data and reader redundancies in *RFID* network as objective and introduced a decentralized *RFID* coverage algorithm. In [14], authors used *RSSI* positioning algorithm based on microzoning methods to measure the distance of tag from antenna base. In [14], the authors propose a simulation strategy for optimal *RFID* reader placement with readers having circular coverage. The authors used *DE* algorithm to solve the *RFID* reader placement problem and they obtained maximum coverage with minimum number of readers for static tags. In [15], the authors used greedy approach to solve the *RFID* reader placement problem. Here, they considered the objects which are static as well as semi-dynamic. The proposed method considers non-sensitive areas, degrees of freedom and reader movements etc. Greedy approach gives maximum tag coverage with minimum number of readers. Though there exists many works in the literature, all of them uses the *RFID* reader with circular coverage. However, recent studies and technical reports from *RFID* research group says that the *RFID* readers available in the market today are having non-circular coverage too. Hence, this work chooses to study the *RFID* reader placement problem using the readers with elliptical coverage. \ Considering the *MOEAs* and *PI* techniques of *EAs*, this paper proposes a Differential Evolution (*DE*) algorithm based *MOEA* which uses *RPI* and *OBLPI* for population initialization and weight vector methods for combining the objectives to solve the three objective *RFID* reader placement problem. This work also chooses to solve the *RFID* reader placement problem with *RFID* readers of non-circular (particularly elliptical) coverage. The objectives considered in the *RFID* reader placement problem are Coverage, Cost and Interference.

III. DESIGN OF EXPERIMENTS

The experimental setup starts with the construction of a four sided rectangular region. A 400 x 400 pixel area is considered as a simulation area of a building. The positions of the *RFID* tags attached objects are assumed to be static. The tag positions are given as user input. The experiment is conducted with 15 static tag positions. Readers are assumed to be of elliptical coverage with maximum coverage capacity of 50 and 30 pixels in the *X* direction and *Y* directions, respectively.

The initial number of readers required for the given simulation area is calculated empirically and its value is obtained as 81.The *RFID* reader placement problem is formulated as a *MOOP*(Henceforth it is denoted as *RFID_MOOP* in this paper). The multiple objectives of the *RFID* reader placement problem considered in the *RFID_MOOP* design are maximum coverage (f_1), minimum cost (f_2) and minimum interference (f_3). The coverage is calculated based on the number of tags covered out of all the tags placed in the building, the cost is calculated proportional to number of readers placed and the interference is calculated as the number of tags covered by more than one reader. There is one maximization objective and two minimization objectives. In the *RFID_MOOP* design, the minimization objectives also converted to maximization by negating the values. Thus the problem has become a multi-objective maximization problem. The *DE* algorithm (Proposed in [16]) is one of the latest additions to *EA* repository, which has become popular for its simplicity and robustness. The behavior of *DE* has been well studied and its performance is improved further by many researchers in the literature [17-19]. Based on the type of evolutionary operators used, the *DE* algorithm has different variants. All the variants for *DE* are also used to solve *MOOPs*. Five variants of *DE* were used to solve five *ZDT* multi-objective functions and performance analysis among these variants is done based on the convergence and diversity nature of the solutions in [20].An *MOEA* which uses the *DE/rand/1/bin* variant of *DE* algorithm is used for the algorithmic framework design in this experiment. This frame work includes two *PI* techniques: *RPI* and *OBLPI*, and weight-vector approach for combining multiple objectives. Different weight vectors are assigned to each of the objective in the *RFID_MOOP* design. A heuristic method is used for generating weight vectors. This heuristic method assigns maximum weightage to most important objective. The weight vectors (w_1, w_2, w_3) used for the 3 objective functions (f_1, f_2, f_3)are (0.5, 0.3, 0.2), (0.3, 0.5, 0.2), (0.3, 0.2, 0.5) and (0.33, 0.33, 0.34).The *DE* algorithm with *RPI* and *OBLPIPI* techniques are named as DE_{RPI} and DE_{OBLPI}, respectively. In DE_{RPI}, the values for each of the component of a chromosome are generated randomly. For the chromosome *i* of the population *X*, the j^{th} component is initialized as follows

$$X_i[j] = xl + (xu - xl) * rand(seed) \qquad (1)$$

where *xl* and *xu* are the lower and upper bound of values of the components and *rand* ( ) is a function to generate random number based on the *seed*.

In DE_{OBLPI}, an initial population is created randomly (as above) then an opposite population is generated with this initial population which contains the opposite of each individual. The opposite candidate (OX_i) for each candidate (X_i) in the population is created using the equation (2). New population is created by combining the initial population and opposite population. Then the best *NP* candidates from the combined population are selected for initial population.

$$OX_i[j] = xl + xu - X_i[j] \qquad (2)$$

The parameter viz Population Size (*NP*), Dimension (*D*), Crossover Rate (C_r), Mutation Step Size (*F*), Maximum number of generation (*MaxGen*) and Number of Runs (*MaxRun*) are set based on our earlier experimental works, and the values used for them are presented in Table I. Since *DE* is an *EA* specifically designed for real-parameter optimization, the candidates in the populations need to have only real values for their gene values. However, for the *RFID_MOOP*, the candidates need to show only presence or absence of the readers in the building, which need only binary representation. So, the design of algorithm included different population initialization technique where each gene values is initialized with a random real number between to 0 to 1. All the genes with values greater than 0.5 are considered to be 1 and other are considered to be 0. A sample initial population for is shown in Table II, for reference.

Table I. The Parameter setup of the experiment

Sno	Parameter	Value
1	Population Size (*NP*)	50
2	Dimension (*D*)	81
3	Crossover Rate (C_r)	0.9
4	Mutation Step Size (*F*)	0.1 to 0.9
5	Maximum Number of Generation (*MaxGen*)	150
6	Number of runs (*MaxRun*)	1

Table II. An initial population of (only with 10) candidate solutions

Dimension / Candidate	0	1	2	3	4	5	6	7	8	9	….	80
0	0.7	0.5	0.9	0.8	0.4	0.5	0.3	0.2	0.7	0.8	….	0.1
1	0.9	0.9	0.9	0.7	0.7	0.9	0.8	0.1	0.3	0.1	….	0.8
2	0.4	0.1	0.1	0.4	0.7	0.7	0.7	0.5	0.4	0.1	….	0.5
3	0.5	0.5	0.4	0.3	0.1	0.4	0.1	0.4	0.7	0.9	….	0.8
4	0.7	0.9	0.5	0.9	0.9	0.1	0.5	0.4	0.1	0.3	….	0.8
5	0.7	0.5	0.5	0.5	0.9	0.4	0.9	0.1	0.8	0.4	….	0.1
6	0.5	0.5	0.5	0.1	0.4	0.7	0.5	0.7	0.7	0.7	….	0.1
7	0.7	0.5	0.4	0.7	0.9	0.7	0.5	0.9	0.8	0.8	….	0.1
8	0.7	0.1	0.5	0.7	0.5	0.7	0.7	0.4	0.1	0.4	….	0.7
9	0.9	0.7	0.1	0.7	0.3	0.9	0.9	0.3	0.9	0.4	….	0.5

IV. RESULTS AND DISCUSSIONS

The results obtained in solving *RFID_MOOP* using the *MOEA* frame work which includes *DE/rand/1/bin* with DE_{RPI} and DE_{OBLPI} algorithms are presented in this section. The results are recorded, initially, for the individual objectives separately, then for the combined objectives with four different schemes. Each scheme differs from each other based on the values assigned for the weight vectors. At each experiment the best objective function value (*ObjValue*) attained by the algorithm is recorded along with number of readers (*NoR#*) selected for the placement. First, the *RFID_MOOP* is solved using DE_{RPI} by setting only the Coverage as the objective (Case 1). Table III shows the results obtained by DE_{RPI} with only coverage as the objective for 3 different runs. The coverage is the objective to be maximized and the *NoR#* is the objective to be minimized. Since the experimental design considers, initially, all the 81 readers are active, all the tags would be covered by one or more readers. Hence the coverage is 100% in the first generation itself. However, *NoR#* is getting reduced from 81 to lower values but it is not getting optimized as it is not included as objective to be optimized in Case 1.Second, the Case 2 implements DE_{RPI} to solve *RFID_MOOP* with only the Cost as objective. The Cost is the objective to be minimized, which is proportional to the *NoR#* selected for placement.

So to optimize the cost the *NoR#* is to be optimized. Table IV shows the results obtained for Case 2 for 3 different runs. As it is seen from Table IV, the *ObjValue* is getting reduced proportional to *NoR#* and reaches to 0, 2.47 and 1.23 for the Run 1, Run 2 and Run 3, respectively. However, this is not a correct optimization process because this case omits the coverage from its objectives hence the DE_{RPI} optimizes only the *NoR#* without focusing on the coverage. Third, the Case 3 is to implement DE_{RPI} to solve *RFID_MOOP* only with the Interference as the objective. The Interference is calculated based on the number of tags covered by more than one reader. The Interference is 100 if all the tags are covered by more than one reader and is 0 if none of the tag is covered by more than one reader. Since this case is not considering the Coverage and/or Cost as objective the *ObjValue* is reduces to 0 within 10 generations itself in all the runs (as shown in Table V).

Table III. Solving *RFID_MOOP* using DE_{RPI} with Coverage as objective.

G	Run 1		Run 2		Run 3	
	ObjValue %	NoR#	ObjValue %	NoR#	ObjValue %	NoR#
1	100	39	100	48	100	48
10	100	43	100	45	100	47
20	100	43	100	46	100	41
30	100	42	100	46	100	53
40	100	55	100	47	100	55
50	100	45	100	46	100	49
60	100	50	100	51	100	50
70	100	36	100	48	100	44
80	100	46	100	44	100	50
90	100	47	100	43	100	42
100	100	47	100	46	100	44
110	100	55	100	46	100	45
120	100	45	100	40	100	41
130	100	51	100	48	100	47
140	100	51	100	39	100	41
150	100	49	100	37	100	44

The Case 1, Case 2 and Case 3 which optimizes the *RFID_MOOP* by DE_{RPI} with Coverage, Cost and Interference as separate objectives, respectively, showed non-favorable results as the objectives are optimized separately. Though all the three objectives are essential, optimizing them individually is not a correct strategy. It necessitates a *MOEA* frame work which combines all the three objectives. The rest of the experiment includes solving *RFID_MOOP* using the proposed *MOEA* frame work which includes the DE_{RPI} and DE_{OBLPI} algorithms with combined objectives of Coverage, Cost and Interference. The *MOEA* framework uses the weight vector based aggregate function approach to combine three objectives as one. The weight values are generated heuristically for 3 objectives with four schemes: Scheme 1 - (0.5, 0.3, 0.2), Scheme 2 - (0.3, 0.5, 0.2), Scheme 3 - (0.3, 0.2, 0.5) and Scheme 4 - (0.33, 0.33, 0.34).Since, the objective of this study also includes comparing the performance of DE_{RPI} and DE_{OBLPI} in solving the *RFID_MOOP*. Their performance is compared in all the four schemes by the optimized *ObjValue* along with the *NoR#* at the end of the run.

Table IV. Solving *RFID_MOOP* using DE_{RPI} with Cost as objective.

G	Run 1		Run 2		Run 3	
	ObjValue %	NoR#	ObjValue %	NoR#	ObjValue %	NoR#
1	37.04	30	37.04	30	37.04	30
10	33.33	27	34.57	28	32.1	26
20	25.93	21	28.4	23	25.93	21
30	18.52	15	23.46	19	22.22	18
40	17.28	14	19.75	16	19.75	16
50	12.35	10	16.05	13	13.58	11
60	11.11	9	12.35	10	13.58	11
70	8.64	7	11.11	9	12.35	10
80	6.17	5	7.41	6	8.64	7
90	3.7	3	6.17	5	7.41	6
100	2.47	2	4.94	4	6.17	5
110	1.23	1	3.7	3	6.17	5
120	1.23	1	3.7	3	4.94	4
130	0	0	2.47	2	3.7	3
140	0	0	2.47	2	2.47	2
150	0	0	2.47	2	1.23	1

Table V. Solving *RFID_MOOP* using DE_{RPI} with Interference as objective.

G	Run 1		Run 2		Run 3	
	ObjValue %	NoR#	ObjValue %	NoR#	ObjValue %	NoR#
1	6.67	28	6.67	44	6.67	44
10	0	35	0	46	0	29
20	0	43	0	35	0	39
40	0	38	0	41	0	36
50	0	32	0	36	0	31
60	0	37	0	45	0	36
70	0	35	0	43	0	32
80	0	34	0	39	0	42
90	0	44	0	34	0	32
100	0	33	0	33	0	38
110	0	37	0	36	0	36
130	0	35	0	39	0	31
140	0	29	0	38	0	34
150	0	37	0	36	0	36

Table VI shows the results obtained at solving the *RFID_MOOP* using the proposed *MOEA* frame work with DE_{RPI} and DE_{OBLPI} with highest weightage for Coverage (Scheme 1). Results shows that the DE_{RPI} gives better performance than DE_{OBLPI} with more *ObjValue* and less *NoR#*. The *ObjValue* and the *NoR#* obtained by DE_{RPI} and DE_{OBLPI} at the end of the run are (44.07, 16) and (42.59, 20), respectively. The optimal result obtained by DE_{RPI} and DE_{OBLPI} at the end of the run is visually presented in Figure 1 and Figure 2, respectively. From the figures it is clear that DE_{RPI} provide 100 % tag coverage with minimum number of *RFID* readers (16 *RFID* readers) compared to DE_{OBLPI} technique. It is also important to note in the Figure 1 that there are two readers which are not covering any tags. Hence, the solution still needs to be optimized to reduce those two readers. This is due to the fact that the scheme 1 gives more weightage to Coverage and the cost is not given much important. However, further reduction on *NoR#* is possible even by increasing the number of generation from 150 to more. The results for solving the *RFID_MOOP* by the *MOEA* framework with Scheme 2 is presented in Table XII.

The Scheme 2 sets more weightage to Cost. The Cost is calculated proportional to the *NoR#*, hence this schemes avoids the unnecessary readers to reduces the number of *NoR#*. This can be verified by comparing Table VI and Table VII. The *NoR#* values of DE_{RPI} and DE_{OBLPI} in Scheme 2 are 14 and 18, respectively which is lesser than the same in Scheme 1. For Scheme 2 also DE_{RPI} provides best solution with more *ObjValue* and less *NoR#* than the DE_{OBLPI}. The optimal solutions obtained at the end of the run are visualized in Figure 3 and Figure 4 for DE_{RPI} and DE_{OBLPI}, respectively. The results obtained for implementing Scheme 3, which give more weightage to Interference, is presented in Table VIII. The results shows that the DE_{RPI} and DE_{OBLPI} have given same result with similar *ObjValue* and *NoR#*. The final optimal results are shown in Figure 5 and Figure 6. Table IX shows the results obtained for Scheme 4 with equal weightage for all the objectives. The comparison shows that DE_{RPI} provides good optimal result with more *ObjValue* and less *NoR#* than DE_{OBLPI}. The final optimal solutions for the Scheme 4 are shown in Figures 7 and Figure 8 for the DE_{RPI} and DE_{OBLPI} algorithms, respectively.

Table VI. Results obtained by the *MOEA* framework for combined objectives (Scheme 1).

0.5(f_1)-0.3(f_2)-0.2(f_3)				
G	DE_{RPI}		DE_{OBLPI}	
	ObjValue %	*NoR#*	*ObjValue* %	*NoR#*
1	30.52	40	24.22	39
10	33.11	42	33.63	37
20	35.19	40	36.07	34
30	36.3	37	36.3	37
40	37.41	34	37.41	34
50	38.15	32	37.78	33
60	39.63	28	38.89	30
70	40.74	25	40	27
80	41.48	23	40.37	26
90	41.85	22	41.11	24
100	42.22	21	41.11	24
110	42.59	20	41.48	23
120	42.96	19	41.85	22
130	43.33	18	42.22	21
140	44.07	16	42.59	20
150	44.07	16	42.59	20

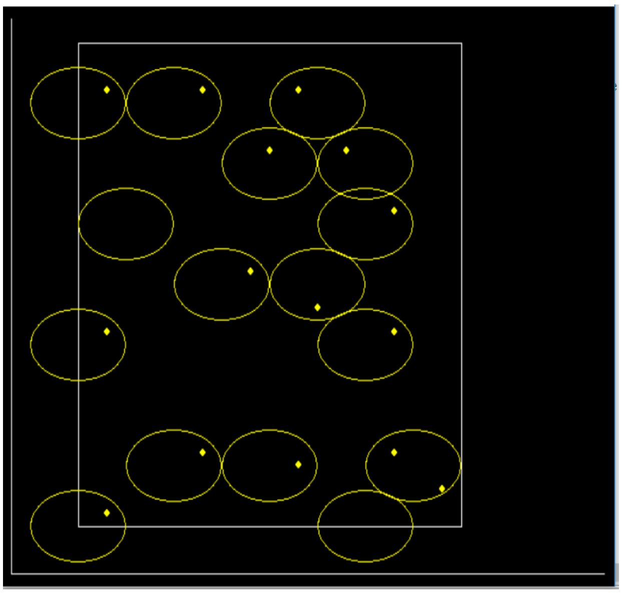

Fig. 1. Scheme 1 – DE_{RPI} Optimal Solution

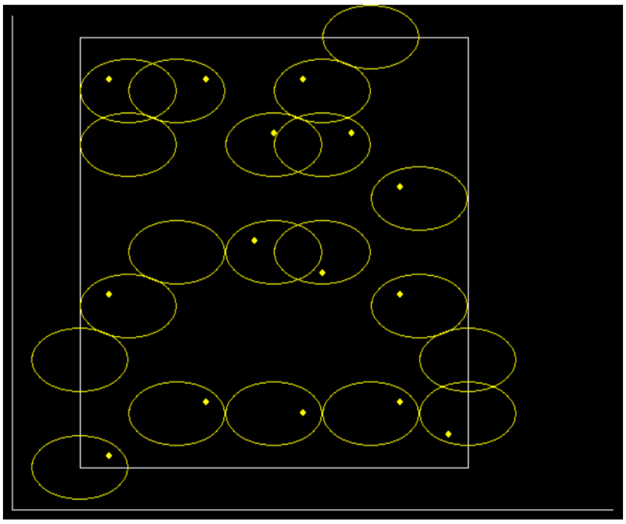

Fig. 2. Scheme 1 – DE_{OBLPI} Optimal Solution

Table VII. Results obtained by the *MOEA* framework for combined objectives (Scheme 2).

0.3(f_1)-0.5(f_2)-0.2(f_3)				
G	DE_{RPI}		DE_{OBLPI}	
	ObjValue %	*NoR#*	*ObjValue* %	*NoR#*
1	1.16	37	-2.59	42
10	6.86	31	3.58	32
20	9.63	33	8.86	31
30	11.48	30	8.86	31
40	11.8	23	8.86	31
50	13.95	26	9.63	33
60	15.19	24	10.86	31
70	17.04	21	12.1	29
80	17.65	20	13.33	27
90	17.65	20	14.57	25
100	19.51	17	15.19	24
110	19.51	17	15.8	23
120	21.36	14	16.42	22
130	21.36	14	17.04	21
140	21.36	14	18.27	19
150	21.36	14	18.89	18

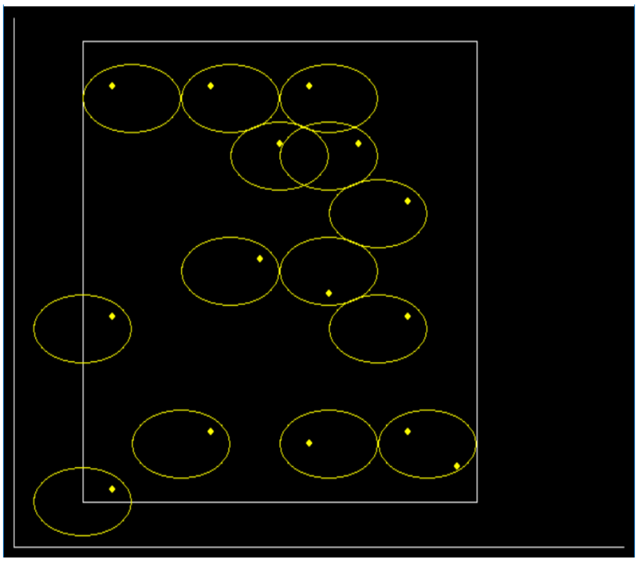

Fig. 3. Scheme 2 – DE_{RPI} Optimal Solution

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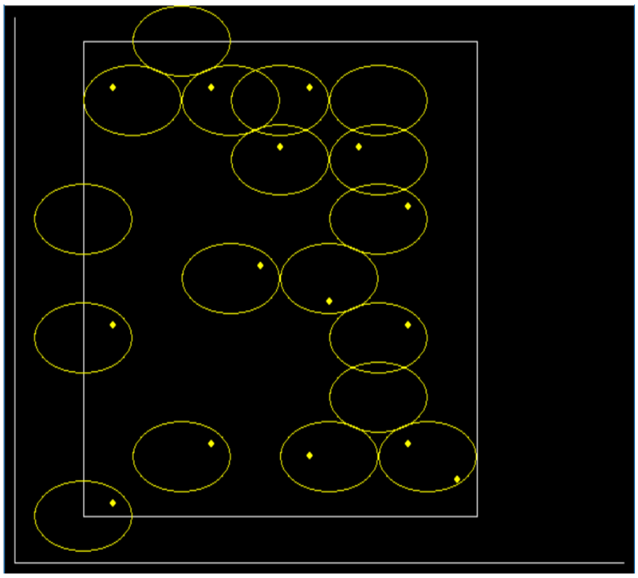

Fig. 4. Scheme 2 – DE_{OBLPI} Optimal Solution

Table VIII. Results obtained by the *MOEA* framework for combined objectives (Scheme 3).

0.3(f_1)-0.2(f_2)-0.5(f_3)				
G	***DE$_{RPI}$***		***DE$_{OBLPI}$***	
	ObjValue %	***NoR#***	***ObjValue %***	***NoR#***
1	13.04	39	10.2	37
10	16.62	38	17.63	42
20	19.63	42	21.6	34
30	20.86	37	21.85	33
40	21.6	34	21.85	33
50	22.35	31	22.35	31
60	22.59	30	23.33	27
70	22.84	29	24.32	23
80	23.09	28	24.32	23
90	23.33	27	24.57	22
100	23.83	25	24.81	21
110	24.32	23	25.06	20
120	24.81	21	25.56	18
130	25.06	20	25.56	18
140	25.56	18	25.56	18
150	25.56	18	25.56	18

Finally, on comparing the performance of DE_{RPI} and DE_{OBLPI}, the results revealed that the DE_{RPI} is performing better that DE_{OBLPI} in 3 out of 4 cases and in the other case both the algorithms perform similar. On comparing the optimal solutions attained at the end of the four schemes (Refer Table X), the Scheme 1 provides solution with highest *ObjValue* but with large *NoR#* value and the Scheme 4 provides solution with less *NoR#* and good *ObjValue*. Thus the Scheme 4 which assigns equal weightage to all the objectives shows good performance among all the schemes. The experiment is concluded stating the DE_{RPI} algorithm with Scheme 4 shows better performance than all other combinations of *PI* techniques and schemes of weights.

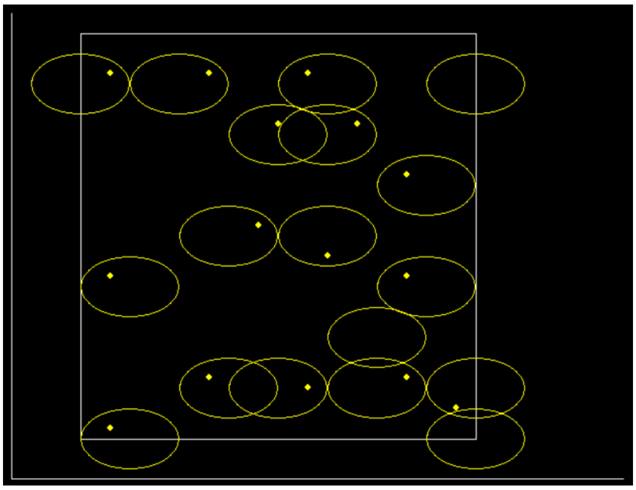

Fig. 5. Scheme 3 – DE_{RPI} Optimal Solution

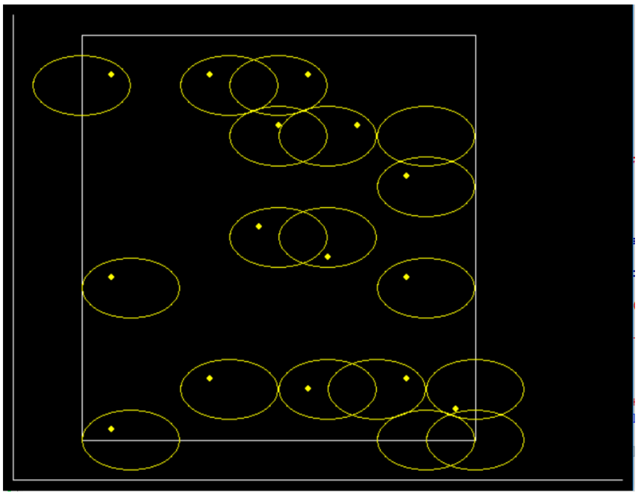

Fig. 6. Scheme 3 – DE_{OBLPI} Optimal Solution

Table IX. Results obtained by the *MOEA* framework for combined objectives (Scheme 4).

0.33(f_1)-0.33(f_2)-0.34(f_3)				
G	***DE$_{RPI}$***		***DE$_{OBLPI}$***	
	ObjValue %	***NoR#***	***ObjValue %***	***NoR#***
1	12.58	39	5	36
10	17.93	37	13.21	43
20	17.93	37	16.54	35
30	18.74	35	18.74	35
40	19.15	34	19.96	32
50	20.37	31	19.96	32
60	20.37	31	21.19	29
70	21.59	28	21.19	29
80	23.22	24	21.59	28
90	23.63	23	22	27
100	24.85	20	22.81	25
110	25.26	19	23.63	23
120	26.07	17	23.63	23
130	26.07	17	24.04	22
140	26.48	16	24.85	20
150	27.32	14	25.67	18

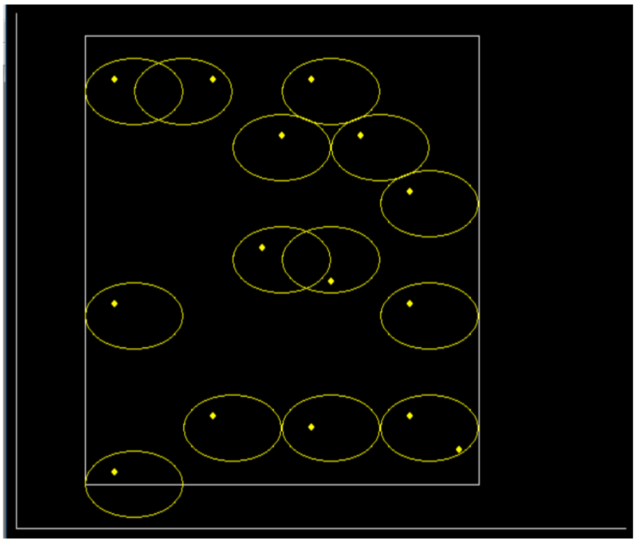

Fig. 7. Scheme 4 – DE_{RPI} Optimal Solution

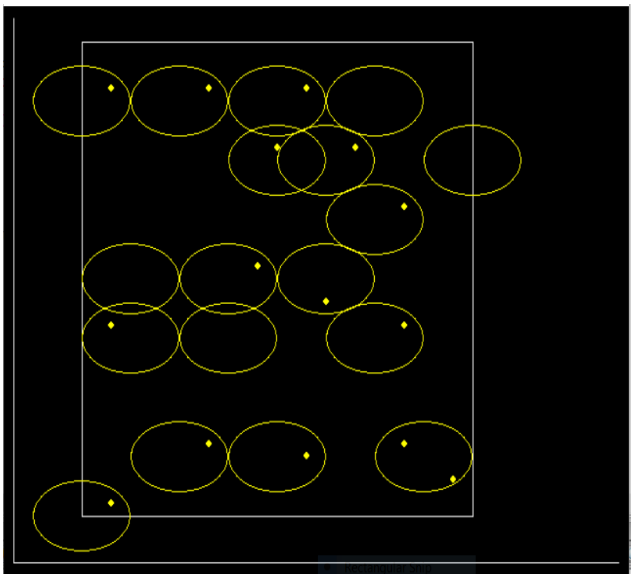

Fig. 8. Scheme 4 – DEOBLPI Optimal Solution

Table X. Comparison of Schemes

Scheme No	ObjValue %	NoR#	Obtained by
1	44.07	16	DE_{RPI}
2	21.36	14	DE_{RPI} and DE_{OBLPI}
3	25.56	18	DE_{RPI}
4	27.32	14	DE_{RPI}

V. CONCLUSIONS

This paper proposed an algorithmic framework to solve the *RFID* reader placement problem as multi-objective optimization problem using Differential Evolution algorithm with two different population initialization techniques and weight vector approach for the aggregation of objectives. Initially, the *RFID* reader placement problem is formulated as a multi-objective optimization problem (*RFID_MOOP*) considering Coverage, Cost and Interference as the objectives. Then, the proposed algorithmic frame work which consists of two different algorithms viz DE_{RPI} and DE_{OBLPI} is used to solve the *RFID_MOOP* with four different schemes with different weight values. The results are studied by comparing the performance of DE_{RPI} and DE_{OBLPI} using the objective function value and number of readers selected. The study also includes comparing the results obtained through four schemes to identify a better scheme. This study revealed that the DE_{RPI} performs better than DE_{OBLPI} and the scheme which gives equal weightage to all the objectives provides good results compared to other schemes.

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AUTHORS PROFILE

Spurti Sachin Shinde received her B.E in Information Technology in 2008, M.E in Information Technology in 2013 from Savitribai Phule Pune University and currently pursuing Ph.D degree in Evolution Algorithms and Optimisation, from Amrita Vishwa Vidyapeetham University, Tamil Nadu, India. She is currently Assistant Professor in Department of Information Technology in Pimpri chinchwad college of Engineering, Savitribai Phule Pune University. Her area of research includes Artificial Intelligence Techniques, Evolutionary Algorithms and Image Processing. She has published few papers in reputed journals and conference proceedings.

She has got best paper award for her research work in M.E. in iPGCON conference organised by Savitribai Phule Pune University. She has guided many student projects belong to the UG courses. She is IBM certified DB2 Trainer. She is member of ISTE-Indian society for technical education.

K. Devika is currently a PhD scholar at Amrita Vishwa Vidyapeetham University, Tamil Nadu, India. She received her bachelor degree (B.Tech) in Information Technology from Calicut University and her master degree (MTech) in Computer Science and Engineering from Amrita Vishwa Vidyapeetham University, Tamil Nadu, India. Her research interests include Artificial Intelligence, Evolutionary Computing, Signal and Image Processing and Deep Learning applications. She has published papers in journals and conferences which are indexed in SCOPUS.

S. Thangavelu is currently working as an Assistant Professor in the Department of Computer Science and Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Tamil Nadu, India since 1998. He received his B.Sc degree in Computer Science in 1993, M.C.A degree in 1996 from Bharathiar University, and Ph.D in Computer Science at 2016, from Amrita Vishwa Vidyapeetham University, Tamil Nadu, India. He is current working in the domain of Evolutionary Algorithms and its Applications.

G. Jeyakumar currently an Associate Professor in the department of Computer Science and Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham University, Tamil Nadu, India since 2000. He received his B.Sc degree in Mathematics in 1994, M.C.A degree (under the faculty of Engineering) in 1998 from Bharathidasan University, and Ph.D degree in Distributed Differential Evolution Algorithm in 2013, from Amrita Vishwa Vidyapeetham University, Tamil Nadu, India. His research interest includes Parallelization and Applications of Evolutionary Algorithms, Artificial Intelligence Techniques and Human Modeling. He has published numerous papers in reputed journals and conference proceedings, out of which majority of the publications are indexed in SCOPUS. He has got best paper awards for few of his publications. He has guided many student projects/thesis belong to the courses B.Tech, M.Tech (CSE), M.Tech (Automative Eng), M.C.A and M,Phil and currently guiding PhD scholars, many UG and PG students.