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Optimization of Bank Portfolio Investment Decision Considering Resistive Economy

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Increasing economy's resistance against the menace of sanctions, various risks, shocks, and internal and external threats are one of the main national policies which can be implemented through bank investments. Investment project selection is a complex and multi-criteria decision-making process that is influenced by multiple and often some conflicting objectives. This paper studies portfolio investment decisions in Iranian Banks. The main contribution of this paper is the creation of a project portfolio selection model that facilitates how Iranian banks would make investment decisions on proposed projects to satisfy bank profit maximization and risk minimization, while focus on national policies such as Resistance Economy Policies. The considered problem is formulated as a multi-objective integer programming model. A framework called Multi-Objective Electromagnetism-like (MOEM) algorithm, is developed to solve this NP-hard problem. To further enhance MOEM, a local search heuristic based on simulated annealing is incorporated in the algorithm. In order to demonstrate the efficiency and reliability of the proposed algorithm, a number of test are performed. The MOEM results are compared with two well-known multi-objective genetic algorithms in the literature, i.e. Non-dominated Sorting Genetic Algorithm (NSGA-II) and Strength Pareto Evolutionary Algorithm (SPEA-II) based on some comparison metrics. Also, these algorithms are compared with an integer linear programming formulation for small instances. Computational experiments indicate the superiority of the MOEM over existing algorithms.

Keywords: Project Portfolio Selection, Bank Investment, Resistive Economy, Multi-Objective Optimization, Electromagnetism-Like Algorithm, Ɛ-Constraint Method.
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1 Introduction

Portfolio selection is concerned with the allocation of capital among various asset classes, such as bonds, stocks, cash, and loans by commercial banks. The corresponding decision model and theory are called portfolio selection model and investment portfolio theory, respectively. Choosing the best project portfolio out of a given set of investment proposals is a common and often critical management issue. Decision-makers regularly consider multi-objectives and often have little a priori preference information available to them. Given these constraints, they can improve their chances of achieving success by following a two-phase procedure that first determines the solution space of all efficient portfolios and then allows them to interactively explore that space. For this reason, project selection is essentially an optimization problem.

Therefore, optimization techniques are the most fundamental quantitative tools for project portfolio selection which can address a high percentage of desired aspects among the available useful approaches. As an example, Aaker & Tyebjee (1978) utilize a quadratic 0–1 programming method to select interdependent R&D projects. Likewise, Mavrotas, Diakoulaki, & Caloghirou (2006) combine MCDA with integer programming for project prioritization under policy restrictions. A discrete dynamic programming algorithm is developed by Carraway & Schmidt (1991) to allocate resources among interdependent projects. An integer linear programming model is presented by Naderi (2013). Huang, Xiang & Islam (2014) consider project selection problem under capital and land resource limitation. The employ net present value method to calculate the investment return, and a mean variance. Schaeffer & Cruz-Reyes (2016) develop a mixed integer programming for R&D project portfolio selection.

Any logical combination of these methods can build an optimal organization portfolio; however, the successful implementations of these techniques are depending on the decision type, information accessibility, resource accessibility, and the decision maker's insight to the technique. As decision makers are bound to take into account multi-objectives, they can enhance their chance of achieving success by following a two-phase procedure by determining the solution space of Pareto-optimal portfolios in the first place, and interactively explore that space afterwards. With the decision makers being confronted by a large number of competing projects, heuristic approaches are applied to provide a tradeoff between the solution space quality and the required computational effort (Doerner, Gutjahr, Hartl, Strauss

& Stummer, 2004). Medaglia, Graves & Ringuest (2007) propose a multi-objective evolutionary method for linearly constrained projects selection under uncertainty. A multi-objective project selection problem is considered by Rabbani, Bajestani & Khoshkhou (2010) with the objective of maximization of total benefits while minimization of total risk and total cost.

Considering the special condition of the resources and their consumption, banks as the major and most effective economic agencies in the economic growth and development of the country, have always been under the magnifier of research and criticism of the stakeholders, entrepreneurs and consumers (Ghorbani Azar, Karimi & Mohammadi, 2013). Wildmann (2011) study portfolio investment decisions of German banks in emerging capital markets from 2002 to 2007. They use a dynamic time-series cross-section framework.

The project portfolio selection analyzed in this research is focused mainly on projects in Iranian banks. These organizations usually undertake projects in order to increase profit through an increase in production, new product development or reduce risk through implementation of new projects. This paper presents a novel framework for the selection of an efficient portfolio for bank investment. This framework integrates bank profit maximization (maximizing return while minimizing risk) with national interest. Achieving a sustainable economic growth, and strengthening the economy against menace of negative and positive shocks is considered as one of the main priorities of policy makers of Iran. Resistive Economy (RE) is a concept that represented to satisfy these properties.

Resistive Economy (RE) is in the line with the reduction of dependencies and emphasis on the advantages of domestic production and making attempt for self-dependency. This is the economic initiative of the country under special conditions which targets the production and distribution of particular goods and investment in reducing the dependency on other countries under critical conditions; i.e., if it could not supply the basic products from other countries in market transaction, it can produce them in bulk relying on domestic products (Norouzi & Faezi, 2014). Also, it can be mentioned that important national subject like food security, and productivity are considered in RE concept.

So, in order to identify the RE criteria which bank can improve them, factor analysis is used. By prioritizing Resistive Economy, it is natural that all capabilities, opportunities and capacities of the country are used to prosper economy, guarantee food security, control market, mange production, and restrain other economic indices with the aim of establishing welfare and justice. According to our research, the closest subject area to the RE issue in literature is the economic resilience.

The main contribution of this paper is the creation of a project portfolio selection model that facilitates how Iranian banks would make investment decisions on proposed projects to satisfy bank profit maximization and risk minimization, while focus on national interest. Increasing economy's resistance against the menace of stochastic changes, various risks, and internal and external threats are one of the main national interests which can be satisfied through banks.

This paper explores models for Project Portfolio Selection (PPS) for Iranian banks that maximizes benefit and minimize risks, considering RE criteria satisfaction requirements and constraints (e.g., financial resources). The proposed model provides a framework to optimize bank objectives in investment on portfolios, which is maximizing bank profit and minimizing risk, and also meet the expectations of RE criteria. These criteria are often conflicting in nature and are quit complex. In general, a Multi-objective Optimization Problem (MOP) does not have a single solution that could optimize all objectives simultaneously. Therefore, MOP is not to search for optimal solutions but for efficient solutions that can be expressed in terms of non-dominated solutions in the objective space. A solution is dominant over another only if it has superior, at least no inferior, performance in all criteria. All non-dominated solutions approximate the Pareto optimal front in the objective space. Therefore, solving any MOP depends on how to find the non-dominated front in the objective space, and subsequently how to rank the non-dominated solutions by subjective judgments or relative preferences of decision-makers.

Due to the NP-hardness (Yu, Wang, Wen & Lai, 2012) and multi-objective nature of the PPS problem, most of the recent studies have looked for an approximation to the Pareto frontier through multi-objective meta-heuristics. (e.g. Chen & Chyu (2010), Carazo, Contreras, Gomez & Perez (2012), Doerner et al. (2004), Ghorbani & Rabbani (2009), Rabbani et al. (2010), Esfahani, hossein Sobhiyah & Yousefi (2016). Multi-objective meta-heuristics have some advantages over classical mathematical programming methods, especially the following: (1) meta-heuristic algorithms are capable of handling highly complex constraints; (2) they are less sensitive to the mathematical properties of the problems; and (3) they can approximate the Pareto frontier by a single run instead of having to perform many runs as in mathematical programming techniques.

Recently, Electromagnetisms-like algorithm (EM) which is known as population-based meta-heuristic algorithm is introduced by Birbil & Fang (2003) to search for the optimal solution of single objective optimization problems. EM originates from the electromagnetism theory of physics by considering potential solutions as electrically charged particles spread around the solution space. This meta-heuristic utilizes an attraction-repulsion mechanism to move the particles towards optimality. The EM has been successfully applied in many areas such as the traveling sales man problem (Wu, Yang & Fang, 2006), single machine scheduling (Chang, Chen & Fan, 2009), flow shop scheduling (B. Naderi, Tavakkoli-Moghaddam & Khalili, 2010), open shop scheduling (B. Naderi, Ghomi, Aminnayeri & Zandieh, 2011), project scheduling (Debels, De Reyck, Leus & Vanhoucke, 2006), numerical optimization (Tan, Dahari, Koh, Koay & Abed, 2016), PID controller optimization, (Lee & Chang, 2010), resource allocation problem (Chu & Chang, 2017), cell formation problem (Jolai, Golmohammadi & Javadi, 2011; Mohammadi & Forghani, 2017), and vehicle routing problem (Yurtkuran & Emel, 2010). But, to the best of our knowledge, there is no study that address the PPS problem with EM algorithm.

In this paper, a multi-objective EM (MOEM) is presented. A local search heuristic based on simulated annealing algorithm is suggested to improve the performance of MOEM algorithm. At first the performance of model is evaluated. Then, the performance of the proposed MOEM algorithm is compared with two well-known multi-objective genetic algorithms, namely NSGAII (Deb, Pratap, Agarwal & Meyarivan, 2002) and SPEA-II (Zitzler, Laumanns & Thiele, 2001). The results clearly show that our MOEM significantly outperforms the above mentioned algorithms.

The remaining contents of this paper are divided into seven sections. The proposed method to select Resistive Economy criteria which can be satisfied through bank investment is presented in Section 2. In section 3, the formulation of multi-objective integer programming model is presented. Section 4 provides the preliminary concepts of multi-objective optimization and review well-known approaches in this area. It is followed by a brief overview of EM algorithm in the section 5. In section 6, the proposed MOEM algorithm is described. In section 7, the experimental results obtained by the proposed solution algorithm is presented and then compared with two multi-objective genetic algorithms, called NSGAII and SPEA-II. Finally, conclusion and some directions for future research are presented in section 8.

2 Selection of RE Criteria

RE is the discourse of achieving to a comprehensive economy in which all national economic activities and majors are correlated with each other, forming a homogenous complex. In order to achieve Resistive Economy, its components which have been extracted from the lectures of Supreme Leader are used in the present research (http://farsi.khamenei.ir, 2011). The great leader has pointed out some illuminating realities which must be considered by the officials in their economic planning in the long term horizon including “popularizing the economy”, “considering the policies of Article 44” discussed in the past, “empowering the private sector”, “encouraging the activity of economic agencies”, “reinforcing the bank system of the country”, “the reduction of dependency on the oil industry”, “paying attention to knowledge-based industries”, and “other various capacities” in Iran are the main components of the resistive economy. Also governmental systems must be accompanied by legislative and judicature.

In order for banks to select the important variable that affect the RE criteria, factor analysis (FA) is applied. The main purpose of FA is to discover the jointly basic factors and apply them to eliminate redundant variables. This method has been widely used in financial analysis. Charbaji (2001) uses FA as a data reduction technique to reduce the financial ratios of Lebanon banks from 52 into 7 financial ratios. FA used by Cheng & Ariff (2007) in Malaysia commercial banks to reduce 21 accounting and financial ratios into four factors. In addition, Öcal, Oral, Erdis & Vural (2007) uses FA for a Turkish construction company’s 50 financial ratios, in order to determine the financial indicators.

This study uses FA based on principal component analysis (PCA) as the extraction method and adopted Varimax with Kaiser Normalization as the rotation method. In this order at first a questionnaire is designed to evaluate the role of Iranian banks in fulfillment of these criteria. After that 50 experts are selected as the statistical sample. To evaluate the reliability of applied questionnaire, Cranach’s alpha is computed (0.77); since the obtained value is higher than 0.7, indicating a high reliability of the model.

The PCA with the varimax rotation is used to extract the components that their eigenvalues are larger than 1 (which is set as the criterion). In PCA key test, KMO and Bartlett’s test are analyzed. In this case, the KMO is greater than 0.7 at 0.81 and Bartlett’s test is significant and, therefore, it seems that the sample is adequate for FA. As a result, the 20 criteria, V_1, V_2, V_3, V_4, V_5, V_7, V_8, V_9, V_{10}, V_{11}, V_{12}, V_{13}, V_{14}, V_{15}, V_{16}, V_{19}, V_{21}, V_{22}, V_{23}, V_{24}, from 24 variables are selected and used in the financial performance evaluation. The number of criteria are exactly as the same as in the source (http://farsi.khamenei.ir, 2011). It is worth mentioning that our result are the same as the result recommended by Ebrahimi and Seif in their paper in 2015.

After the selection of RE criteria which banks can improve them through investment, the weight of each criterion is determined by entropy weight method. This method have been widely used for evaluation of weight of indicators (e.g. (Hsu & Hsu, 2008), (Liu, Zhou, An, Zhang & Yang, 2010), (Šaparauskas, Kazimieras Zavadskas & Turskis, 2011)).

3 Problem Definition and Mathematical Modeling

Project selection is a complex multi-criteria decision making process that is influenced by multiple and often conflicting objectives. The complexity of the selection problem is mainly due to the high number of projects from which an appropriate collection (an effective portfolio) must be selected.

The structure of the problem is presented in Figure 1. At the first level of the figure, the criteria exist. There are *M* number of investment domain, such as oil and petroleum, medicine, agricultural, textile industry and etc. that related to the criteria. When investment in one domain is enough to meet threshold (β_j), it can be said that domain satisfy the related criterion. S_{jk} shows the score of domain *j* on criterion *k*. the projects are in the third level of problem. Each project is related to only one investment domain.

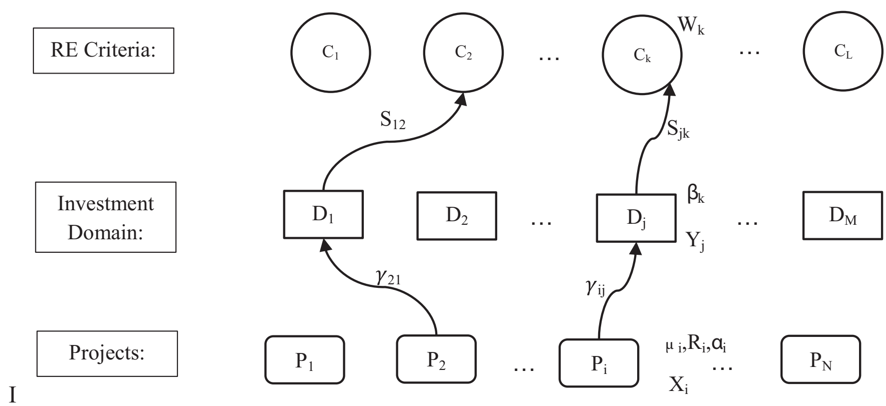

Figure 1. The structure of the problem. *Source*: Research Findings

Suppose there are *N* projects to be invested, and decision variable x_i denotes whether proposed project is included in investment portfolio ($x_i=1$) or not

($x_i=0$). Each project is related to one investment domain, which is announced by Ministry of Industry, Mine and Trade in each year. Let W_k be the preference degree on criterion k according to the selection result of RE criteria step. S_{jk} is the score of domain j on criterion k. β_j is defined as minimum proportion of bank assets that must be held on domain j so can say domain j is selected for investment. γ_{ij} shows whether project i is related to investment domain j or not. μ_i and R_i show the expected return and expected risk of implementation of project i.

The considered optimization problem as stated in Equation (1), (2), and (3) is a multi-objective optimization problem with three objectives. The objective of the project selection process is to derive a portfolio of projects providing maximum benefit subjected to resources constrains and other limitations imposed by the organizations. Portfolio selection seeks the best balance in terms of return, risk, and RE criteria satisfaction.

The notation for parameters and variables used in the model are as follows:

Indices

- i Index for project
- j Index for investment domain
- k Index for criterion
- N Total number of projects
- M Total number of investment domains
- L Total number of criteria

Parameters:

- W_k Preference degree on criterion k
- S_{jk} Score of domain j on criterion k
- μ_i Expected return of implementation of project i
- R_i Expected Risk of implementation of project i
- α_i Proportion of bank assets that needs to invest on project i ($0 \leq \alpha_i \leq 1$)
- β_j Minimum proportion of bank assets that must be held on domain j if any of domain j is held ($0 \leq \beta_j \leq 1$)
- γ_{ij} 1, if project i is related to investment domain j; 0, otherwise

Decision variables:

- X_i 1, if project i is selected; 0, otherwise
- Y_j 1, if *domain* j is selected for investment; 0, otherwise

The following integer linear programming (ILP) model is proposed:

$$Max\ Z_1 = \sum_{i=1}^{N} \mu_i x_i \quad (1)$$
$$Min\ Z_2 = \sum_{i=1}^{N} R_i x_i \quad (2)$$
$$Max\ Z_3 = \sum_{k=1}^{L} \sum_{j=1}^{M} W_k S_{jk} y_j \quad (3)$$

Subject to

$$\sum_{i=1}^{N} \alpha_i x_i = 1 \quad (4)$$
$$\sum_{i=1}^{N} \alpha_i \gamma_{ij} x_i \geq \beta_j y_j \quad j = 1, \ldots, M \quad (5)$$
$$x_i, y_j \in \{0,1\} \quad i = 0,1, \ldots, N, j = 1, \ldots, M \quad (6)$$

The objective functions are (1) maximizing the total expected return of investment, (2) minimizing total risk of the selected projects, and (3) is maximizing the total score of selected domain for investment according to the criteria of Resistive Economy. Constraint (4) ensures total proportions add to one. Constraint (5) define lower limits on the proportion of each investment domain which can be held. Lastly, constraints (6) indicate the range of variables in the model. This ILP model will be used later in the computational experiments.

Preposition. The considered problem is NP-hard

In order to prove that the considered problem is NP-hard, it is sufficient to reduce the known NP-complete problem to a new one with a polynomial transformation. In this order, Knapsack Problem (KP) is considered. KP is a typical model for portfolio optimization. In the classical 0-1 KP, it is considered to pack a subset of *n* given items in a knapsack of capacity *C*. Each item has a profit R_j and a weight w_j and the problem is to select a subset of the items whose total weight does not exceed *C* and whose total profit is a maximum. Introducing the binary decision variables x_j, with $x_j = 1$ if item *j* is selected, and $x_j = 0$ otherwise, we get the integer linear programming (ILP) model for KP. This is shown in literature that KP is NP-complete (Garey, 1979). Now consider the KP problem with lower limit and three objectives. So, the KP can be summarized to our problem.

4 Background Information on Multi-Objective Optimization

Multi-objective optimization deals with optimization problems which are formulated with some or possibly all of the objective functions in conflict with each other. Such problems can be formulated as a vector of objective functions such as $f(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x}))$, optimized subject to a vector of input parameters $\mathbf{x} = (x_1, x_2, \ldots, x_m)$, where *n* is the number of objectives, and *m* is the number of parameters. A solution **x** dominates a solution **y** if objective function $f_i(\mathbf{x})$ is no worse than objective function $f_i(\mathbf{y})$ for all n objectives and there exists some objective j such that $f_j(\mathbf{x})$ is better than $f_j(\mathbf{y})$. The non-dominated solutions in a population are those solutions which are not dominated by any other individual in the population.

In a single-objective problem, the goodness is directly obtained by the objective function value. However, in multi-objective problems, the procedure becomes more complicated. It should be in such a way that all the objectives are considered simultaneously. The objective of multi-objective optimization methods is to find a set of non-dominated solutions that provide a reasonable approximation of the Pareto set of solutions. Efficient solutions mean that the improvement of some objectives could only be achieved at the expense of other objectives. In a MOP problem there are normally infinite numbers of efficient solutions due to the conflicts among objectives (Balderud, 2006).

Many approaches have been proposed to solve the multi-objective optimization problems. With comparison to traditional optimization methods, evolutionary algorithms can find several non-dominated solutions because of their population-based approach. The potential of evolutionary algorithms for solving multi-objective optimization problems was hinted at in the late 1960s by Rosenberg (Rosenberg, 1970). The first actual implementation of what is now called a multi-objective evolutionary algorithm (MOEA) was introduced by Schaffer (Schaffer, 1985) named vector evaluated genetic algorithm. Since then, a wide variety of algorithms have been proposed in the literature such as: Multi-Objective Genetic Algorithm (MOGA) (Fonseca & Fleming, 1993), Niched Pareto Genetic Algorithm (NPGA) (Horn, Nafpliotis & Goldberg, 1994), Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas & Deb, 1994), Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler & Thiele, 1999), improved SPEA (SPEA II) (Zitzler et al., 2001), fast Non-dominated Sorting Genetic Algorithm (NSGA II) (Deb, Agrawal, Pratap & Meyarivan, 2000). In addition to MOEAs, many researchers have been studying swarm intelligence approaches such as multi-objective particle swarm optimization (Coello Coello & Lechuga, 2002), multi-objective ant colony optimization (Yagmahan & Yenisey, 2010).

5 Overview of EM

The EM-like mechanism (EM) is a new meta-heuristic introduced by Birbil and Fang (Birbil & Fang, 2003) for optimization problem with lower and upper bounds on each dimension. The EM is considered as a population-based algorithm and the idea comes from the attraction-repulsion mechanism of the electromagnetism theory which is based on Coulomb's law. The EM algorithm starts with a population of randomly generated particles from the feasible region. Each solution can be thought of as a particle charged according to its objective function value. The direction of this charge for candidate particle is determined by adding vectorially the forces from each of other particles on candidate particle. Then, an analogy of the attraction-repulsion mechanism of the electromagnetism theory can be applied. The principle behind the algorithm is that superior particles with lower objective function values attract others while those with higher function values repel. Moreover, some solutions are improved by a local search. The general scheme for the EM algorithm is shown in Figure 2.

```
Algorithm EM
Initialization
iteration ←1
while termination criterion is not
satisfied do
    Local search engine
    Compute total forces
    Move by forces
    iteration ←iteration + 1
end while
```

Figure 2. General scheme for the EM. *Source*: Research Findings

The EM algorithm comprises four main procedures: 1) the initialization of the population of the particles; 2) the application of the local search; 3) the computation of total force exerted on each particle; 4) the movement according to the total force. The initialization procedure is used to generate the initial population, which consist of *NP* particles of the feasible region. The local search procedure provides the EM algorithm with a good balance between the exploration and exploitation of the feasible region. Birbil and Fang (2003) propose two approaches according to the particles to which the local search can be applied: 1) local search applied to all particles and 2) local search applied only to the current best particle. After initialization and local search, the charge of each particle belonging to the population *P*, which determines the intensity of attraction or repulsion of the particle, is determined according to the equation (10).

$$\boldsymbol{q^i} = exp\left(-n\frac{f(x^i)-f(x^{best})}{\sum_{j=1}^{m}\left(f(x^j)-f(x^{best})\right)}\right) \quad i = 1,2,\ldots,NP \tag{7}$$

In which q^i is the charge of particle i, n is the dimension of the problem, NP is the number of particles, and $f(x^i)$, $f(x^{best})$, $f(x^j)$ are the objective value of particle i, the best particle, and particle j respectively. In this way the particles that have better objective function values possess higher charges. A different approach to evaluate the charges is adopted in (Debels et al., 2006). The force that is exerted on each particle is evaluated by following formula:

$$\boldsymbol{F^i} = \sum_{j\neq i}^{m}\begin{cases}(x^j - x^i)\frac{q^i q^j}{\|x^j-x^i\|^2} & if \quad f(x^j) < f(x^i)\\(x^i - x^j)\frac{q^i q^j}{\|x^j-x^i\|^2} & else \quad f(x^j) \geq f(x^i)\end{cases} \quad i = 1,2,\ldots,NP \tag{8}$$

Where F^i is the force that exerted on the ith particle and x^i and x^j are the ith and jth particles, and $\|x^j - x^i\|$ is the Euclidean distance between two particles. Finally, each particle belonging to the population P is moved toward the force vector according to the next equation. Moving the particles is as follows:

$$\boldsymbol{x^i} = x^i + \gamma \times \frac{F^i}{\|F^i\|} \quad i = 1,2,\ldots,NP \tag{9}$$

where γ denotes a random number uniformly distributed between 0 and 1 and $\|F^i\|$ is the norm of the force vector. The parameter γ is used to ensure that the particle have a nonzero probability of moving to the unvisited regions in this direction. Furthermore, the force applied to each particle is normalized, so the feasibility is maintained (i.e., each dimension of each particle will be between lower bound l_k and upper bound u_k).

6 Proposed Hybrid EM-Like Approach

In the previous section the main procedures of the EM-like algorithm are described. This paper proposes a hybrid framework that combines EM-like algorithm and Simulated Annealing (SA) for solving multi-objective problems with sequence dependent setup times, which is an NP-hard problem. The procedure of the proposed Hybrid multi-objective EM-like algorithm to solve multi-objective project portfolio selection problem, is discussed in the following subsections:

6.1 Encoding Scheme and Initialization

Since EM algorithm is originally designed to solve problems with continuous variables. In order to enable EM to solve scheduling problem the Random Key (RK) representation, proposed by Bean (Bean, 1994), is used to encode solutions. RK allows a straightforward application of this type of meta-heuristics to solve combinatorial optimization problems. To the best of our knowledge, most of the papers in which an EM algorithm is proposed to solve a combinatorial optimization problem, RK method is used ((Debels et al., 2006); (Chang et al., 2009), (B. Naderi et al., 2011; B. Naderi et al., 2010), (Yurtkuran & Emel, 2010)) and (Govindan, Jafarian & Nourbakhsh, 2015). Because RK have been effectively applied to the EM-like meta-heuristic to solve several combinatorial problems, it is also used in this paper in the proposed MOEM algorithm. Based on this representation scheme, the selection of each project can be converted to continuous position values. Thus, each solution is encoded as a vector of random keys. The solution representation based on this technique is best illustrated with an example.

Consider a problem with 6 projects. For all solutions, a random number from a uniform distribution U(0,1) for each dimension of each particle exists. Then, if random number in dimension is greater than 0.5, it is replaced by 1; otherwise it is replaced by 0. This procedure is shown in Figure 3.

Projects:	P_1	P_2	P_3	P_4	P_5	P_6
Random Particle:	0.45	0.93	0.84	0.27	0.54	0.05
Selected Projects	0	1	1	0	1	0

Figure 3. EM particle encoding scheme example. *Source*: Research Findings

The initial population of particles P consists of $2NP$ solutions generated randomly. After all particles are generated, the RK method is used to generate solutions. As soon as the selected projects is obtained, the objective values of these particles are obtained and current best solution (x_{best}) from the population can be determined. The procedure of initialization is shown in Figure 4.

Procedure Initialization
for *i*= 1 to m **do**
for *k*= 1 to n **do**
$\gamma \leftarrow U(0,1)$
$x_k^i \leftarrow \begin{cases} 1 & if\ \gamma \geq 0.5 \\ 0 & if\ \gamma < 0.5 \end{cases}$
end for
end for
find selected projects by RK method
calculate the objective value of particles $(f(x^i)$

Figure 4. Procedure of initialization. *Source*: Research Findings

6.2 Total Force and Movement

As mentioned before, in MOP there is not a single solution that could optimize all objectives simultaneously. In order to calculate the charge of each particle, first the values of objective functions for each solution are evaluated: maximize the total expected return (f_2), minimize the total expected risk (f_2), and maximize the total score of selected domain for investment (f_3) according to equations (1), (2) and (3). Then, dominated solutions are eliminated from the feasible set *P*. The average of total expected return ($\bar{f_1}$), total expected risk ($\bar{f_2}$), and score of selected domain ($\bar{f_3}$), in the updated *P* are computed. After that for each solution, the normalized distance (*Dist*) in a two-dimensional objective space from the origin is computed as follows:

$$Dist(x^i) = \sqrt{\left(f_1^i/\bar{f}_1\right)^2 + \left(f_2^i/\bar{f}_2\right)^2 + \left(f_3^i/\bar{f}_3\right)^2} \quad (10)$$

Subsequently, the calculation for the charge of particle *i* is modified according to the equation (11).

$$\boldsymbol{q^i} = exp\left(-n\frac{Dist(x^i)-Dist(x^{best})}{\sum_{j=1}^{m}\left(Dist(x^j)-Dist(x^{best})\right)}\right) \qquad i = 1,2,\dots,NP \quad (11)$$

If the normalized distance value of particle *i* ($Dist(x^i)$) is larger than *j* ($Dist(x^j)$), particle *j* will attract particle *i*. On the other hand, when $Dist(x^i) < Dist(x^j)$, a repulsion effect is occurred. After the $\boldsymbol{q^i}$ is computed, the force on particle *i* is determined by the following equation:

$$\boldsymbol{F^i} = \sum_{j\neq i}^{m} \begin{cases} (x^j - x^i)\frac{q^i q^j}{\|x^j - x^i\|^2} & if \quad Dist(x^j) < Dist(x^i) \\ (x^i - x^j)\frac{q^i q^j}{\|x^j - x^i\|^2} & else \quad Dist(x^j) \geq Dist(x^i) \end{cases} \qquad i = 1,2,\dots,NP \tag{12}$$

The outline of calculation total force is shown in Figure 5. After this, particle *i* moves toward the force vector according to equation (10).

Procedure calculation of total force
for *i*= 1 to m **do**

$$Dist(x^i) = \sqrt{\left(f_1^i/\bar{f}_1\right)^2 + \left(f_2^i/\bar{f}_2\right)^2 + \left(f_3^i/\bar{f}_3\right)^2}$$

end for
$x^{best} \leftarrow argmin\{Dist(x^i), \forall i\}$
for *i*= 1 to m **do**

$$\boldsymbol{q^i} = exp\left(-n\frac{Dist(x^i) - Dist(x^{best})}{\sum_{j=1}^{m}\left(Dist(x^j) - Dist(x^{best})\right)}\right)$$

end for
for *i*= 1 to m **do**
  for *j*= 1 to m **do**
    if $Dist(x^j) < Dist(x^i)$ **then**

$$F^i = F^i + (x^j - x^i)\frac{q^i q^j}{\|x^j - x^i\|^2}$$

    else

$$F^i = F^i + (x^i - x^j)\frac{q^i q^j}{\|x^j - x^i\|^2}$$

    end if
  end for
end for

Figure 5. Procedure of total force calculation. *Source*: Research Findings

6.3 Local Search Engine

Simulated Annealing (SA) is an effective optimization algorithm motivated from an analogy between the simulation of the annealing of solid and the strategy of solving combinatorial optimization (Kirkpatrick, 1984). In the proposed algorithm, EM combine with a local search heuristic based on SA algorithm to increase the performance of the proposed MOEM. All current solutions are improved by using SA. The applied SA could be briefly introduced as follows: It starts with an initial solution, each solution of the current iteration, and for each particle a neighbor solution is generated. In the proposed SA, a neighbor solution N^i is generated by changing the RK value of the one randomly chosen dimension in the sequence of candidate particle. Let $Dist(x^i)$ and $Dist(N^i)$ denote the distance values of the current solution and the neighbor solution, respectively, and define Δ as the difference between these distances; that is $\Delta = D(x^i) - D(N^i)$. If $\Delta \leq 0$ the neighbor solution is accepted; otherwise it is accepted with probability equal to $e^{-\Delta/T}$, where T is the temperature parameter such that $T > 0$. At the beginning, the temperature is set at the initial temperature T_0. Then T is decreased after generations according to the formula $T=\alpha\times T$, where α is the coefficient controlling the cooling schedule (0<α<1). The procedure is repeated until a stopping criterion is met. The overall procedure of SA algorithm is outlined in Figure 6.

Procedure Simulated annealing
$T = T_0$
while termination criterion is not satisfied **do**
    $k \leftarrow U(1,n)$
    $\gamma \leftarrow U(0,1)$
    $N_k^i \leftarrow \begin{cases} 1 & if\ \gamma \geq 0.5 \\ 0 & if\ \gamma < 0.5 \end{cases}$
    if $D(N^i) < D(x^i)$
        $x^i \leftarrow N^i$
    else
        $\Delta \leftarrow D(x^i) - D(N^i)$
        if $rand < e^{-\Delta/T}$
            $x^i \leftarrow N^i$
        end if
    end if
    $T \leftarrow \alpha \times T$
end while

Figure 6. Procedure of local search heuristic. *Source*: Research Findings

7 Computational Experiments

This section gives experimentation results on the performance of proposed MOEM. Also, the performance of the MOEM is compared with two well-known multi-objective genetic algorithms in the literature, i.e. NSGA-II and SPEA-II. In the first step, the parameters of MOEM are tuned. Then, using a set of small size problems, the general performance of all algorithms in comparison to optimal solution obtained, is evaluated by solving ILP model with applying ε-constraint method. Finally, through experiment with large size problems, the performance of the tested algorithms is comparatively evaluated. All algorithms are coded in MATLAB and executed on an Intel® Core 2 DuoE4500 at 2.20 GHz with 2.0GB of RAM.

7.1 Ɛ-Constraint Method

ε-constraint method is introduced by Haimes (1971) and extensively discussed by Chankong & Haimes (2008). In this method, all but one objective, are converted into constraints by setting an upper or lower bound to each of them, and only one objective is to be optimized. The multi-objective problem like (13) is transformed as (14):

$$Min\left\{\boldsymbol{f}(\boldsymbol{x}) = \left(f_1(\boldsymbol{x})\right), f_2(\boldsymbol{x})), \dots, f_K(\boldsymbol{x}))\right\} \quad x \in S \tag{13}$$

$$Min\ f_m(\boldsymbol{x})$$
$$x \in S$$
S.T.
$$f_k(\boldsymbol{x}) \leq \epsilon_k, \quad \forall k \in \{1,2, \dots K\} \backslash m \tag{14}$$

7.2 Test Problems and Parameter Setting

Data required for a problem consist of a number of investment domain (*M*), number of projects (*N*), score of domain j on each criterion (S_{jk}), expected return of each project (μ_i), expected risk of each project (R_i), proportion of bank assets that needs to invest on each project (α_i), minimum proportion of bank assets that must be held on domain (β_j), and matrix of relation between projects and domains (γ_{ij}). Size of the problem is dependent on number of domains and projects, which are considered in different values. γ_{ij} is generated as a binary matrix which contain only one value in each row. Other parameters are randomly generated by uniform distribution as follows[1]:

$$\mu_i \sim U(0.5,4), R_i \sim U(0.1,0.9), \alpha_i \sim U(0.01,0.1), \beta_j \sim U(0.08,0.2) \tag{15}$$

The quality of algorithms is significantly influenced by the values of their parameters. In order to determine appropriate values for the parameters required by MOEM, separate extensive experiments with different set of parameters to study the behavior of the proposed algorithm are performed.

[1] All data created during this research will be available for interested readers through correspondence with the authors.

There are four parameters that should be set in MOEM, population size, number of local search, cooling rate (α), and initial temperature (T_0). In this study, the T_0 is determined by the following empirical equation:

$$T_0 = -\frac{f_{max} - f_{min}}{\ln(0.1)} \quad (16)$$

where f_{max} and f_{min} are the maximum and minimum objective function values of the initial population, respectively. The different values considered for remained parameters are shown in Table 1. Experiment instances are randomly generated by varying the total number of domains and projects (i.e. (m,n)= (5,20), (10, 40), (15, 60), (20,80), (30, 120)). For each size ten instances are generated for a total of 150. All the data for experiments are generated by the simulation method.

Table 1
Experimental Parameters of MOEM

Parameters	Level 1	Level 2	Level 3
Population size	50	70	100
Number of local search	10	20	30
Cooling rate (α)	0.98	0.95	

Source: Research Findings

Statistical experiments are carried out by means of a Design of Experiments (DOE) (Montgomery, 2006). Confidence level is selected as %95 in this study. Based on these experiments the following values are considered: the initial population size is set to 70. In addition, the number of local search, and the cooling rate are set to 20, 0.95, respectively.

7.3 Computational Results

In order to make a fair comparison between algorithms, CPU time is chosen as a stopping criterion. The computational time limit for all meta-heuristics is calculated according to N×Ω, where Ω is a constant coefficient. While different limits could be obtained by different values of Ω, the preliminary tests indicated its proper amount as 0.2.

Two sets of the test problems are considered. The first set consists of 7 classes of problems called small problems, and each class contains 10 randomly generated problem instances. Therefore, 70 problem instances are considered for the small size problems. The problems are described by providing the number of domains (N) and the number of related projects (M)

in Table 2. The algorithms are replicated five times on each one of the instances. In small size, the comparisons of algorithms are made in terms of the solution quality. The computational results of these tests are summarized in Table 3. In this table, the solution quality of each objective is measured by average gap of two objectives given in equations (1) and (2) between the optimal solution and the results obtained by algorithms. The optimal solution is obtained by ε-constraint method.

To be more specific average gap is computed as follows:

$$Gap_{f_i} = \sum_{r=1}^{R} \left(\frac{Method_{Sol} - Opt_{Sol}}{Opt_{Sol}} \times 100 \right) / R \tag{17}$$

where $Method_{Sol}$ is the value of the objective function f_1 and f_2 found by any of algorithms (i.e., MOEM, NSGA-II, and SPEA-II), and Opt_{Sol} is the corresponding optimal solution obtained by solving MILP model, and R is total number of replications. In order to solve proposed ILP model, the CPLEX solver in GAMS is used.

As seen in Table 2, the MOEM has the best performance with the average gaps of 4.74, 5.36, and 5.03 in for f_1, f_2 and f_3 respectively. The average gaps of the results of MOEM for f_1, f_2 and f_3 are less than the results obtained by SPEA -II and NSGA-II. Also, in order to show difference between algorithm, the significance level (with alpha= 0.05) are tested. The results for p-value are obtained according to the last row in Table 3. The result shows that there is significant difference between MOEM and other algorithm, specifically in third objective.

Table 2

Small Size Problems and CPU Times

Problem Class	**Number of Domains**	**Number of Projects**	**Average CPU time of GAMS (s)**
S1	5	20	2.71
S2	10	40	7.24
S3	10	60	15.35
S4	15	70	95.86
S5	15	100	112.52
S6	20	120	366.02
S7	20	150	441.17

Source: Research Findings

Table 3

Comparison Results for Small Size Instances

Problem Class	Average Gap for f_1(%)			Average Gap for f_2(%)			Average Gap for f_3(%)		
	MOEM	NSGA-II	SPEA-II	MOEM	NSGA-II	SPEA-II	MOEM	NSGA-II	SPEA-II
S1	0.90	1.74	1.28	1.34	1.17	1.10	1.21	2.38	0.32
S2	2.32	3.91	2.77	3.75	0.91	2.06	1.12	3.88	1.88
S3	3.12	5.55	2.31	2.08	1.71	2.76	2.56	3.69	2.54
S4	5.18	7.39	3.40	5.25	5.03	3.89	5.94	7.82	8.10
S5	4.90	7.93	9.08	5.57	7.05	6.84	5.23	8.91	10.93
S6	6.64	12.14	9.76	8.93	13.86	12.55	8.49	12.80	6.07
S7	10.13	13.89	13.76	10.63	10.02	11.52	10.65	15.96	12.91
Average	4.74	7.51	6.05	5.36	5.68	5.82	5.03	7.92	6.11
p-value	0.043	0.061		0.033	0.056		0.014	0.045	

Source: Research Findings

Because the developed algorithm is applicable to solve bank project portfolio selection in real-world instances, another experiment is executed for large-sized problem. The second set called large size problems includes 8 classes of problems. Table 4 reports the parameters of these classes. Each class of this set contains 10 randomly generated problems, and a total of 80 problem instances are considered as large size problems. In the experiments, each problem instance is solved by each algorithm in five replication runs. To validate the accuracy and the diversity of the proposed MOEM, the following comparison metrics are used.

1) Error ratio: This metric measures the non-convergence of the algorithms towards the real Pareto optimal frontier. The Error ratio is defined as follows:

$$ER = \frac{\sum_{i=1}^{N} e_i}{N} \quad (18)$$

where, N is the number of non-dominated solutions found, and

$$e_i = \begin{cases} 1 & \text{if the solution i belongs to Pareto front} \\ 0 & \text{Otherwise} \end{cases}$$

The closer this metric is to 1, the less the solution has converged towards the Pareto optimal frontier.

2) Spacing metric: Spacing metric is used to provide a measure of uniformity of the spread of non-dominated solutions. This metric is given by equation (19).

$$SM = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\bar{d} - d_i)^2} \quad (19)$$

Where

$$d_i = \min_{j \in NDS \wedge j \neq i} \sum_{k=1}^{K} \left|F_k^i - F_k^j\right| \quad (20)$$

and $\bar{d}$ is the mean of all d_i, n is the size of obtained non-dominated solutions and F_k^i is the function value of the k^{th} objective function for solution i. The lower values of the SM are preferred.

3) Diversification metric: The spread of the tradeoff surface is measured by this metric. Its definition is the following:

$$D = \sqrt{\sum_{l=1}^{L} max\left(\left\|S_l - S_l'\right\|\right)} \quad (21)$$

where $\left\|S_l - S_l'\right\|$ is the Euclidean distance between the non-dominated solution S_l and S_l'.

Table 4

Large Size Problems and CPU Times

Problem Class	**Number of Domains**	**Number of Projects**
LS1	25	200
LS2	25	250
LS3	30	300
LS4	30	350
LS5	35	400
LS6	35	450
LS7	40	500

Source: Research Findings

Table 5 reports the related computational results for large size problem instances. The results show that the three algorithm have similar and good performance in error ratio. Moreover, the finding resulted from algorithms' implementations indicate that the proposed algorithm provides non-dominated solutions that have less average values of the spacing metric. The results reveal that the proposed MOEM can achieve a greater number of Pareto optimal solutions with higher qualities than NSGA-II.

Table 5
Comparison results for large size instances

Problem Class	Error ratio			Spacing metric			Diversification metric		
	MO EM	NSG A-II	SPE A-II	MO EM	NSG A-II	SPE A-II	MO EM	NSG A-II	SPE A-II
50	0.11	0.06	0.13	2.28	2.44	3.20	7.64	6.46	7.28
80	0.05	0.06	0.10	2.50	2.18	3.23	9.07	7.02	10.66
100	0.17	0.12	0.25	3.25	2.98	5.01	13.0	8.74	14.75
120	0.03	0.20	0.21	3.67	2.98	5.08	14.3	11.81	13.07
150	0.15	0.29	0.36	5.69	5.98	7.81	11.2	11.52	13.40
200	0.28	0.14	0.35	5.17	5.36	6.27	14.3	11.49	13.25
250	0.12	0.26	0.41	6.12	8.22	11.27	18.5	14.25	15.90
300	0.29	0.36	0.38	4.35	8.78	8.85	21.7	17.27	22.55
Average	0.15	0.18	0.2	4.13	4.86	6.34	13.7	11.07	13.86

Source: Research Findings

8 Conclusion

In this paper, we deal with the project portfolio selection of Iranian banks considering Resistive Economy (RE) criteria. This problem is considered as a three-objective case that maximizes expected benefits, minimizes expected risk, and maximize the satisfaction of RE criteria. In order to select the RE criteria which have to be satisfied through bank investment, the factor analysis is used. Then the weight of each criterion is determined by entropy weight method. The problem is formulated as an integer linear programming. Furthermore, a Multi-objective Electromagnetism-like algorithm, namely MOEM, is developed to solve this NP-hard problem. The proposed MOEM approach uses a random key scheme to encode solutions. Also, the local search heuristic based on simulated annealing algorithm is included within the algorithm to further enhance the exploitation of the MOEM. The parameters associated with the proposed algorithm are tuned to ensure that the algorithm performs in a high quality. To investigate the effectiveness of proposed approach, computational experiments are conducted and the results are compared with two well-known multi-objective genetic algorithms, i.e. NSGAII and SPEA-II. The results clearly show that the MOEM significantly outperforms the above mentioned algorithms. The data regarding the randomly generated instances are accessible through correspondence with the authors. For further research three areas are proposed: first is adding other real-world constraint such as consideration of uncertainty in the problem. Second is changing the proposed model and algorithm to a multi-period one, and third could be the extension of proposed algorithm to solve other multi-objective problem.

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