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Loans Portfolio Optimization of Commercial Banks using Genetic Algorithm: A Case Study of Saudi Arabia

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Abstract

This study aims at testing the optimal mechanism of bank lending decisions using artificial intelligence techniques. It is based on a sectoral diversification strategy to minimise risk and maximise return of credits facilities portfolio and support bank managers in their decision making. In this context, we suggest a dynamically self-regulating method to optimise the bank lending decisions, by the application of the meta-heuristic approach represented by genetic algorithms optimization. It has been used and improved in more recent empirical studies; the method has become a hot research topic. The reason for choosing GA is its convergence and flexibility in solving multi-objective optimization problems, such as credit assessment, portfolio optimization, and bank lending decision. Furthermore, we have also used Markowitz model to construct a mean-variance optimization problem, based on estimate expected return and risk. Finally, the optimal loans portfolio, among 11 economic activity sectors in the Kingdom of Saudi Arabia during the period 1998-2020, has been selected. We have also compared the results of the genetic algorithm with the classic Markowitz model in its static form.

Keywords: Credit Risks, Optimal Loans Portfolio, Return & Risk, Sectoral Diversification, Genetic Algorithms optimization

Introduction

Nowadays, bank lending is characterised by a steady increase in demand for credit resources, while increasing the share of overdue debt in the bank's credit portfolio. Credit operations are one of the main activities of the bank and contribute a significant part to its income. The reliability and financial stability of banks depend on the composition and structure of the credit portfolio, as well as the adequate management process. Regarding this, the design of a high-quality credit portfolio structure that is directly related to the credit risk level is a priority for any bank (Orlova, 2020). Therefore, a lot of contemporary studies have focused their attention on how to manage banking risks, control them, and make investment and financial decisions in the light of strict regulations, and administrative systems and methods that ensure the bank to define and accurately assess these risks, classify, and measure them. Appropriate decisions can be taken to reduce the risks. Banking risks management using traditional ways, according to the requirements of the new Basel banking standards (Basel I, II, III), credit risk insurance, credit rating systems and its role in mitigating and controlling credit risk, Credit-Scoring (Z-Score), credit derivatives, and the Tobin's Q equation, were adopted.

Consequently, our research paper is the justification and development of new techniques and models for the management of bank lending that reduces credit risks and increases the efficiency of bank lending decisions effectively. The success of any bank in this very competitive lending environment depends largely on the way and manner in which the loan portfolio of the banks is managed. So, lending to firms is the basic business activity for every commercial bank. This means portfolio management is the most important activity for getting maximum returns and minimum risk from bank

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loans. It is an indisputable fact that most banks operating in the world are faced with the complex problem of how to manage their loans portfolio in such a manner that the goals of the bank are best achieved (Gupta, 2018).

Recently, the optimization problems we faced have become more complicated. In many cases, we need to consider several conflicting objectives and satisfy a variety of conditions. Such problems can be modelled as multi-objective optimization problems (MOPs) (Jiaxu Ning et al., 2018). Some methods based on artificial intelligence, such as genetic algorithm, have been applied to overcome this problem. GAs are stochastic, heuristic techniques based on the natural selection principles, and they can deal with nonlinear optimization problems with non-smooth and even non-continuous objectives, and continuous and/or integer variables (Lin et al., 2005). So, our search results will try to answer the following question.

- *How do genetic algorithms perform better, compared to traditional approaches for loans portfolio optimization?*

Research Background

Computational finance is an emerging application field of meta-heuristic algorithms. In particular, these optimization methods are becoming the alternative when dealing with realistic versions of several decision-making problems in finance, such as rich portfolio optimization and risk management. In order to better understand this, we present some recent studies on our research.

The researcher El Hachloufi Mostafa (2013), in his study, used the genetic algorithms and the model of Markowitz to solve portfolio optimization for loans in Islamic banks, using the Islamic financing formulae like speculation and murabaha, and concluded, through simulation results, that financing in the form of murabaha is less risky than speculation.

The study conducted by Misra (2013) has built portfolio with mean-variance dominating, for both AAA rating and AA rating. The GA technique was applied to a leading bank in India. The portfolio, designed as per Indian Banking Regulations, has outperformed the current portfolio of the bank. This model can be further improved if optimization is also done inside each asset class, taking into account the credit class of each asset.

Majid Abdolbaghi and All (2013) presented research, which was done in the framework of the granted facilities. The paper covers one of the commercial banks, from 2010 to 2012, and studies the effective interest rate, dishonoring rate of the granted facilities within the format of Islamic contracts in different sections, and determines the real portfolio of granting facilities. It then determines the optimum facilities portfolio using the multi-purpose genetic algorithm. The findings show that the resulting optimum facilities portfolio is different from the current portfolio of the bank, and can be tackled with different limitations and policies in granting facilities. They also indicate that the effective interest rate and the degree of efficiency of facilities based on the presented model are higher than those of the current facilities portfolio.

The researcher Bushra Abdullah Sht (2014), has used genetic algorithms to choose the best borrowers to avoid the risk of non-payment of loans (credit risk), relying on the bank's database; it contains a set of characteristics of each borrowed customer and from it simulation of genetic algorithms arranges the granted loans according to the return and risk system.

The main contribution of the paper by Roxana Fekri and Al (2016) 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 maximisation and risk minimisation, while focusing 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 tests are performed. The MOEM results are compared with two well-known multi-objective genetic algorithms in literature, i.e. Non-dominated Sorting Genetic Algorithm (NSGA-II) and Strength Pareto Evolutionary Algorithm (SPEA-II) based on some comparison metrics. In addition, these algorithms are compared with an integer linear programming formulation for small instances. Computational experiments indicate the superiority of the MOEM over existing algorithms.

The researchers Noura Metawa and Al (2017) developed a GA model that facilitates how banks would make an efficient decision in case of a cutback on lending supply when faced with a negative liquidity shock, while staying focused on the main objective of bank profit maximisation. The proposed model is tested using both simulated and real data. The results show that the proposed GA model greatly increases bank profit using the suggested lending decision in the case of real data. For future research, we suggest using this GA model for loan portfolio optimization using small and medium business customers, instead of regular customers.

Portfolio Optimization - A Theoretical Perspective

Portfolio optimization is one of the most challenging problems in the field of finance. Selecting the weights of assets to invest in a portfolio to meet the expectations about risk and returns makes this problem crucial. In dealing with this problem, Harry Markowitz (1952) developed a quantitative model in its static and dynamic form, also called mean-variance model within multi-objective optimization problems form (MOP), respectively (S. Slimane & M. Benbouziane, 2012). Although Markowitz's theory uses only mean and variance to describe the characteristics of returns, his theory about the structures of a portfolio became a cornerstone to modern portfolio theory (Fama, 1970; Hakansson, 1970; Hakansson, 1974; Merton, 1990; Mossin, 1969).

Mathematical Model of Markowitz

Consider a more general case with n risky securities. Notations: for i = 1, ..., n

W= $(w_1, \dots, w_n)$: is the vector of portfolio weights.

R= $(R_1, \dots, R_n)$: is the vector of asset returns.

$\bar{R}$= $(\bar{R}_1, \dots, \bar{R}_n)$: is the vector of asset returns expectations.

e= $(1, \dots, 1)$: is the vector with all components equal to 1.

V = $[\sigma_{ij}]_{1 \le i,j \le n}$: is the $(n \times n)$ variance-covariance matrix of returns. The matrix V is supposed to be invertible.

Á is the vector deduced from transposition of the vector **A**. For each given expected return, we have to determine the minimal variance portfolio.

Therefore, following the Markowitz approach to determine optimal weights of portfolio, we have to determine the set of portfolios which minimise the variance for given expected returns. This leads to the following quadratic optimization problem (Jean-Luc Prigent, 2007).

$$\left\{ \begin{array}{c} \text{Min } w' \; V w, \\ \text{with } w' \; \bar{R} = \mathbb{E}[R_P], \\ w' \; e = 1 \end{array} \right\} \qquad (1)$$

The first constraint corresponds to the fixed expectation level. The second constraint is simply that w is a vector of weights. However, short-selling is allowed and no other specific constraints are introduced.

The expected return of any portfolio P with weights *w* is given by:

$$\mathbb{E}[R_P] = \sum_{i=1}^{n} w_i \mathbb{E}[R_i] = w.\bar{R}' \qquad (2)$$

The variance of the return of P is equal to:

$$\sigma^2(R_P) = w' \; V w = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n}\sum_{j=i+1}^{n} w_i w_j \sigma_{ij} + \sum_{i=1}^{n} w_i^2 \sigma_i^2 \qquad (3)$$

The previous relation shows the decomposition of the variance of the portfolio returns into two components. This relation proves that the marginal contribution of a given asset to the risk of the whole portfolio is not reduced to its own risk (its variance), but also takes account of its potential correlation to other securities. This latter property induces the diversification effect.

From equation 2, the partial derivative with respect to any weight $\boldsymbol{w_i}$ is deduced as:

$$\frac{\partial \sigma^2(R_P)}{\partial w_i} = 2 \sum_{j=1}^{n} w_i \sigma_{ij} \qquad (4)$$

σ_{iP} is the correlation coefficient between asset i and portfolio P. Then:

$$\sum_{j=1}^{n} w_j \sigma_{ij} = \sum_{j=1}^{n} w_j \, Cov(R_i, R_j) =$$

$$Cov\left(R_i, \sum_{j=1}^{n} w_j . R_j\right) = Cov(R_i, R_j) = \sigma_i P \qquad (5)$$

And, finally:

$$\frac{\partial\sigma^2(R_P)}{\partial w_i} = 2\sigma_i P. \qquad (6)$$

Genetic Algorithm Specifications

Genetic algorithms are implemented in a computer simulation environment in which a population of abstract representations (called chromosomes or the genotype of the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves towards better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated; multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. The conception of the new population is made by applying the genetic operators, which are selection, crossover, and mutation (Randy L. Haupt et al., 2004).

- *Selection*: The new individuals selection is made as follows. Calculate the reproduction probability for each individual.

$$P_i = \frac{f_i}{\sum_{i=1}^{n} f_i}$$

Where, f is the fitness of the individual i (a fitness function is needed to evaluate the quality of each candidate solution with regard to the task to be performed); n is the size of the population. Each time a single chromosome is selected for the new population. This is achieved by generating a random number *r* from the interval [0, 1]. If *r* P_1, then select the first chromosome, otherwise select the i^{th} chromosome, such as

- *Crossover:* The crossover operator is as follows. Population resulting from selection is divided into two parts. Each pair formed will undergo the crossover with a certain probability P_c. Many different types of crossovers exist in literature; for example, single point crossover, two-point crossover, and arithmetic crossover.
- *Mutation:* The individuals in the population after crossover will then undergo a process of mutation; this process is to randomly change some bits, with a certain probability m P. Genetic algorithms are more flexible than most search methods because they require only information concerning the quality of the solution produced by each parameter set (objective function values) and not like many optimization methods, which require derivative information, or even more, complete knowledge of the problem structure and parameters (Bouktir et al., 2004).

There are some differences between GAs and traditional searching algorithms (Augusto et al., 2006). They could be summarised as follows:

- They work with a coding of the parameter set and not the parameters themselves;
- They search from a population of points and not a single point;
- They use information concerning payoff and not derivatives or other auxiliary knowledge;
- They use probabilistic transition rules and not deterministic rules.

Descriptive Data Analysis

We seek to determine the optimal weights for the banking credit portfolios in Saudi Arabia for a period of 22 years (1998-2020) using SAMA (Saudi Arabian Monetary Authority) database. Therefore, we will present the statistical characteristics of our time series of database that have been selected. It includes 11 economic activity sectors (agriculture and fishing, manufacturing and processing, mining and quarrying, electricity, water, gas and health services, building and construction, commerce, transport and communications, finance, services, miscellaneous, and government and quasi govt.). For simplicity, we calculated the following historical returns of assets. The portfolio average return and the portfolio variance are estimated using these historical data.

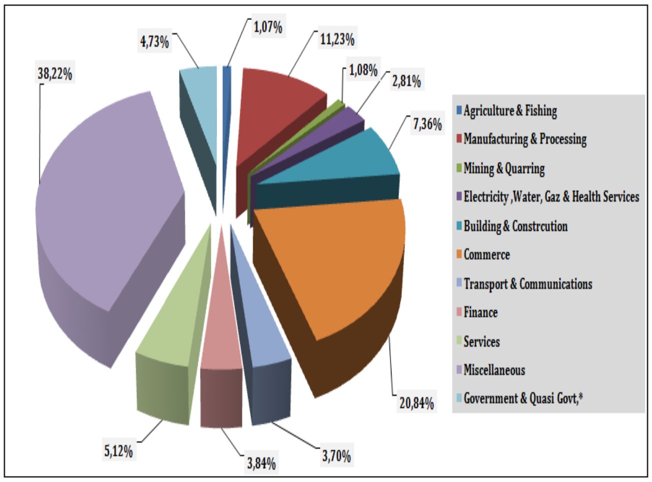

Fig. 1: Distribution of Bank Credit Classified By Economic Activity (%)

Before applying the genetic algorithms, we calculated the requirements for using the model of Markowitz in credit current portfolio like value of mean-variance, standard deviation of returns for each asset, and the coefficient of correlation between returns. Moreover, we will develop an idea about the possibility of the success of the investment diversification process for portfolio optimization. It is shown in Table 1, 2, and 3.

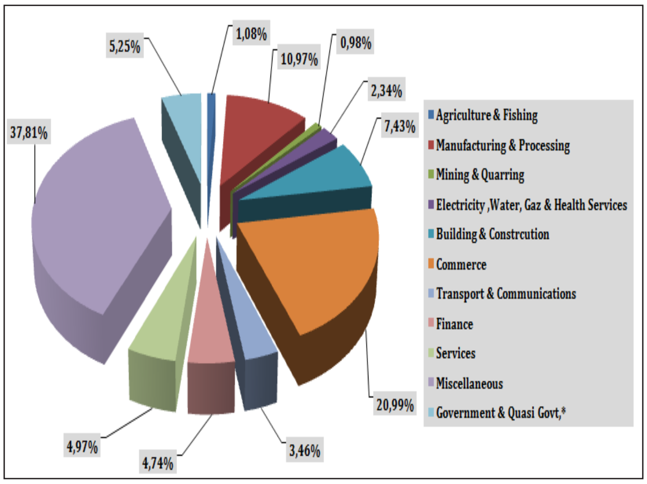

Fig. 2: Distribution of Assets Return of the Banking Loans Portfolio (%)

Table 1: The Mean and Standard Deviation Returns for Each Asset (Million/SAR)

	Credit1	*Credit2*	*Credit3*	*Credit4*	*Credit5*	*Credit6*	*Credit7*	*Credit8*	*Credit9*	*Credit10*	*Credit11*
Mean return ri	4044,07	41102,84	3654,54	8759,24	27855,54	78659,16	12951,05	17767,12	18638,53	141701,63	19679,13
St. dev.	125,81	1107,01	141,65	430,94	674,35	2118,81	333,67	889,01	534,50	4475,24	541,09

Table 2: The Variance-Covariance Matrix

	Credit1	Credit2	Credit3	Credit4	Credit5	Credit6	Credit7	Credit8	Credit9	Credit10	Credit11
Credit1	15140,57	107519,14	10872,74	30882,76	71831,52	235711,31	34025,11	77892,12	52347,35	481359,07	50439,78
Credit2	107519,14	1172187,85	139451,02	395476,96	664466,53	2121696,84	306023,16	299687,59	555554,07	4484241,80	371942,62
Credit3	10872,74	139451,02	19193,95	55647,92	70688,19	231047,60	34097,55	15319,00	67150,65	539980,11	34257,66
Credit4	30882,76	395476,96	55647,92	177642,30	186796,81	648014,02	103951,49	20711,89	194124,19	1623561,36	76930,22
Credit5	71831,52	664466,53	70688,19	186796,81	434987,31	1329412,02	171632,89	329106,30	318396,95	2596760,02	299897,02
Credit6	235711,31	2121696,84	231047,60	648014,02	1329412,02	4294175,97	579040,51	998219,66	1016703,44	8595005,86	880217,83
Credit7	34025,11	306023,16	34097,55	103951,49	171632,89	579040,51	106500,82	87157,40	147778,57	1265692,17	90928,71
Credit8	77892,12	299687,59	15319,00	20711,89	329106,30	998219,66	87157,40	755981,43	161015,62	1746573,69	349219,04
Credit9	52347,35	555554,07	67150,65	194124,19	318396,95	1016703,44	147778,57	161015,62	273273,55	2186536,74	187920,79
Credit10	481359,07	4484241,80	539980,11	1623561,36	2596760,02	8595005,86	1265692,17	1746573,69	2186536,74	19157031,15	1549193,78
Credit11	50439,78	371942,62	34257,66	76930,22	299897,02	880217,83	90928,71	349219,04	187920,79	1549193,78	280051,09

Table 3: The Correlation Matrix

	Credit1	*Credit2*	*Credit3*	*Credit4*	*Credit5*	*Credit6*	*Credit7*	*Credit8*	*Credit9*	*Credit10*	*Credit11*
Credit1	1	0,8071	0,6378	0,5955	0,8851	0,9244	0,8473	0,7281	0,8138	0,8938	0,7746
Credit2	0,8071	1	0,9297	0,8667	0,9305	0,9457	0,8661	0,3184	0,9816	0,9463	0,6492

	Credit1	*Credit2*	*Credit3*	*Credit4*	*Credit5*	*Credit6*	*Credit7*	*Credit8*	*Credit9*	*Credit10*	*Credit11*
Credit3	0,6378	0,9297	1	0,9530	0,7736	0,8048	0,7542	0,1272	0,9272	0,8905	0,4673
Credit4	0,5955	0,8667	0,9530	1	0,6720	0,7419	0,7558	0,0565	0,8811	0,8801	0,3449
Credit5	0,8851	0,9305	0,7736	0,6720	1	0,9727	0,7974	0,5739	0,9235	0,8996	0,8592
Credit6	0,9244	0,9457	0,8048	0,7419	0,9727	1	0,8562	0,5540	0,9385	0,9476	0,8027
Credit7	0,8473	0,8661	0,7542	0,7558	0,7974	0,8562	1	0,3072	0,8662	0,8861	0,5265
Credit8	0,7281	0,3184	0,1272	0,0565	0,5739	0,5540	0,3072	1	0,3543	0,4590	0,7590
Credit9	0,8138	0,9816	0,9272	0,8811	0,9235	0,9385	0,8662	0,3543	1	0,9556	0,6793
Credit10	0,8938	0,9463	0,8905	0,8801	0,8996	0,9476	0,8861	0,4590	0,9556	1	0,6688
Credit11	0,7746	0,6492	0,4673	0,3449	0,8592	0,8027	0,5265	0,7590	0,6793	0,6688	1

Mean-Variance Portfolio Optimization using GA

In this part, the portfolio optimization calculations are done. Portfolio optimization was carried out with equation 1, using genetic algorithm optimization. In order to solve equation 1, we applied the GA proposed by Holland in 1975. The GA initially generates a random value of 'gen' w within a certain interval, which is associated in a 'chromosome'. This algorithm allows the competition between each chromosome, which brings each potential solution to the optimization problem. A set of chromosomes called 'population' are produced; hence, an iteration (generation) is performed to determine the fittest parameters of the 'objective function'. In this case, equation 1 is the objective function.

The generation process consists of evaluating the 'fitness function' adapted to create a new population, until the optimum chromosomes have been addressed. This operation is made by setting the genetic operator; number of population and chromosome are 100 and 11 variables, number of generation is 200, the crossover and mutation rates are set at 0.25.

Since we wanted to maximise the objective function, we adopted the 'roulette-wheel' selection, where w_i is the new individual of each w and f is the fitness value for each individual; n is the size of population. In this case, we applied a random crossover and mutation algorithm, which has a probability of 0.25, for each gen in the chromosomes to be crossed over or mutated.

The data used for process optimization are the values of the mean and variance. They are given in Table 1 and Table 2. We defined the fitness function to evaluate the right solution as follows.

$$fitness\ function = \frac{\sigma_p}{R_p}$$

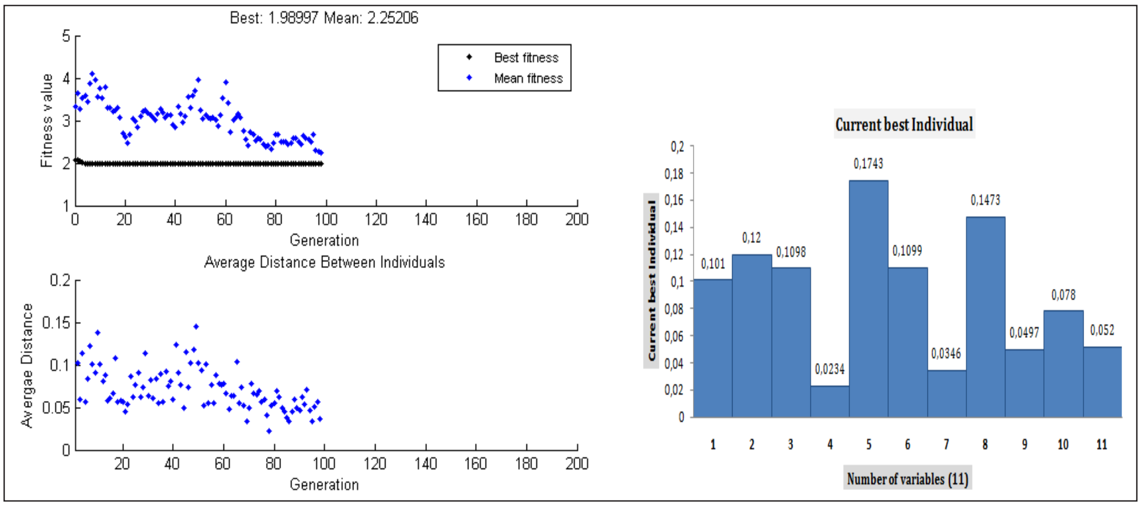

Fig. 3: The Variation of the GA Functions According to Generation under the Arithmetic Crossover Procedure

In general, the best fitness gives us an idea of the algorithm's performance or of the most optimal solutions. So in our case, a good solution will have a low value of fitness function, whereas a bad solution will have a high value (the equations 2 and 3 are used to estimate risk-return of loan optimal portfolio).

The results simulation from using MATLAB for each crossover procedure can be seen in Fig. 3 and Table 4; it illustrates the functions of genetic algorithm simulation results obtained via crossover procedures.

Results and Discussions

The performance of different optimization methods (Markowitz and GA optimization) are compared, as seen in Fig. 3 and Table 4. For the application of the GA, an objective function (fitness function) was formulated to evaluate the crossover procedure that scored less on the fitness scale, and consequently which would lead to the optimal portfolio.

The results show that the arithmetic crossover procedure gives best results (Best = 1.9899) and the arithmetic procedure should lead to the best choice of weights (w_1 = 0.1010%, w_2 = 0.1200, w_3 = 0.1098%, w_4 = 0.0234%, w_5 = 0.1743%, w_6 = 0.1099%, w_7 =0.0346, w_8 = 0.1473%, w_9 = 0.0497%, w_{10} = 0.0780%, and w_{11} = 0.0520%); and thus producing the optimal portfolio with a highest return of 0.79% and lowest risk of 1.58%.

This time, the genetic algorithm makes progress, but because the average distance between individuals is so large, the best individuals are far from the optimal solution.

As illustrated in Fig. 3, the GA can converge towards the optimal solution in a very short time: 3.3 seconds for the single point.

Table 4: A Performance Comparison between Markowitz Optimization and GA Optimization

Asset Class	*Markowitz Optimization Weight (%)*	*GA Optimization Weight (%)*
Agriculture and Fishing	0.1020	0.1010
Manufacturing and Processing	0.1100	0.1200
Mining & Quarrying	0.1088	0.1098
Electricity ,Water, Gas and Health Services	0.1254	0.0234
Building & Construction	0.0743	0.1743
Commerce	0.1079	0.1099
Transport and Communica-tions	0.1346	0.0346
Finance	0.0473	0.1473
Services	0.0597	0.0497
Miscellaneous	0.0680	0.0780
Government & Quasi Govt.	0.0620	0.0520
Optimal Portfolio Risk [σP] (%)	1.71	1.58
Optimal Portfolio Return [RP] (%)	0.091	0.79

The results show that the Markowitz optimization gives poorer results (optimal weights w_1 = 0.1020%, w_2 = 0.1100%, w_3 = 0.1088%, w_4 = 0.1254%, w_5 = 0.0743%, w_6 = 0.1079%, w_7 = 0.1346%, w_8 = 0.0473%, w_9 = 0.0597%, w_{10} = 0.0680, and w_{11} = 0.0620%); thus producing the optimal portfolio with a lowest return of 0.091% and highest risk of 1.71%.

Conclusion

In this paper, we have proved that under conditions of growing demand on credit resources in the economics of Saudi Arabia, during the period 1998-2020, credit risk management system is vital. This period was characterised by crisis on all economic activities, like the financial crisis of 2008, Greece debt crisis 2011, the oil crisis of 2014, and the Covid-19 crisis in 2020. In addition, according to the SAMA database, commercial banks of KSA have estimated the highest amount of non-performing loans (net provisions to capital) in the same period, totalling 4,13,265.035 million Riyals.

In this context, we propose GA to increase the performance of lending portfolio optimization; it becomes a new approach, and the tool has not only theoretical, but also practical importance, to the quality of risk management of the credit portfolio.

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