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Optimization Financial Time Series by Robust Regression and Hybrid Optimization Methods

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ABSTRACT

The optimization problem is the problem of finding the best solution from feasible solution. There are many methods of optimization and there are continuous search for new methods and improve the traditional methods. There is no single method available for solving all optimization problems efficiently and effectively. The common methods for solving the portfolio selection optimization problem are quadratic programming, but it used to solve programming problems with a quadratic objective function and linear constraints. Genetic Algorithm, which is used to solve nonlinear programming problems, where the objective and constraint functions are nonlinear. In this paper, we introduce comparison between many optimization methods to determine the best one for optimization of financial time series. We apply the proposed methodology on the data of the Egyptian Stock Market. The results of the study indicates that the the hybrid optimization method better than genetic algorithm.

Keywords : Financial Time Series, Robust R egression, Multi-collinearity, Linear Regression, Principle Component Regression, Quadratic Programming, Genetic Algorithm, Hybrid Optimization Methods, Modern Portfolio Theory, Egyptian Stock Market.

1 INTRODUCTION

Financial time series analysis is important to study the behavior of the series and ability to predict the movements of it in the future [16]. We have main consider points in our study; analysis the outlier and suggest adequate solver for it, study of multi-collinearity among the stocks and determine the multi-collinearity groups. Defining the most stocks affected on the stock market movement and defining the outstanding stocks. Finally, study of the performance of Hybrid optimization methods.

Abdel Bary introduces approach to put constrains on selection the stocks to construct optimal portfolio. The newly born market and non-efficient have a good advantage that it is possible gain an exception return by studding the market and determines the good chances [15], [16].

Genetic Algorithms (GA) are stochastic search techniques based on the mechanics of natural selection and natural genetics. In this paper, the adaptive genetic algorithms are applied to solve the portfolio construct problem in which there exist probability constraint on lowest rate of the portfolio and highest rate of the risk of the portfolio and lower and upper bounds constraints on the investment rates to assets based on the analysis of the time series of the stocks.

The aim of this work is compare between performance of genetic algorithm and Hybrid optimization methods by using the suggested portfolio frame [15], [16]. The suggested construct of optimal portfolio allow to use non-linear constrain. This approach adequate the non-efficient market. The non-efficient market, there are chance to construct portfolio with rate more than the market rate and the same time rate of risk less than the risk rate of the market while in the efficient market, it is impossible to make rate more than the market rate without increase the risk rate more than the market risk.

So, we introduce structure to construct optimal portfolio adequate the non-efficient stock market. Additionally; we introduce the compare between genetic algorithm and hybrid methods as methods of optimization.

2 LITERATURE REVIEW

It is possible to distinguish three methods of searching for optimal points; analytical or based on calculus method, enumerative method, and stochastic or random method. The analytical methods are among the most common.

This method is essentially a mechanism to find local optimums that is based on the existence of derivatives, been dependent of the searching starting point. The enumerative method is the most effective of all searching methods, but has the problem of been inefficient.

A genetic algorithm is a randomized search procedure working on a population of individuals or solutions. The power of GA comes from the fact that technique is robust, and can deal successfully with a wide range of problem areas, including those which are difficult for other methods to solve (see; [3],

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[6], [8], and [13]). Genetic Algorithms (GAs) are adaptive methods which may be used to solve and optimization problems [1].

Markowitz indicates to that if an investor invests in a portfolio which perfectly positively correlated returns, and then it does not at all lower his risk, because the returns move in only one direction and the investor in such a portfolio can suffer significant losses. In case, portfolio has negatively correlated return, then the returns have an inverse movement [11]. Assets with non-correlated returns create a portfolio in which the returns have no relation to one another.

At the most previous study if is not for all, do not importance with the study of the stocks and the relation between the stocks inter the portfolio. There are rare of the financial studies and especially that consider with the non-efficient market.

Sharp aims at finding the best set of asset class exposures by using of quadratic programming for the purpose of determining a fund's exposures to changes in there turns of major asset classes is termed style analysis [18]. In addition to that, the style identified in such an analysis is an average of potentially changing styles over the period covered. The deviations of the fund's return from that of style itself can arise from the selection of specific securities with in one or more asset classes, or rotation among asset classes, or both stock selection and asset class rotation.

Deng et al consider with the problem of optimal portfolio and equilibrium when the target is to maximize the weighted criteria under the worst possible evolution of the rates returns on the risky assets [7]. The optimal portfolio was analytically presented, which can be obtained using linear programming technique [7].

Mitra et al illustrate that mean-variance rule for investor behavior that implies justification of diversification is affected by risk averse investors [14]. According to Markowitz determining the efficient set from the investment opportunity set, these to fall possible portfolios, requires the formulation and solution of a parametric quadratic program

Portfolio theory was improved after the mid-1980s and it dealt with alternative portfolio selection models such as mean-semi variance model, mean-absolute deviation model, mean-variance Skewness model, and minimal models. Lai et al indicates to use Genetic algorithm (GA) to identify good quality assets in terms of asset ranking [9]. Additionally, investment allocation in the selected good quality asset is optimized using GA based on Markowitz's theory.

Zhang et al discuss the portfolio selection in which there are exit both probability constraint on the lowest return rate of the portfolio and upper bounds constraints on investment rates to assets [19]. Among the studies addressing the issue of portfolio was the study of [10]. This study uses linear programming methods to allocation of the investment that would enable to create an optimal portfolio under an effective investment strategy to prove the inefficiency of the Egyptian Stock Market.

3 METHODOLOGY

3.1 TRADITIONAL PORTFOLIO SELECTION FRAME:

According to Markowitz's theory investors are risk averse and they will create portfolios with the aim of achieving the largest return for the minimum risk. The investor can first set a minimum level of desirable expected return of the portfolio, say μ_{min} then choose the weights to minimize the expected risk of the portfolio. That is,

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \quad (1)$$

Subject to:

$$\sum_{i=1}^{n} \mu_i w_i \geq \mu_{min,} \quad (2)$$

$$\sum_{i=1}^{n} w_i = 1,$$

$$w_i \geq 0, \quad i = 1, 2, \dots, n.$$

Alternatively, the investor can set a maximum level of acceptable risk of the portfolio, say σ^2_{max}, then choose the weights to maximize the expected return on weights to maximize the expected return on the portfolio. That is

$$\max \sum_{i=1}^{n} w_i \mu_i \quad (3)$$

Subject to:

$$\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \leq \sigma^2_{max}, \quad (4)$$

$$\sum_{i=1}^{n} w_i = 1,$$

$$w_i \geq 0, \quad i = 1, 2, \dots, n.$$

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Modern Portfolio Theory defines an efficient frontier of optimal portfolios to be a set of portfolios that maximizes expected return for a given level of risk or that minimizes risk for a given level of return. When the portfolio return equation is solved to obtain the maximum return of the portfolio, the portfolio risk is held constant. An example of a frontier curve is shown in Fig. (1) the area below and to the right of the efficient frontier curve contains various risky assets. The frontier curve gives the portfolios with the maximum rate of return for a given level of risk (measured by the standard deviations of the portfolio's returns).

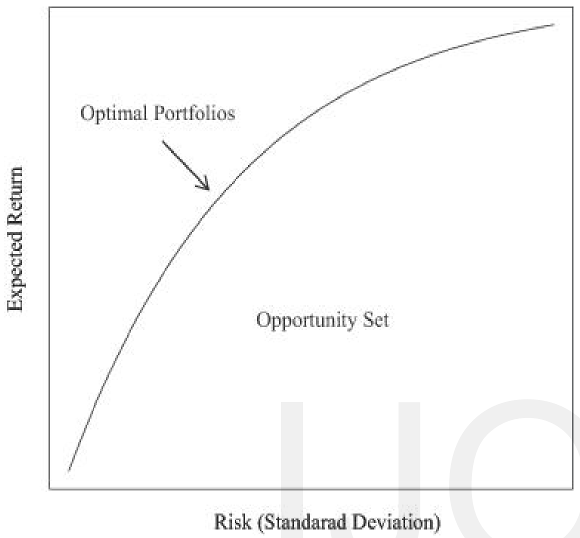

Fig. 1: Frontier Curve

Accordingly, for a given expected return, one can find the weights of the investment by minimizing the variance or standard deviation of a portfolio; or for a given risk level that the investor can tolerate, one can find the weights by maximizing the expected returns of a portfolio.

According to the formulation of the Markowitz mean-variance method, a portfolio is said to be efficient if it has the highest expected return for a given variance, or, equivalently, if it has smallest variance for a given expected return. It should be noted here that the portfolio selection problem can alternatively be formulated as one optimization problem, instead of the two formulations in (1) – (4), as follows:

$$\max(1-\alpha)\sum_{i=1}^{n} w_i\mu_i - \alpha\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \quad (5)$$

Subject to:

$$0 \le \alpha \le 1, \quad (6)$$

$$\sum_{i=1}^{n} w_i = 1,$$

$$w_i \ge 0, \quad i = 1, 2, \ldots, n.$$

where α is a parameter reflecting the investor's risk aversion.

Note here that the constraint in (2) and (4) are now incorporated in the objective function in (5).

We can summer the modern portfolio theory and the most of the previous studies problems in the following points (see; Fig. 2):

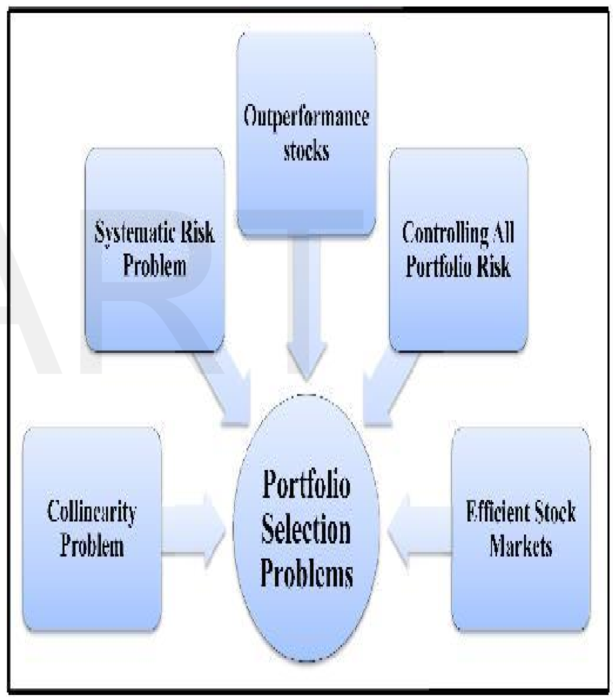

Fig. 2: Prtfolio Selection Problem

The problems of traditional portfolio selection frame:

- It doesn't consider the collinearity among the stocks.
- It doesn't consider systematic risk (active stocks).
- It doesn't consider high performance stocks.
- It doesn't consider controlling overall portfolio risk.
- It assumes efficient stock markets.

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3.2 INTRODUCTION NEW CONSTRAINTS:

We propose an alternative formulation the problem given (5)-(6) by introducing new constraints that take into account the following:

- The collinearity problem to decrease the portfolio risk.
- The special preference of active stocks to avoid the systematic risk.
- The special preference of stocks with outstanding performance to increase the expected return.
- Control the overall risk of the portfolio.

3.2.1 COLLINEARITY PROBLEM:

We need to pay more attention to the problem of collinearity. It has been well-documented that the optimal solutions of the above optimization problems to diversify the investment.

Diversification usually lowers the risk, but the greatest benefits of diversification are realized when the stocks in a portfolio are not highly correlated.

The analysis of all pairwise correlation coefficients is necessary but not sufficient for that detection of collinearity because collinearity can be among a set of variables. One way to detect collinearity and to identify the variables involved is to compute the Eigen values and Eigen vectors of the correlation matrix. Collinearity exists when some of the condition *indices* of the correlation matrix are large. The *i*-th condition index of the matrix is defined as

$$k_j = \sqrt{\frac{\lambda_1}{\lambda_j}}\ , j = 1, 2, \ldots, n \qquad (7)$$

Where λ_i is the j -th largest eigenvalue and λ_n is the smallest eigenvalue of the correlation matrix. An evidence of collinearity in the data is indicated if any of the condition indices exceeds 10 (see, e.g., [2], [4], and [5]).

Suppose then that there are k collinear sets denoted by $C_1, \ldots, C_k$. Then for each of these sets, we add the following constraint to the problem in (5):

$$\sum_{i\in C_j} w_i \ \le\ C_j;\quad j = 1, 2, \ldots, \mathrm{k}. \qquad (8)$$

Where C_j contains the indices of the stocks in the *j*-th collinear set and $C_1 \le C_2 \le \ldots \le C_k$ are constants specified by the investor.

3.2.2 ACTIVE STOCKS:

Active stocks are those that control the movement of the stock market. Not all stocks in the market are active. Since active stocks are risky, the investor may wish to invest less in the set of active stocks when the stock market isn't stable or invest more in it when the stock market is stable. The diversification of the portfolio leads to avoiding the non-systematic risk but doesn't avoid the systematic risk.

Because the active stocks reflect the market activities, we can avoid the systematic risk by putting constraints on this group of stocks. So, to control the sum of portfolio weights in this group of stocks, one can add the following constraint to the problem in (5):

$$\sum_{i\in A} w_i \ \le\ a \qquad (9)$$

where A is the set containing the indices of active stocks and *a* is the maximum investment in the set of active stocks.

3.2.3 HIGH PERFORMANCE STOCKS:

We suggest using the return to risk ratio, that is,

$$R_i = \frac{\mu_i}{\sigma_i} \qquad (10)$$

where μ_i is the expected return of stock i and σ_i is the stock risk (standard deviation). This measure is the inverse of the well-known coefficient of variation. The higher R_i the better the performance of the ith stock. Let H be the set containing the indices of high performance stock. This suggests including the following constraint to the problem in (5):

$$\sum_{i\in H} w_i \ \ge\ h \qquad (11)$$

where *h* is the minimum investment in all high performance stocks.

3.2.4 CONTROLLING THE OVERALL RISK:

Different kinds of investors can tolerate different levels of risk. We can incorporate this observation by controlling the risk of a portfolio through adding the following constraint:

$$\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \ \le r \qquad (12)$$

where *r* is an upper bound to the overall risk.

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By putting all suggested constraints together, **we obtain a new portfolio model** [15], [16]:

$$\max(1-\alpha)\sum_{i=1}^{n} w_i\mu_i - \alpha\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \quad (13)$$

subject to:

$$0 \leq \alpha \leq 1,$$

$$w_i \geq 0, \quad i = 1, 2, \ldots, n,$$

$$\sum_{i=1}^{n} w_i = 1,$$

$$\sum_{i \in C_j} w_i \leq C_j; \quad j = 1, 2, \ldots, k$$

$$\sum_{i \in A} w_i \leq a$$

$$\sum_{i \in H} w_i \geq h$$

$$\sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \leq r$$

where C_j contains the indices of the stocks in the j–th collinear set, A is the set containing the indices of active stocks, and H is the set containing the indices of high performance stock. The constants C_j, a, h, and r are constants specified by the investor.

The last constraint is a non-linear constraint. Hence quadratic programming cannot be used, which leaves us with the genetic algorithm to solve this optimization problem.

3.3 OPTIMIZATION TECHNIQUES:

Optimization is the act of obtaining the best results under given circumstances. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions that give the maximum or minimum a value of a function. It can be seen from Figure (2) that if a point x* corresponds to the minimum value of function *f(x)*, the same point also corresponds to the maximum value of the negative of the function, *-f(x)*.

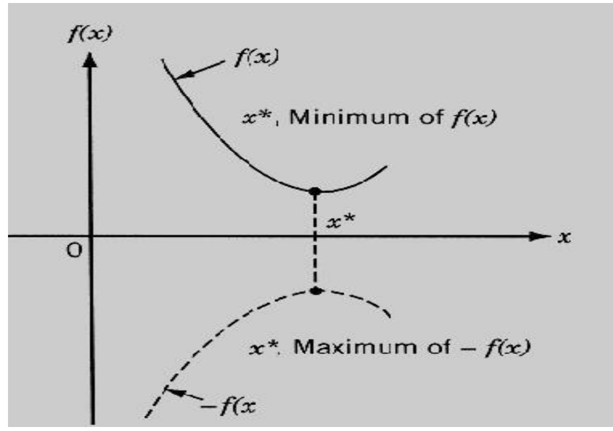

Fig. 3. The minimum of f(x) is same as maximum of -f(x) . Source: [17], p. 2.

Thus without loss of generality, optimization can be taken to mean minimization since the maximum of a function can be found by seeking the minimum of the negative of the same function. In addition, the following operations on the objective function will not change the optimum solution x* as seen from Figure (4).

- Multiplication (or division) of *f(x)* by a positive constant c.
- Addition (or subtraction) of a positive constant c to (or from) f*(x)*.

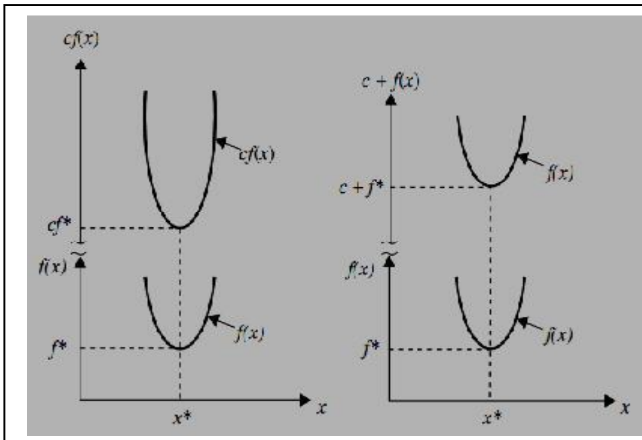

Fig. 4. ***Optimum solution of cf(x) or c+f(x) same as that of (x) . Source: [17], p. 2..***

Fig. 5 shows a hypothetical two-dimensional design space where the infeasible region is indicated by hatched lines. A design point

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that lies on one or more than one constraint surface is called abound point and the associated constraint is called an activeconstraint. Design points that do not lie on any constraint surfaceare known as free points. Depending on whether a particular design point belongs to the acceptable or unacceptable region, it can be identified as one of the following four types: (1) Free and acceptable point. (2) Free and unacceptable point. (3) Bound and acceptable point. (4) Bound and unacceptable point.

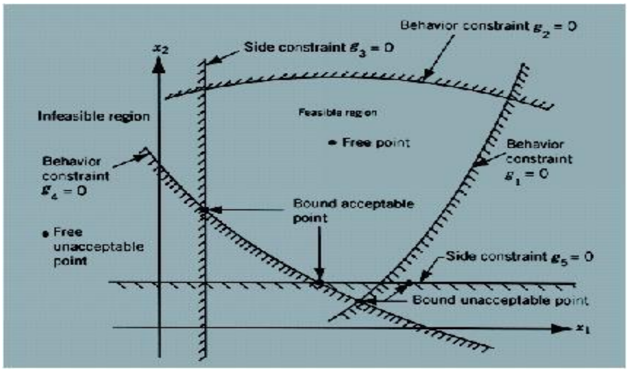

Fig. 5 Acceptable and Unacceptable Region. ***Source: [17]***, **p. 8.**

The conventional design procedures aim at finding an acceptable With multiple objectives there arises a possibility of conflict, and one simple way to handle the problem is to construct an overall objective function as a linear combination of the conflicting multiple objective functions. Thus if $f_1(x)$ and $f_2(x)$ denote two objective functions, construct a new (overall) objective function for optimization as:

$$f(x) = a_1 f_1(x) + a_2 f_2(x) \quad (14)$$

where α_1 and α_2 are constants whose values indicate the relative importance of one objective function relative to the other.

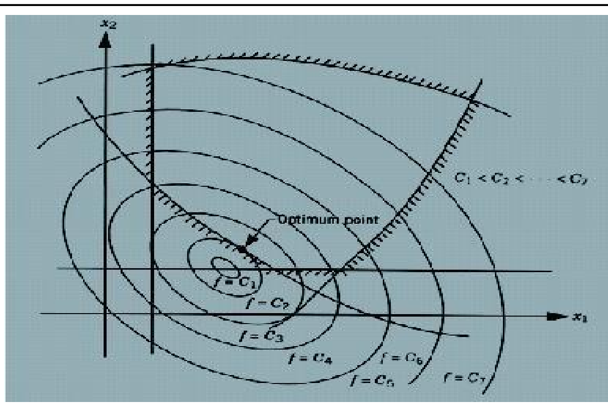

Fig. 6 Contours of the objective function. ***Source: [17]***, **p. 10.**

The locus of all points satisfying *f(x) = C*, where *C* is a constant, forms a hyper-surface in the design space, and each value of *C* corresponds to a different member of a family of surfaces. These surfaces, called objective function surfaces, are shown in a hypothetical two-dimensional design space in Fig. 6.

There is no single method available for solving all optimization problems efficiently and effectively. Hence a number of optimization methods have been developed for solving different types of optimization problems. The common methods for solving the portfolio selection optimization problem are quadratic programming (QP), used to solve programming problems with a quadratic objective function and linear constraints, and Genetic Algorithm, which is used to solve nonlinear programming problems, where the objective and constraint functions are nonlinear.

3.4 EXPERIMENT:

We apply the proposed methodology on the data of the Egyptian Stock Market. We use the 45 stocks from the highest 100 stocks which have complete monthly time series data on the close price over the period from January, 2004 to April, 2008.

3.4.1 FINANCIAL TIME SERIES ANALYSIS:

The Egyptian Stock Market data show that there are k=5 collinear sets as follows: (1) Stocks 16, 35, 36, 40, (2) Stocks 18, 19, 27, (3) Stocks 01, 21, 24, (4) Stocks 24, 30, 43 (5)m Stocks 11, 29, 31. These 5 sets have the largest Pearson correlation coefficient for pairwise correlation coefficients (see; Fig. 7-- Fig. 11).

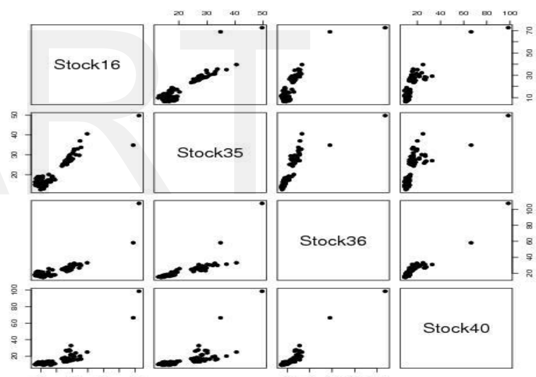

Fig. 7: Plot Matrix of the Stocks's Prices of the Collinearity Set 1.

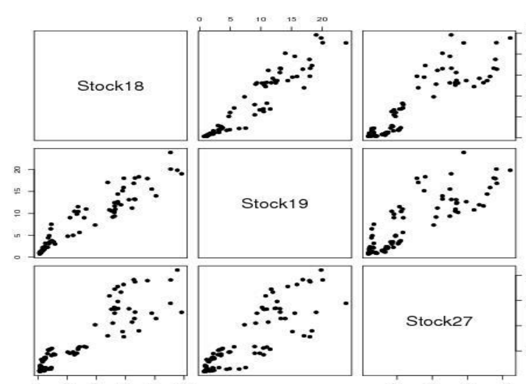

Fig. 8: Plot Matrix of the Stocks's Prices of the Collinearity Set 2.

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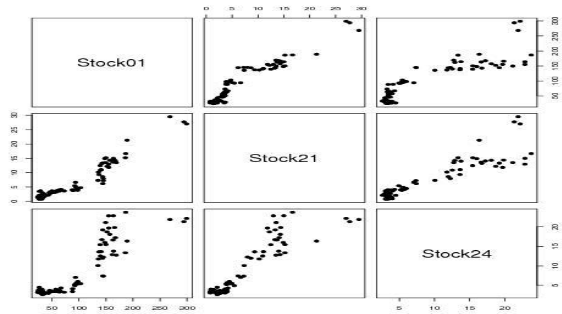

Fig 9: Plot Matrix of the Stocks's Prices of the Collinearity Set 3.

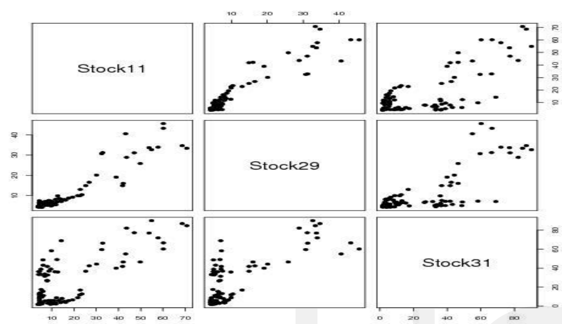

Fig10: Plot Matrix of the Stocks's Prices of the Collinearity Set 4.

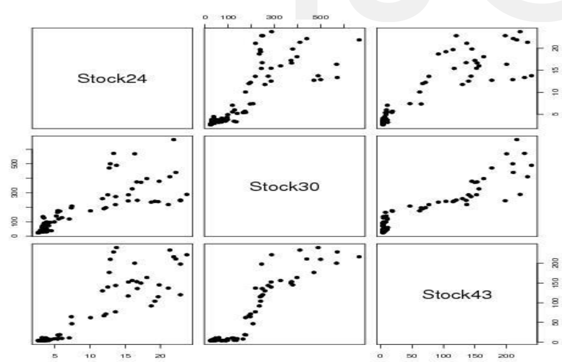

Fig 11: Plot Matrix of the Stocks's Prices of the Collinearity Set 5.

An evidence of collinearity in the data is indicated if any of the condition indices exceeds 10. The condition indices and k_j are shown in Table 1.

TABLE 1

THE EIGEN VALUE (λ_i) AND KAPPA VALUE (k) OF THE EGYPTIAN STOCK MARKET DATA.

j	34	38	43	44	45
λ_i	0.007	0.004	0.002	0.002	0.001
k_i	63.336	83.785	118.49	118.49	167.57

Determining the active stocks, using Principle Component Regression (PCR), by regressing the stock market index(dependent variable) on the stock market prices (independent variables) and choose the significant stocks in this regression as active stocks. These stocks control the movement of the stock market. Table 1 shows that there are nine active stocks: 01, 02, 14, 16, 18, 27, 30, 31, and 39. These stocks have significant relationship with the Stock Market index.

TABLE 2

ESTIMATION OF THE PARAMETERS B'S OF PCR

j	B_j	t-value	j	B_j	t-value	j	B_j	t-value
01	0.099	**05.66**	16	0.0999	**02.010**	31	00.136	**04.370**
02	0.135	**04.21**	17	0.0143	00.380	32	00.001	00.010
03	-0.037	-00.69	18	0.0733	**02.330**	33	00.019	00.450
04	-0.004	-00.06	19	-00.007	-00.210	34	-00.032	-00.830
05	0.0320	00.57	20	-00.070	-01.600	35	00.028	00.730
06	0.0222	00.40	21	-00.024	-00.880	36	-00.051	-01.140
07	0.0530	01.02	22	-00.025	-00.440	37	-00.005	-00.134
08	0.0257	00.75	23	00.056	01.480	38	-0.0177	-00.420
09	-0.015	-00.44	24	-00.032	-00.840	39	00.082	**02.380**
10	-0.053	-01.01	25	-00.017	-00.290	40	-00.015	-00.420
11	0.0561	01.84	26	00.010	00.180	41	-00.059	-01.200
12	-0.023	-00.45	27	00.117	**04.780**	42	00.064	01.980
13	0.0169	00.27	28	00.001	00.020	43	00.041	01.050
14	0.2322	**05.81**	29	-00.011	-00.270	44	-00.047	-00.780
15	0.0249	00.45	30	00.114	**03.050**	45	-00.001	-00.028

3.4.2 THE OPTIMAL PORTFOLIO BY GENETIC ALGORITHM:

Table (3) shows the results of the traditional portfolio model by using GA.

TABLE 3

TRADITIONAL OPTIMAL PORTFOLIO FRAME BY GA

Performance					
Return=0.0655		Risk=0.0925			
Weights					
Stocks	w_i	Stocks	w_i	Stocks	w_i
04	0.0660	11	0.0222	41	0.0222
23	0.0391	12	0.0222	45	0.0222
30	0.0378	13	0.0222	10	0.0221
28	0.0374	14	0.0222	07	0.0220
44	0.0374	15	0.0222	01	0,0219
22	0.0310	16	0.0222	19	0,0211
37	0.0260	18	0.0222	36	0.0171
29	0.0225	21	0.0222	26	0.0157
33	0.0225	24	0.0222	43	0.0083
02	0.0222	27	0.0222	35	0.0082
03	0.0222	31	0.0222	42	0.0071
05	0.0222	32	0.0222	25	0.0070
06	0.0222	38	0.0222	34	0.0068
08	0.0222	39	0.0222	20	0.0067
09	0.0222	40	0.0222	17	0.0066

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The optimal Portfolio includes all 45. The return-to-risk ratio of this portfolio is 0.7081.

Using proposed optimal portfolio frame with:
cj = 0.30, j = 1,..., 5, a = 0.15, h = 0.40, r = 0.08, we obtain the results shown in Table 4.

TABLE 4
PROPOSAL OPTIMAL PORTFOLIO FRAME BY GA

Performance					
Return = 0.1070		Risk = 0.08			
Weights					
Stock	wi	Stock	wi	Stock	wi
04	0.4000	18	0.0119	40	0.0074
01	0.1992	35	0.0118	41	0.0069
02	0.0190	39	0.0115	42	0.0067
14	0.0186	12	0.0113	32	0.0055
06	0.0172	36	0.0112	11	0.0054
26	0.0162	16	0.0111	13	0.0047
30	0.0157	44	0.0111	22	0.0044
45	0.0151	23	0.0107	15	0.0042
29	0.0150	25	0.0105	33	0.0007
09	0.0142	07	0.0104	37	0.0007
20	0.0130	05	0.0104	19	0.0000
27	0.0130	28	0.0101	21	0.0000
10	0.0126	34	0.0101	24	0.0000
17	0.0124	03	0.0100	31	0.0000
08	0.0120	38	0.0079	43	0.0000

The results show clearly that adding these constraints leads to increasing the return to the risk ratio from 0.7081 to 1:34.
The number of stocks in the portfolio decreased from 45 to 25.

3.4.3 THE OPTIMAL PORTFOLIO BY HIBRID OPTIMAL METHOD:

We will use a hybrid function to solve the optimization problem, i.e., when GA stops (or you ask it to stop) this hybrid function will start from the final point returned by GA.

Functions PATTERNSEARCH, or FMINUNC. Since this optimization example is smooth, i.e., continuously differentiable. Since FMINUNC has its own options structure, we provide it as an additional argument when specifying the hybrid function.

Then GA terminated, FMINCON (the hybrid function) was automatically called with the best point found by GA so far.

The solution by the hybrid function using GA and FMINUNC together. As shown here, using the hybrid function can improve the accuracy of the solution efficiently.

Find minimum of constrained nonlinear multivariable functionfmincon attempts to find a constrained minimum of a scalar function of several variables starting at an initial estimate. This is generally referred to as constrained nonlinear optimization or nonlinear programming.

Table (5) shows the results of the proposed portfolio frame by using the Patternsearch function as hybrid function.

TABLE 5
SUGGESTED PORTFOLIO MODEL BY HYBRID METHOD

Performance PATTERNSEARCH			
Return = 0.0936		Risk = 0.0593	
Stock	Weights (wi)	Stock	Weights (wi)
Stock 2	0.1847	Stock14	0.0476
Stock 4	0.3070	Stock18	0.0203
Stock 6	0.0691	Stock23	0.0392
Stock 9	0.0741	Stock26	0.0534
Stock29	0.0996	Stock31	0.0023
Stock30	0.0324	Stock33	0.0044
Stock36	0.0166	Stock44	0.0097
Stock37	0.0008	Stock45	0.0398

Table (6) shows the results of using the Fminunc function as hybrid function to get the optimal portfolio by using the proposed portfolio frame.

TABLE 6
SUGGESTED PORTFOLIO MODEL BY HYBRID MEHOD

Performance Fminunc			
Return = 0.1416		Risk = 0.0850	
Stock	Weights (wi)	Stock	Weights (wi)
stock2	0.0179	Stock26	0.0248
stock4	0.5786	Stock29	0.0826
stock6	0.0923	Stock31	0.0426
stock9	0.0224	Stock36	0.0294
Stock29	0.0996	Stock45	0.0849

The results show clearly that adding these constraints leads to increasing the return to the risk ratio from 0.7081 to 1:34.
The number of stocks in the portfolio decreased from 45 to 25.

4 CONCLUSIONS:

The results of the study can be summarized as follows:

- Analysis of time series data for the stocks before construction of the portfolio is very important.
- There is no single method available for solving all optimization problems efficiently and effectively. Hence a number of optimization methods have been developed for solving different types of optimization problems.
- The study shows outstanding performance for Hybrid Optimization methods and particular FMINUNC function.

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