Ensembled Utilization of The Binary Coded Genetic (BCG) Algorithm for The Instinctive Spontaneous Allocation of Weights for the Intensification of The Superior Capitulating Scripts in An Optimized Selection of Portfolio

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Summary
The dexterity of portfolio management and selection of scripts has always been a challenging realm for the researchers. After the advent of the modern computing methods and machine learning environment much of the automation activity has been adopted by the computational finance researchers but still there is room for betterment. The current research is extension of the automated portfolio selection being previously carried out, in which chameleon and dynamic K-Means algorithms were modified through ensembled learning through which a set of scripts are being selected. Current research undertakes the adjustment of the weightage of the selection in the portfolio for the diminution of the risk and amplification / upsurge of the return through the dividend yield and the capital growth by utilizing the binary coded genetic algorithm.

Key words:
Binary Coded Genetic Algorithm; Chromosome; Dynamic Weight Assignment; modified k-means; dynamic clustering; performance evaluation.

1. Introduction

Most of the espoused methods in portfolio management, selection and optimization are based on the concept of variance and standard deviation (like markovitz) of the return metrics, but unfortunately these are not the only metrics that should be accounted for, as there are different types of risks that are attached with certain markets and certain scripts as well, along with that there is an individual financial position of a company (along with a financial position of that company's script in a specific market) and there are operational limitations as well as liquidity measures and all these needs to be catered while evaluating any script, therefore the primordial methods of evaluation, selection and optimization of the portfolio are no more useful in the portfolio management.
A novel approach has been conceived in the current undertaken research and represented in this paper for the evaluation and selection of scripts in the portfolio using financial position of the firm through it's key performance ratios (KPRs), which is further being utilized with weighted average adjustments to optimize values of single script (individual company), the weighted average methodology is though a bit old but it's being re-designed with modern machine learning algorithm namely Binary Coded Genetic (BCG) Algorithm that dynamically re- positions the weights and thus yields in regulated ratios which in turn helps in maximization of the return and minimization of the associated risks.

2. Overview of Ratios (Constituent Parts of the BCG Weight Assignments)

Financial Ratios

Return on Equity (Roe) Ratio:
The return on equity ratio measures a firm capability to generate benefits from the investments made by the investor in the firm. ROE exhibits the benefit that is produced by every dollar invested by the regular investors. For example, a return of 1 shows that a net income of $1 is created with each dollar of a regular investor's equity.
For potential investors this measure is helpful in perceiving and creating a net income.
FORMULA:
ROE ratio is derived through this formula.

$$Return\ On\ Equity\ (Ratio) = \frac{Net\ Income}{Shareholder's\ Equity}$$

Dividend Yield Ratio:

The dividend yield ratio is a measure of money profits disseminated to regular shareholders of the firm. The profit is circulized according to the market esteem value per share. Investors use this measure to demonstrate how their investment results in either cash flow divided or in stock

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appreciation. Sometimes the dividend is circulated on a regular basis to good an investor's inter (these are known as income stock). The other times the dividend instead of issuing is reinvested in the business we call it stock growth.

Formula:

Divide the cash dividend per share to market value per share to compute the DYR

$$Dividend\ Yield\ (Ratio) = \frac{Cash\ Dividends\ Per\ Share}{Market\ Value\ Per\ Share}$$

Dividends are a regular part of any firm's financial statements yet are announced sometimes as gross dividends distributed which is calculated by dividing gross dividend distributed to the average exceptional regular stock amid the year.

The shares' market value is obtained from the open stock exchange cost of the last day of the period.

Operational Ratios

NET PROFIT RATIO:

Also known as net margin, this profitability metric measures that how much net profit a business generates from every dollar of its sales, at the end of a year.

Investors and creditors analyze the company's efficiency to convert sales into net income. This measure helps them in analyzing that after all expenses are paid, what percentage income does the business is able to generate which can be distributed or reinvested in the business.

A higher margin implies that at the end of year, business is able to covert a greater sale into profit. This margin changes fundamentally among the firms and a lower average margin doesn't mean that a firm's less productive. For example, retailing business may have a lower average margin as compared to other business

Formula:

The net profit margin is simply the ratio of

$$Net\ Profit\ Margin\ (Ratio) = \frac{Net\ Profit}{Total\ Revenue}$$

Net profit to total revenue

Ratio of Receivable Turnover or Ratio of Debtors Turnover

This is an efficiency measure that show how often a firm's account receivables are turned into cash.

Account receivable includes the bills receivables and also the exchange indebted individuals. The debtor's turnover ratio has a coordinate effect on the liquidity of the business i.e. the faster the conversion of receivables into cash more liquid the company

Formula:

$$Receivables\ Turnover\ \ (Ratio) = \frac{Annual\ Net\ Credit\ Sales}{Average\ Accounts\ Receivables}$$

Higher this ratio, more the company's efficiency to collect the receivable.

Liquidity Ratios:

Also known as the cash ratio, this shows how well a company performs in paying off its current liabilities through cash only or equivalents of cash. This is different from current or quick ratio because only cash can be used to pay off the debt. For creditors it is a company's performance indicator that shows how well a company maintain its cash balances. It shows of the business has the capability of raising cash or changing resource into money. Since inventory selling may take time and receivable may or may not get collected so they are left out of the equation. Some widely recognized ratios include.

Current Ratio:

How well a company works in paying off the short-term liabilities with its current resources is show by this efficiency measure. Since short-term liabilities are due next year, this measure is an important liquidity measure.

The business has to raise funds in limited time to pay of the liabilities. The larger the current assets more the efficiency in paying off the debts.

Formula:

$$Current\ \ (Ratio) = \frac{Current\ Assets}{Current\ liabilities}$$

A higher ratio is more favorable for the investors + creditors

Quick Ratio:

Acid test a quick ratio shows how efficiently a business pays off the liabilities (current) with its quick assets.

Quick assets are easily converted into cash in a short-time period, usually of 90 days, for example the marketable securities or current account receivables

Formula:

$$Quick(Ratio) = \frac{Cash + Cash\ Equivalents + Short\ Term\ Investment + Current\ Receivables}{Current\ liabilities}$$

If the company doesn't show the quick assets on its balance sheet, then quick ratio can calculate with the following formula

$$Quick(Ratio) = \frac{Total\ Current\ Assets - Inventory - Prepaid\ Expenses}{Current\ liabilities}$$

A quick ratio of 1 indicates that quick assets and current assets are equal more than 1 ratio shows that quick assets are higher than current liabilities and company will not have to sell the long-term assets for paying the liabilities.

3. Binary Genetic Algorithm (Bga)

Fundamental Genetic Algorithm (GAs) involve 3 operators, namely reproduction, crossover, and mutation. The Genetic Algorithm (Gas) often applied is of binary nature. (Singla R.K., Das R. (2017)). It is presented similarly as in group of bits; these arrangements are in a binary series of 0s & 1s with additional encodings differing from the rest. (García-Martínez C., Lozano M. (2007)).
The process starts by a group of randomly generated individual put together during generation. For BGAs the following are the elementary operations to be processed upon generation.

Chromosome:

In order to generate a genetic algorithm a potential solution has to be encoded (Jiří,2005). For instance, a string of real numbers can be displayed as a binary string i.e. ""100011010101010101111011101111" (García-Martínez, Lozano, Molina, 2006). In doing that a large number of chromosomes is brought to existence, with each exhibiting a potential solution. Since there will be a number of different solutions the fitness function will evaluate their competencies by valuing how good each is. (Hajela P. 2002).

Coding and Endcoding:

Genetic algorithms are applicable on a large variety of issues for achieving a near to correct solution. To interpret the chromosomes within the fitness function, the only thing required is a unique decoder (Herrera, Lozano, Verdegay, 1998).
Firstly each chromosome is encoded into a binary string (0's and 1's). In the formula below "k" is the accuracy set by "l^k" (string of length) and "r_k" (desired resolution), and U_{max} and U_{min} denote the high and low limits in the range respectively. (Deb, K., Dhebar, Y. D., & Pavan, N. V. (2012) therefore we get:

$$r_k = \frac{u_{max} - u_{min}}{2^{l^k} - 1} + u_{min}$$

However, it has been encouraged by researchers to apply the base-10 version as further encoding and decoding is not needed. Decoding and coding methods are inversely proportional to each other.

Fitness Function:

Fitness function in Genetic Algorithms (GAs) evaluates the optimality of chromosomes (solutions). It grades them to as per their fitness values in comparison to each other (Patel, P. B., & Marwala, T. (2009). A positive fitness function is considered generally. Upon generation of the fitness values, chromosomes with a high fitness values are bread and blended with other chromosomes. The above is enabled by the crossover process (explained later) which helps generate a replacement generation ideally being improved than its predecessor. (Kieś, 2001).

Reproduction:

In this process, the best fitness chromosome from one set receives an equally considerable amount of copies (as per their fitness value) within the next generation. The higher the result in the present population, the higher the imitation in the next generation. This is conducted by the reproduction operator.
There are two phases for production. In the first phase, reproduce a chromosome near the global optimum. This is done by the winner-replacing step. In the second phase also the last one, spin a roulette wheel in accordance with the estimated spaces in accordance with its function a multiple times and upon each turn one chromosome is chosen for another population. (Kwak, Lee, 2016). This not only results to an improved chromosome but also to an improved solution for the optimization problem. The following formula helps in identifying the survival probability of each chromosome. This is proportional to its fitness value.

$$p_i = \frac{f_i^{GA}}{\sum_{k=1}^{n} f_k^{GA}}$$

The chromosomes that survive to successive generation are placed during a mating pool for crossover and mutation operations.

Crossover:

In a crossover superior features of the previous generation are used to obtain mew chromosomes. To get this only those pair of parents are selected whose probability equivates to the cross rate. (Barrios, D., Carrascal, A., Manrique, D., & R Os, J. ,2003). Amongst the many crossover operators Single-point, two-point and uniform crossovers are the most common with the premier being the most basic as well, because it helps select the random point on the genetic code where the two point parent chromosome were replaced. (Ortiz-Boyer, Hervás-Martínez, García-Pedrajas, 2007).

Single point crossover:

It is used in traditional genetic algorithms. As the name describes it involves only a single point for cutting the two mating chromosomes which can be selected randomly along the lengths of the mated strings. Combining good parents results to a better offspring. The quality of the offspring can be detected by which point was selected. For example in the below chromosome the string's quality has been severely distorted as the points selected were not appropriate.

A= 0 1 0 1 1 | 0 0 0 0 1 1
B= 1 0 0 1 0 | 1 0 1 1 1 0

After crossover, the generated chromosomes result in:

A= 0 1 0 1 1 | 1 0 1 1 1 0
B= 1 0 0 1 0 | 0 0 0 0 1 1

Two-point crossover:

two crossover points are selected from where contents will be exchanged from two mated parents. This benefits the transfer of the head and tail of one chromosome simultaneously to the offspring. This contradicts the single-point crossover's philosophy.

A= 1 1 | 0 0 1 | 0 1
B= 0 0 | 1 0 1 | 0 0

After crossover, the generated chromosomes are

A= 1 1 1 0 1 0 1
B= 0 0 0 0 1 0 0

Uniform Crossover:

It differs from the N-point crossover solely because it is created when one parent is copied with a randomly created binary crossover mask. This mask has the same length as of chromosome A. in the below representation 1 is a crossover mask obtained from the first parent and 0 being the second parent. In each pair a randomly selected new crossover mask is selected thus the combination of these genes is transferred to the offspring.

A= 1 0 1 0 0 1 0
B= 1 1 0 0 1 1 1

After crossover, the generated chromosomes will be:

A= 1 1 1 0 1 1 1
B= 1 0 0 0 0 1 0

Mutation:

A mutation operator can automatically create a new chromosome. This is favorable because crossovers have the tendency to exploit gene potentials and also in crossover combination would only happen if all the encoded information isn't contained in the population (Munteanu, Lazarescu, 1999)

Mutation introduces new genetic components to existing chromosomes thereby modifying them. The mutation process also its own means to calculate distortion for example if the mutation rate's value is low, the amount of distortion present in the solution would also be low. This can be further supported by the following equation: $0<P\_m \leq 1$. Here P_m denotes the mutation (probability) rate (Deep, Katiyar, 2012). The next benefit is that it takes a gene by gene basis methodology.

Before mutation:

A= 0 1 0 1 1 0 0 0 0 1 1

After mutation:

A= 0 1 0 1 1 1 0 0 0 1 1

Termination:

The genetic algorithm comes to an end and is discontinued once the optimal solution is near or found, by near it elaborates to approximation. (García-Martínez, Lozano, Molina, 2006).

Genetic Algorithm Steps:

Step (i): initialize: - Randomly Nth no of chromosome is generated as an initial population.
Step (ii): Selection: - Compute the fitness for every single chromosome of the population.
Step (iii): Perform Reproduction: - Choose the better chromosome based on their fitness probability
Step (iv): Perform Crossover: - A crossover is performed on chromosome generated in above step by crossover probability
Step (v): Mutation: By mutation probability, a mutation is performed on chromosome generated through step iv
Step (vi): The procedure can be stopped when an optimal solution is obtained, else repeat steps 2-6
Step (vii): Find the optimal solution

Parameter:

According to Merek (1998) there are many parameters for the operations of genetic algorithms. But some of the parameters mentioned below are namely crossover probability, mutation probability, population, and natural selection.

Crossover Probability:

The underlying concept of crossover probability is that it depends on percentages. 100% crossover probability would mean that all the offspring present in the population are made by crossovers. Likewise, a 0% probability would imply that the old population will form a new generation entirely. 80 to 95 % are considered to be generally high.

Mutation Probability:

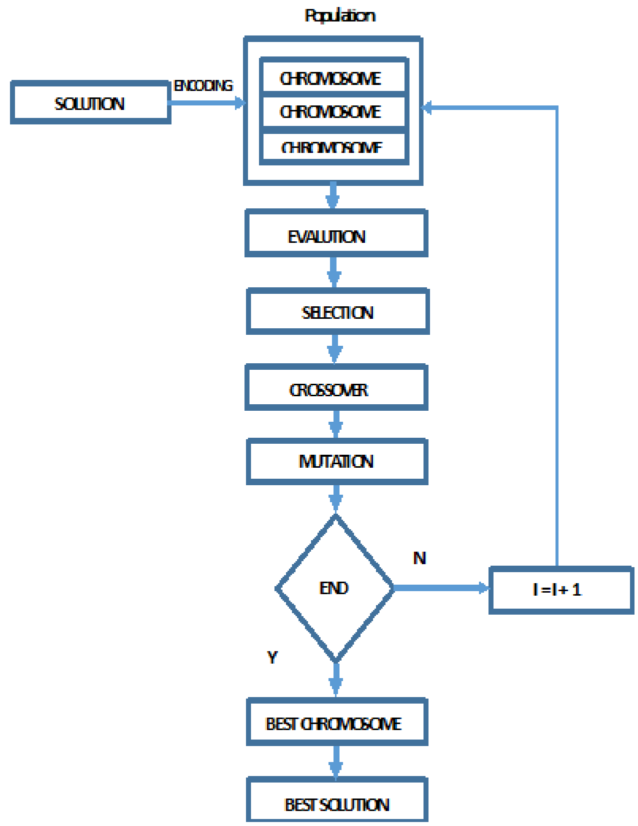
The mutation probability however determines which parts of the chromosomes can be mutated and their frequency. Here a 100% probability would mean that the chromosome should be completely changed while vice versa 0% probability would indicate no change. Ideally for a better mutation probability, it is best to range from 0.5% to 1%.

Population:

In genetic algorithm populace is the term given to define the portrayal of chromosomes. This includes of Npop chromosomes (a Npop*Nbits network). Created by the following formula:
pop= round (rand (npop, nbits)
the framework of this formula is that firstly, (Npop, Nbits) is made by Npop*Nbits network of arbitrary numbers of 0 and 1. Secondly, the number has to be rounded off to the nearest whole number (0 or 1). Lastly and most importantly, each line should be a chromosome which should have the ability to react to sever approximation of the longitude and latitude.

Natural Selection :

In this parameter, the concept is that each iteration should be a naturally selected. This means that the top chromosome is selected from mating among the Npop gereration. The remaining chromosomes which were either close of farther are discarded so as to make room for the new offspring. Normally the decision regarding the quantity to keep is irregular because keeping the whole quantity would result to limitation in genes for the offspring but still usually 50% are kept in the process.



The afore drawn flow chart is a step by step execution for the Binary Coded Genetic algorithm.

4. Proposed Algorithm for Optimized Portfolio

<u>Step 1</u>: Select highly traded volume based scripts.
<u>Step 2</u>: Extract at-least 15 sectors from highly traded scripts.
<u>Step 3</u>: Select 10 top most highly traded scripts by volume in each sector.
<u>Step 4</u>: Extract the following financial ratios, operational ratios and liquidity ratios from individual company financial report.

I. [Loop]: for (c [i] = 1 ; c [i] < n ; c [i] ++)
   i. SET c = [company(ies)]
   ii. SET r ={ratios}
   iii. Let RF, RO and RL be the ratios of all companies.
      - FR: = {frc1, frc2, frc3,….., frcn}
      - OR: = {orc1, orc2, orc3, ….., orcn}
      - LR: = {lrc1, lrc2, lrc3, …., lrcn}
      - Where frc1 = (DYR + ROE)
      - orc1 = (NPR + RTP)
      - lrc1 = (CR + QR)

II. Extract the first ratio r for company C[i] that is given by frc and store as FR[i]=frc[i]

III. Extract the second ratio r for company C[i] that is given by orc and store as OR[i]=orc[i]

IV. Extract the third ratio r for company C[i] that is given by *lrc* and store as LR[i]=lrc[i]

a) [Inner loop]: for [w=1; w<=10; w++]
[Generate random numbers]: W1 [j] = rand (0-1)
[Compute]: W2 [K] =1-W1
[Compute]:W1 [j] (CRP+ERP) + W2 [k] (FR+OR+LR)
Store the computed value in D[i]

b) Generate random values between (0-1) equal to the size of data set and save it to variable m1

c) Repeat step (b) and save it to m2

d) Calculate max from m1 and save the index of the position having max value to variable max_m1

e) Repeat step (d) for m2 and save the index of the position having max value to variable max_m2

f) Take value from w1 [max_m1] and save it to variable w1'[n_i]

g) Take value from w1 [max_m2] and save it to variable w1'[n_i]

h) Select solutions w1'[n_1] and w1'[n_2] from w1'[n_i]

i) Generate w1'[n_3] and w1'[n_4] by uniform point crossover to w1'[n_1] and w1'[n_2] and save w1'[n_3] and w1'[n_4] into w1” [n_i]

j) Select a solution w1'[n_3] from w1” [n_i]

k) utate a random bit of w1'[n_3] and generate new solution w1" [n_1] and save it to w1” [n_i]

l) Repeat step (j) and step (k) for w1'[n_4] from w1” [n_i] and save it to w1” [n_i]

m) Find w2'[m_1] by subtracting w1” [n_i] from 1 and save it w2’ [m_i]

n) New values of w1” [n_i] and w2'[m_i] derived will be inserted in the fitness function.

o) Compare new values and old values of fitness function.

p) Highest value of fitness function will be selected.

Step 5: Let D as the final data set of Binary Coded Genetic optimized script values
Obtained from step 4

4.1 Iption of Adopted and Modified Genetic Algorithm

4.1.1 Data Selection Methodolgy:

i. The process of the proposed algorithm starts by selecting the scripts based on the traded volume. The criteria shall be extended on basis of the frequency of volume. For instance, a daily highly traded volume scripts can be utilized with mathematical intersection function (set theory) in order to calculate the monthly highest traded scripts. In return theses shall be used for all 12 months to with the set intersection function to get the annual highest trade by volume.

ii. In the next step sectors of highly traded (volume based scripts) is identified. The 15 top most sectors from the highly traded scripts shall be chosen.

iii. After examining each of 15 determined sectors, choose the top 10 highly exchanged volume-based scripts in each sector (the scripts may vary in the selected (sector wise) list when compared with the step one selected scripts due to each script in an individual sector being not present in the most highly exchanged script of the first step. This step normalizes the data (widening the base of the chosen data set).

4.1.2 Extraction of Ratios from Current Fiscal Report of The Selected Script’S Companies:

iv. Upon completion of the previous stage, the algorithm will extract the financial, operational and liquidity ratios from the current year financial report of each script. The ratios with increasing value indicating of higher return would be selected only. The ratios obtained will be portrayed in an array separately.

Financial Ratios:

1. Dividend Yield Ratio: It shows how much “dividend” the company pays to its shareholders in a financial year. The higher the estimation of profit, the more the extreme point is derived in the computation exhibiting the greater contribution of the specific script in algorithm.
2. Return On Equity: It computes the amount of return a company is able to generate to its shareholders. In order to attract potential investors the company would need to yield a higher return. The proposed algorithm would calculate and the maximum point would be plotted on

the outer/ higher side of the algorithm. Thus the outer the cluster, the maximum the return.

Operational Ratios:

1. Net Profit Ratio: This shows the amount of profit an entity can produce over its investment. A greater value would signify that the chances of maximum value would lie on the positive side. Making work for the selection of the specific script in the undertaken research's algorithm.
2. Receivable Turnover Period: This shows whether the organization's account receivable is effective and also whether the organization has reliable clients that payoff their obligations. Therefore, a high proportion indicates that a conventional strategy for credit is being used. Furthermore, a high value would highlight a higher chance by the algorithm to be plotted on the outer side, maximizing the probability that the script may be placed in the top/outer most cluster.

Liquidity Ratios:

1. Current Ratio: This ratio represents the organization's current assets against its current liabilities. If the proportion is of high value this means that the organization has the capability and capacity to cover its short term obligations and would present the organization more profitable for portfolio selections. Similarly it would increase the chances of selecting a particular script within the algorithm in the selection of the portfolio.
2. Quick Ratio: As compared to current ratio, the quick ratio is more effective as it does not take current stock and other current resources into consideration which is difficult to convert to money.
3. A high liquid current position from the quick ratio reflects a positive attitude within the algorithm and helps in plotting the point on the outer/higher side through the modified K-means. This increases the chance of the scripts to be selected in the optimized cluster.

4.1.3 Application of The Binary Coded Genetic Algorithm for yhe Maximization of The Weighted Average Ratios:

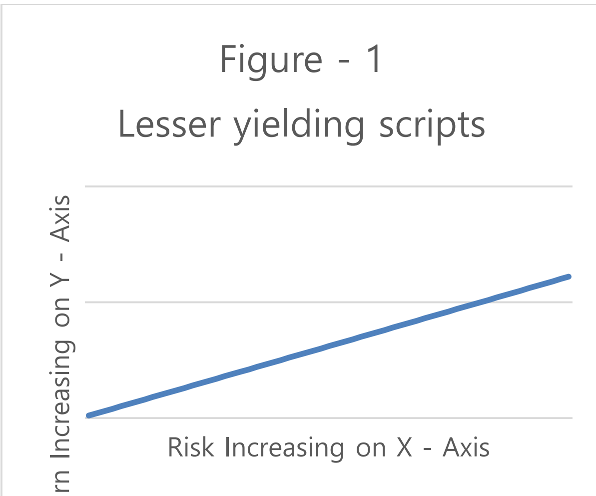
A binary coded genetic algorithm is approached to attain the maximum value representing profit of shares. This is only enabled when the method used currently is modified for the data under consideration. Currently, data is divided into set of two where one set is based on the financial, liquidity, and operational ratios (related to each organization), and the other set based on two variables ERP and CRP. The latter set has an indirect impact on the organization. Therefore a binary genetic coded algorithm is used to adjust the weight of the fitness function. The equation W1 (EQRP+CRP) +W2 (FR+OR+LR) works as a fitness function and the value of variables W1 and W2 must equate to the maximum value of 1.

A) Value of W1:
Generate a random value of W1 between (0-1)
B) VALUE OF W2:
A new value of W2 is created when W1 is subtracted from1.
C) FITNESS FUNCTION:
Now W1 and W2 are placed in an equation of fitness function.
D) GENERATE RANDOM VALUE:
Simultaneously create another random value, select the Maximum value and select the corresponding value of w1 and repeat step (d) with the next iteration.
E) ENCODING
Take two random values of W1 and binary encoding is applied.
F) CROSSOVER AND MUTATION:
Apply the crossover and mutation on W1 values which are denoted as the parent value. The value will change and a new value of W1' will be generated, denoted as a child value
G) FIND THE W2' AGAIN:
Subtract the value of W1' from 1
H) DERVIED VALUE OF W1' and W2':
Insert derived value of W1' and W2' in the fitness function.
I)COMPARE NEW AND OLD VALUE
Compare new value (child value) or old value (parent value) of fitness function.
J) STORE IN NEW VARIABLE
The highest value of fitness function is stored in a new variable.

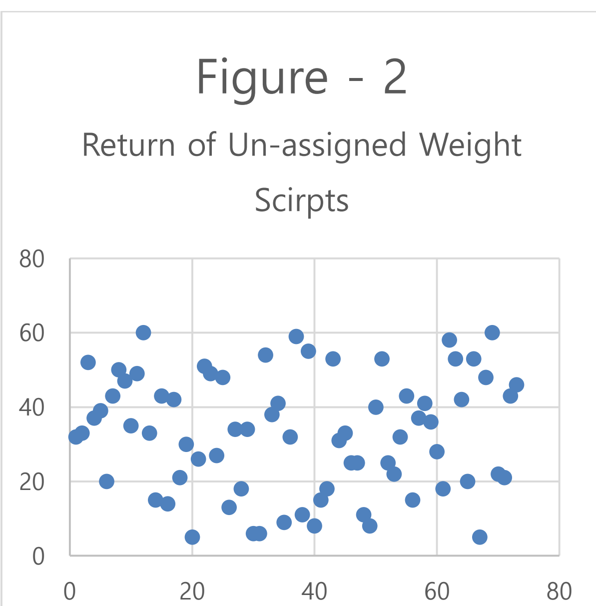
The utilization of different Key performance ratios (KPRs) of a script makes unquestionable and undisputable verification of the financial position of a firm and fusion of these different KPRs into a solitary denomination will help represent a single point over graph for plotting of different clusters thus yielding different portfolio combinations (S. M. Khalid, 2019).
Earlier to getting a fused solitary denomination the different KPRs, binary coded genetic algorithm will help to embed

different weights to the company's different ratios on dynamic basis that keep on changing as per the "natural selection", "mutation", "crossover", "reproduction", and "chromosome" adjustments, thus providing ground for the adjustment of maximization of quantity of those scripts which are engendering greater returns therefore yielding superior profits for the selected optimized portfolio.

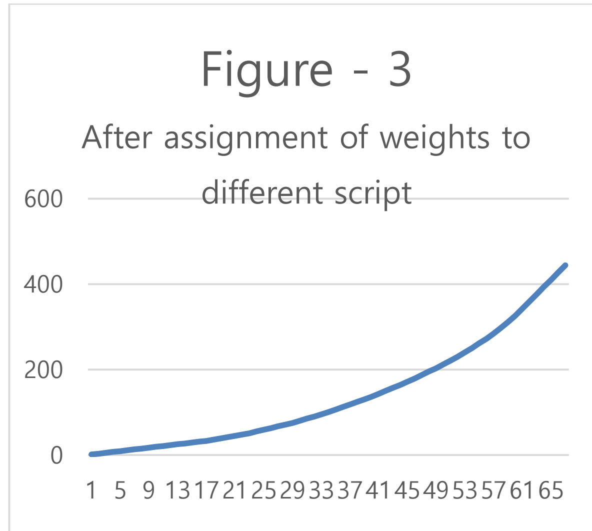
5. Results:



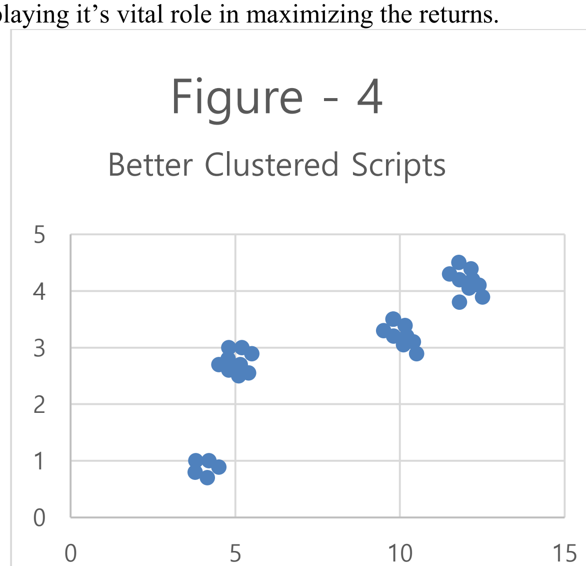
The linear trend plotted over the graph-1 is a representative of the fact that without assigning the weights to the scripts (i.e. every script has equal opportunity to participate in the risk-return calculation with equal weightage) there is a greater probability that the overall selected portfolio will yield lesser returns with same risk factor.



The scatter plot in Figure-2 is having approximately all points which are not able to become part of any of the clustering utilizations, because the points (a single point is representing a single company's script) are so evenly scattered that they are not converging to any cluster, so it's difficult to figure out that what similarity each script has (in terms of risk and return) without assignment of weights to each script.



After the assignment of weights to different scripts through the Binary Coded Genetic (BCG) algorithm, certain scripts are now additionally participating in the overall calculation of returns (and only those scripts are being assigned larger weights, which are yielding farther returns). It is obvious from the line plot of Figure-3 that that the returns (on y-axis) are getting over the higher side as the calculation proceeds further which is a clear indication of the fact that the Binary Coded Genetic (BCG) algorithm has started playing it's vital role in maximizing the returns.



After the allocation of weights through the dynamic assignment by Binary Coded Genetic (BCG) algorithm, only those scripts are being now being selected in the process who are having higher weights attached to them and that is because of the fact that these scripts are performing far better than the other scripts, the four different clusters are being selected (S. M. Khalid Jamal, 2019) utilizing the Chameleon & modified dynamic K-Means clustering approach after the BCG has performed its operations over the selected scripts. The outer and the upper most cluster is the highest yielding set of scripts in Figure-4.

Conclusion

The current undertaken research has efficaciously discovered that BCG has greater enactment impact over the selection of the number of scripts through dynamic repositioning of weights while utilizing different KPRs (which represent the actual financial standing of a firm). The adjusted different KPR values will be fused to a single solitary value which in turn will be provided to machine learning algorithm along with other scripts to recommend a set of considerable soprano yielding scripts which was the ultimate aspiration of the current undertaken investigation.

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