USING GENETIC ALGORITHMS IN PANEL DATA MODELING: THE RELATIONSHIP BETWEEN STOCK PRICES AND FINANCIAL PERFORMANCE OF SAUDI ARABIA'S LISTED COMPANIES

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SUMMARY

This study aims to use Genetic Algorithms in Panel Data modeling optimization, so we applied it to measure the relationship between the stock price and financial performance indicators of ten of leading listed companies in Saudi Arabia depending on annual time series of the last twelve years. Thus, we formulated a Mixed Effects Panel Data model containing Stock price related to: Return on Equity, Return on Assets, Earning per Share, Financial Leverage and Current Ratio; then we estimated this model by maximizing an adapted Quasi-Likelihood function using Genetic Algorithms depending on Evolver software, In addition, we estimated Fixed Effects and Random effects models using usual econometric methods, all the models indicate significant impact of: ROE, ROA and EPS. The optimum Mixed Effects model estimated by Genetic Algorithms shows more accurate results with relatively better statistical characteristics and allows more usage flexibility.

KEY WORDS: genetic algorithm, panel data, econometrics, stock market.

JEL CLASSIFICATION: C01, C33, C58, C61, G17.

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استخدام الخوارزميات الجينية في نمذجة بيانات بانل: العلاقة بين أسعار الأسهم والأداء المالي للشركات السعودية المدرجة

ملخص

تهدفه ذه الدراسة إلى استخدام الخوارزميات الجينية في أمثلية نمذجة بيانات بانل، لذلك قمنا بتطبيقها لقياس العلاقة بين سعر السهم ومؤشرات الأداء المالي لعشر من الشركات المدرجة الرائدة في المملكة العربية السعودية اعتماداً على السلاسل الزمنية السنوية للاثني عشر سنة الماضية. وبالتالي، قمنا بصياغة نموذج بيانات بانل مع التأثيرات المختلطة الذي يحتوي على سعر السهم مرتبطا بـــ: العائد على حقوقا لملكية، العائد على الأصول، ربحية السهم، الرفع المالي ونسبة التداول؛ ثم قمنا بتقدير هذا النموذج من خلال تعظيم دالة الأرجحية باستخدام الخوارزميات الجينية اعتماداً على برنامج Evolver، إضافة إلى ذلك قمنا بتقدير نماذج التأثيرات الثابتة والتأثيرات العشوائية باستخدام طرق الاقتصاد القياسي المعتادة، تشير جميع النماذج المقدرة إلى تأثير معنوي لـــ: العائد على حقوق الملكية، العائد على الأصول وربحية السهم. أظهر نموذج التأثيرات المختلطة الأمثل المقدر باستعمال الخوارزميات الجينية نتائج أكثر دقة مع خصائص إحصائية أفضل نسبيًا كما يسمح بمرونة أكثر في الاستخدام.

كلمات المفتاحية

خوارزميات جينية، بيانات بانل، اقتصاد قياسي، أسواق مالية.

L'UTILISATION DES ALGORITHMES GÉNÉTIQUES DANS LA MODÉLISATION DES DONNÉES DE PANEL: LA RELATION ENTRE LES PRIX DES ACTIONS ET LA PERFORMANCE FINANCIÈRE DES SOCIÉTÉS COTÉES EN ARABIE SAOUDITE

RÉSUMÉ

Nous avons utilisé les algorithmes génétiques dans l'optimisation de la modélisation des données de panel, afin de mesurer la relation entre les prix des actions et la performance financière de dix sociétés cotées en Arabie Saoudite en prenant les séries temporelles annuelles des douze dernières années. Ainsi, nous avons formulé un modèle de données de panel à effets mixtes contenant le prix d'action lié au : rentabilité des Capitaux Propres, Rentabilité des Actifs, Bénéfice par Action, Levier Financier et Ratio Courant; puis nous avons estimé ce modèle en maximisant la fonction quasi-vraisemblance par les algorithmes génétiques à l'aide du Evolver, De plus nous avons estimé les modèles à effets fixes et à effets aléatoires par Eviews, tous les modèles indiquent un impact significatif de : ROE, ROA et EPS. Le modèle à effets mixtes donne des résultats plus précis avec mieux caractéristiques statistiques ainsi qu'il permet plus de flexibilité d'utilisation.

MOTS CLÉS: algorithmes génétiques, données de panel, économétrie, marchés financiers.

INTRODUCTION

It is very important to analyze quantitative data for decision support in economy and management activities, where there are many methods such as econometrics used to provide quantitative models that explain phenomena depending on related variables.

Among these methods, there is Panel Data modeling which is used to study behaviors of a group of individuals in a specific period, so it results in one model that explains these behaviors statistically by measuring relationship between variables depending on their data.

There are two types of Panel Model commonly used: Fixed Effects and Random Effects, the estimation of these models is complicated especially for Random Effects that needs efficient algorithms.

Due to development of artificial intelligence, new methods are created such as those which simulate nature phenomena like Genetic Algorithms that has a wide scope of application in various kinds of domain including econometric modeling optimization.

Then, Genetic Algorithms as a proven method that could be used in Panel Data modeling in order to optimize the estimation of parameters, which may provide more accurate results and better performance, especially if Fixed effects and Random effects are mixed.

The Investors and advisors in stock markets need such models to study stock prices behaviors and affecting factors like financial performance indicators of companies for example.

Thus, the main question of our study is: how Genetic Algorithms can be used in Panel Data modeling of the relationship between stock prices and financial performance indicators of leading Saudi Arabia's listed companies ?

In order to answer this question: first we introduce a literature review about Genetic Algorithms containing some of its applications in Econometric modeling, definition, basic elements and operations; then, we perform an empirical study applying Genetic Algorithms to obtain the optimum Panel Data model relating Saudi Arabia's leading listed companies stock prices with financial performance indicators; at last, we test its efficiency comparing to usual econometric methods.

1- LITERATURE REVIEW

Holland (1975) was the first who integrated biological concepts about genetics and natural selection in computing to introduce the Genetic Algorithms and their theoretical aspects.

De Jong (1980) works were the first efforts to determine the application parameters where he proved the efficiency of using Genetic Algorithms in function optimization.

Goldberg (1981, 1989) contributions and his success in solving a complicated problem of pipeline operations using Genetic Algorithms, have introduced it as an effective tool and made it more famous.

Due to the simplicity and application ability of Genetic Algorithms, it has been used to solve various types of problems in various domains including economics, where it is applied as a quantitative method that provides data needed in decision support by being integrated in Operational Research, data mining, econometrics… (Alander, 2012). The following studies are some of Genetic Algorithms applications in econometric modeling:

- Koza (1990) has shown how Genetic Algorithms can be used efficiently to estimate the well-known non-linear econometric "exchange equation" model parameters relating the price level, gross national product, money supply, and velocity of money in an economy, with high statistical significance ($R^2 = 0,99$).
- Shi and Aoyama (1997) presented Genetic Algorithms as a novel method for optimal estimation of the exponential autoregressive time series model, results of the simulation shows the efficiency of this approach which it is self-organizing and globally optimizing with greater accuracy and less calculation.
- Shin and Lee (2002) proposed Genetic Algorithms application in bankruptcy prediction modeling and illustrate how it is capable of extracting related rules, the preliminary results of the obtained model was promising.
- Ong et al. (2005) provided a Genetic Algorithms based model which is suitable for any ARIMA model identification, after its application in DRAM (semiconductor industry) price forecasting depending on three time series data , the comparison results with

the traditional identification methods showed that Genetic Algorithms provided a more correct model, more accurate results and more identification flexibility.

- Hung (2009) used genetic algorithms to estimate parameters of a fuzzy GARCH model, from the simulation results depending on stock market data from the Taiwan weighted index and the NASDAQ composite index, it was concluded that the performance is significantly improved if the leverage effect of clustering is considered in the GARCH model.
- Hong et al. (2013) proposed Chaotic Genetic Algorithms which employs internal randomness of chaos iterations to overcome premature local optimum in determining three parameters of a Support Vector Regression model of cyclic electric load. The forecasting results indicate that the proposed model yields more accurate forecasting results than ARIMA and usual SVR models.
- Karathanasopoulos et al. (2016) proposed a hybrid method for forecasting movement of the ASE20 Greek stock index that consists of a combination of Genetic Algorithms with autoregressive inputs and moving averages of the ASE20 index and other four financial indexes, to uncover effective short-term trading models and overcome the limitations of existing methods.
- Dharma et al. (2020) proposed to use a Genetic Algorithm-based regression model for predicting inflation levels using official CPI data obtained from the Indonesian Central Bank, the experiment results proved the effectiveness of the proposed model.
- Deif et al. (2021) used Genetic Algorithm in ARIMA model estimation for forecasting the mortality rates of COVID-19 in six of the top most affected countries, the study findings revealed high prediction accuracy compared to the traditional ARIMA model.

2.1- Genetic Algorithms Definition

Genetic Algorithms is an artificial intelligence technique based on genetics and natural selection principals, it can be used as a heuristic quantitative method to solve various kind of problems. It allows under specific constrains to find the optimum solution among all the possible solutions by achieving the highest fitness value (goal function) (Coley, 1999).

Goldberg (1989) defined Genetic Algorithms as follows:
"… Search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure. While randomized, genetic algorithms are no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance"

2.2- Genetic Algorithms Basic Elements

Genetic Algorithms depends on the following basics elements: population, individual, encoding and fitness; where the population consists of a number of individuals, each individual is represented by an encoded string that is evaluated according to the fitness function related to a specific environment which is the search space.

2.2.1. Population

The population is a group of individuals subject to Genetic Algorithms operations lives in the studied environment. There are two important concepts about population (Sivanandam, Deepa, 2008):

- The population size (n): it is chosen according to problem or study complication, the bigger the size the better performance, but in the other side the more needed time.
- The initial generation: it is the group of individuals that form the population at the launch of the algorithm, it is often chosen randomly in order to diversify population characteristics.

2.2.2. Individuals

Individuals are the possible solutions of the study problem; each individual is represented by a chromosome containing a group of genes that form the needed raw genetic information (Genotype), while the Phenotype is the real value expressed by the chromosome. The genes constitute the basic parameters of the Genetic Algorithm by explaining every possible solution through the determination of variables and factors values. Every solution must be represented by one chromosome at least to cover all the search space (Sivanandam, Deepa, 2008).

2.2.3. Encoding

The linking between genetic information and real values is done through the encoding that converts every possible solution to a string of codes containing: bits, numbers, letters… which allows its adaptation to Genetic Algorithms processes. The binary encoding is the most common way, where each chromosome is represented by a binary string of bits: 0 and 1 (Adeli, Sarma, 2006). For example:

Chromosome 1 →0010110011

Chromosome 2 →1001101001

2.2.4. Fitness

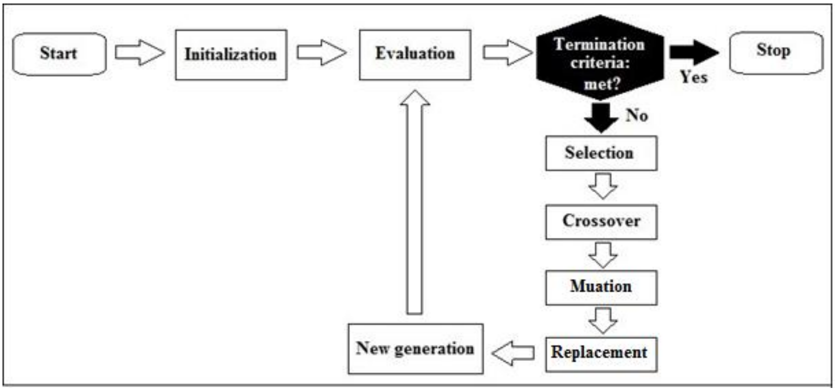
The fitness is the basic criterion of individuals evaluation; where the fitness function measures the of the solutions quality whether the related to initial generation of the population or all the solutions that the Genetic Algorithm has generated, The design of the fitness function is part of the modeling process (Kramer, 2017), it can take any form of functions that could be evaluated under specific conditions according to problem nature and the optimization goal (maximization or minimization or equalizing a specific value), hence, it can be: linear, non-linear, logarithmic, exponential…(Rothlauf, 2006).

2.3- Genetic Algorithms Steps and Operations

Inspiring from genetics concepts that explain genes transmission among species through generations and natural selection imposing the mechanism of "Survival of the fittest", in order to obtain the optimum solution, Genetic algorithms run through the following steps (Sastry et al, 2014):

1- Initialization: forming randomly the initial generation of population with a specific size.
2- Evaluation: evaluating every candidate solution using the fitness function.
3- Selection: selecting fit parents for reproduction.
4- Reproduction: reproducing offspring through crossover between chromosomes.
5- Mutation: Involving one or more changes on a chromosome to create new genotypes.
6- Replacement: The offspring created replaces worse individuals of the parental population to form the new generation.
7- Repeating steps 2–6 until termination criteria are met, and afterwards, taking the fittest individual as the optimum solution.

Figure 1. Genetic Algorithms steps



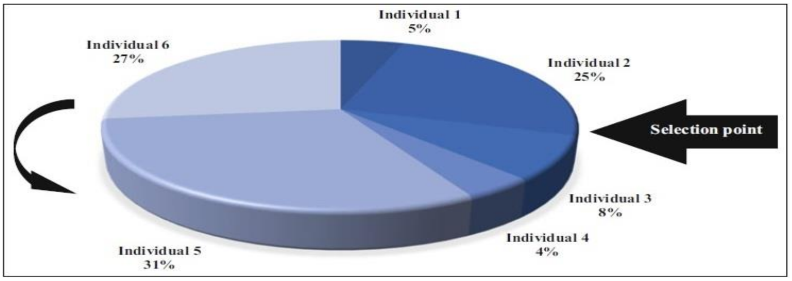
Source: by the researchers depending on: Sastry et al, 2014

2.3.1. Selection

Selection is the process that determines the individuals who participate as parents in the reproduction, with hope of having fitter individuals in next generations simulating natural selection. The selection pressure means how much to prefer higher fitness selection, it is important to balance between exploitation and exploration of the Genetic Algorithm, where strong pressure leads to better convergence, while low pressure may lead to to better diversification of genes (Jebari, 2013).

Inspiring from natural selection, where the fittest individuals have a higher chance to survive and mating, the more common technique of selection is the Roulette Wheel (Figure 2), it assigns probabilities to individuals calculated according to fitness function, and the corresponding individuals to the random selection point are chosen for reproduction (Blickle,Thiele, 1996; Mirjalili, 2019).

Figure 2. Example of Roulette Wheel (The best individual 5 has the largest share of the roulette wheel, while the worst individual 4 has the lowest share)



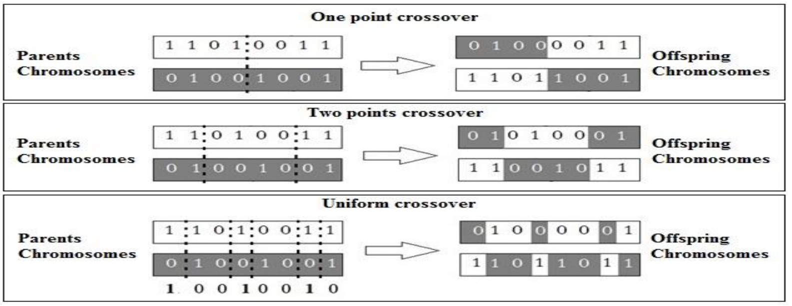
Source: Mirjalili, 2019, p.45

The well-known selection techniques besides the Roulette Wheel are (Katoch et al, 2021): rank selection (Holland, 1975), tournament (Goldberg, 1989), Boltzmann selection (Goldberg, 1990) and stochastic universal sampling (Blickle,Thiele, 1996).

2.3.2. Reproduction

The selected individuals genes are combined to reproduce new offspring, crossover operators are used to exchange chromosomes parts of the parents in one or more points to create new offspring with new Genotypes. There are different methods of crossover in the literature and the most common are illustrated in figure 3 that differ in terms of the crossover points: one point crossover, two points crossover and uniform crossover (Sastry et al, 2014).

Figure 3. Crossover methods

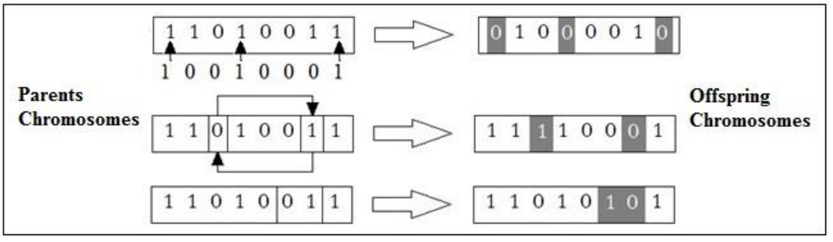


Source: Sastry et al, 2014, p.97

2.3.3. Mutation

Mutation is an operator that maintains the genetic diversity of the population over generations, by introducing another level of randomness and covering lost genes, which allows to increase exploration of search space (Mirjalili, 2019), the mutation creates new genotypes by changing gene codes with a specific rate, commonly through (figure 4): flipping codes, interchanging specific points, or reversing codes in specific points (Sivanandam, Deepa, 2008).

Figure 4. Mutation methods



Source: Sivanandam, Deepa, 2008

As the mutation is based on random changes, it disturbs individual genes, the strength of this disturbance is called mutation rate. There are three main requirements for mutation operators: reachability (each point in search space must be reachable), unbiasedness (not induce a drift to a particular direction) and scalability (offer an adaptable degree of freedom) (Kramer, 2017).

2.3.4. Replacement

Replacement is the final process of Genetic Algorithms operations loop, where the new offspring created by crossover and mutation is introduced to replace the weakest individuals of the current generation according to fitness function evaluations, while the population size still the same, thus, this operation results the creation of a new generation of the population employing the mechanism of "Survival of the Fittest" (Haupt, Haupt, 2006).

2.3.5. Termination

The termination criteria defines when the Genetic Algorithms operations loop must stop, then the best individual is taken as the optimum solution, the Genetic Algorithm can stop whether: after a specific time, a specific predefined number of generations or after a while of no change in the fitness. It can also terminate according to one of the following conditions (Sivanandam, Deepa, 2008):

- The best individual fitness overpasses a convergence value; this guarantees a good solution at least.
- The worst individual fitness overpasses a convergence value; this guarantees an entire good population, although the best individual may not be significantly better than the others.
- The sum of fitness overpasses a convergence value considering the population size, this guarantees the population to be in a specific level of fitness, but the extreme values can affect this sum.
- The median fitness overpasses a convergence value; this guarantees at least half population of good solutions.

3- EMPIRICAL STUDY

The aim of our study is to apply Genetic Algorithms in Panel Data modeling optimization, focusing on integrating Fixed Effects (FE) and Random effects (RE) models estimations to have a Mixed Effect Panel Data Model that measures the impact of financial performance variables on the stock price of ten (10) of leading listed companies in Saudi Arabia stock market in the last twelve (12) years.

3.1- Data and Variables

We have chosen ten (N=10) of leading listed companies in Saudi Arabia stock market based on Forbes-Middle-East list of top performing Arab companies[1] and the availability of financial data. The chosen companies are as follows: SABIC, SEC, STC, ZAIN, RABIGH, KAYAN, SIPCHEM, MOBILY, SAVOLA and TASNEE.

Then, in order to obtain their stock price Panel Data model, we created annual time series from 2010 to 2021 (T=12 years) related to the companies above containing the variables below calculated according to the official financial statements:

- Stock Price (SP as dependent variable)
- Return On Equity (ROE) = Net Return / Total Equity
- Return On Assets (ROA) = Net Return / Total Assets
- Earnings Per Share (EPS)
- Financial Leverage (FL) = Total Liabilities / Total Equity
- Current Ratio (CR) = Current Assets / Current Liabilities

These explanatory variables were selected focusing on the effects of profitability, capital structure and liquidity; and depending on some related previous studies (Barakat, 2014; Sukmawati, Garsela, 2016; Asmirantho, Somantri, 2017; Christina, Robiyanto, 2018; Mohamed et al., 2021).

3.2- The Study Methodology

For reason of results confirmation and comparison, first, we estimate Fixed Effects model with Least Squares with Dummy Variables (LSDV) and Random Effect Model with Generalized Least Squares method (GLS), using Eviews software.

The models equations are written as follows (Bourbonnais, 2011):

$$\text{FE}: y_{it} = c_i + a' x_{kt} + \varepsilon_{it}$$

[1] https://www.forbesmiddleeast.com/ar/lists/top-100-listed- companies-2022/

$$\text{RE:}y_{it} = c + a'x_{kt} + (c_i + \lambda_t + v_{it})$$

y_{it} : The dependent variable, x_{kt} : Independent variables,
ε_{it} : Random error, c : Constant coefficient,
a' : Independent variables coefficients, c_i : Fixed effect coefficient,
v_{it} : Random effect coefficient, λ_t : Time effect coefficient.

Afterward, the models of our study are written as follows:

$$\text{FE:}SP_{it} = c_i + a_1ROE_{it} + a_2ROA_{it} + a_3EPS_{it} + a_4FL_{it} + a_5CR_{it} + \varepsilon_{it}$$

$$\text{RE:}y_{it} = c + a_1ROE_{it} + a_2ROA_{it} + a_3EPS_{it} + a_4FL_{it} + a_5CR_{it} + (c_i + \lambda_t + v_{it})$$

Next, we perform Hausman test (1978) to select between FE and RE:

$$\begin{cases} H_0: \hat{a}_{LSDV} - \hat{a}_{GLS} = 0 \rightarrow RE\ is\ the\ must\ selected\ model \\ H_1: \hat{a}_{LSDV} - \hat{a}_{GLS} \neq 0 \rightarrow FE\ is\ the\ must\ selected\ model \end{cases}$$

$$H = (\hat{a}_{LSDV} - \hat{a}_{GLS})'[Var(\hat{a}_{LSDV}) - Var(\hat{a}_{GLS})]^{-1}(\hat{a}_{LSDV} - \hat{a}_{GLS})$$

H is distributed according to Chi-square with k as degree of freedom, then, we accept H_0 if $H > \chi^2(k)$.

After estimating models and performing test using Eviews software, we pass to use our proposed Genetic Algorithm method to estimate Mixed Effects model (ME) by maximizing the Quasi-Likelihood function.

Quasi-likelihood is an approximate likelihood function for estimating generalized linear models with an easier use, and it gives fitter estimation when its density is normally distributed (Wedderburn, 1974; Bollerslev, Wooldridge, 1992); so it can also be used efficiently to estimate RE models (Breslow, Clayton, 1993). Afterward the Fitness Function for Mixed Effects model is formulated as follows:

$$f(SP) = Max \sum_{it=1}^{NT} \ln\left(\frac{1}{\sqrt{2\pi(\widehat{SP}_t + v_t)}} e^{\frac{-0,5[(SSR+SSR_{RE})/(NT-k)]}{\widehat{SP}_{it}+v_{it}}}\right)$$

$$\widehat{SP}_{it} = c + c_i + a_1 ROE_{it} + a_2 ROA_{it} + a_3 EPS_{it} + a_4 FL_{it} + a_5 CR_{it}$$

$$SSR_{RE} = \sum_{it=1}^{NT} u_{it}^2$$

$$u_{it} = SP_{it} - \widehat{SP}_{it} - v_{it}$$

$$SSR = \sum_{it=1}^{NT} e_{it}^2$$

$$e_{it} = SP_{it} - \widehat{SP}_{it}$$

$f(SP)$ allows to maximize likelihood in order to minimize model errors and normally distributed Random Effects variance, we can add the Fitness Function of the Fixed Effects model estimation that minimize Sum Squared Residuals:

$$f(SP_{FE}) = Min\ (SSR_{FE} = \sum_{it=1}^{t} e_{itFE}^2)$$

$$\widehat{SP}_{itFE} = c + c_i + a_1 ROE_{it} + a_2 ROA_{it} + a_3 EPS_{it} + a_4 FL_{it} + a_5 CR_{it}$$

Evolver software is one of Palisade Decision Tools pack of decision support that works as an Excel add-in to solve various kinds of problems using Genetic Algorithms. Thus, we form the model study in Excel sheet like a dashboard including: Fitness Function and variables besides statistical tests needed: Student of coefficient significance and Hausman test.

After setting Fitness Function and variables in Evolver, we run the Genetic Algorithm iterations of the repeated operations loop: selection, reproduction, mutation and replacement. We prefer that the termination will be unspecified, so we let the algorithm limitless as we watch results generations, then we stop it when satisfying results are achieved.

3.3- Results and Discussions

The results obtained by Eviews software are as shown in table 1:

Table 1. Eviews Results

	Random Effects Model			Fixed Effects Model		
Variable	**Coefficient**	**t-Statistic**	**P**	**Coefficient**	**t-Statistic**	**Prob**
C	25,7956	3,627939	**0,0004**	26,1716	6,96758	**0,0000**
ROE	-28,2797	-2,119263	**0,0362**	-26,7891	-1,9987	**0,0482**
ROA	126,2979	2,323513	**0,0219**	130,1319	2,38123	**0,0191**
EPS	2,1920	2,842675	**0,0053**	2,015	2,59542	**0,0108**
FL	-0,8965	-1,017881	0,3109	-0,7195	-0,8007	0,4251
CR	0,2631	0,124482	0,9012	-0,1858	-0,0858	0,9318
C_1	52,3358			54,6572		
C_2	-6,60893			-7,4855		
C_3	-14,6270			-14,5039		
C_4	-9,0011			-9,8443		
C_5	-8,6444			-9,7824		
C_6	-11,7382			-11,7987		
C_7	-8,7996			-8,4691		
C_8	7,4754			7,3618		
C_9	10,5975			10,596		
C_{10}	-10,9893			-10,731		
R^2	0,8993			0.9079		
SSR	7961,3835	**SSR-RE**	751,621	7933,221		
		Chi-Sq. Statistic		**df**		**P**
Hausman Test		6,32		5		**0,2762**

Source: by the researchers depending on Eviews outputs.

The Table 1 shows that in both estimated models (RE and FE) ROE, ROA and EPS have a significant impact ($P < 0,05$) on the dependent variable SP, while FL and CR haven't ($P > 0,05$).

From Hausman test we see that $P > 0,05$ so we accept H_0 and conclude that is preferable to take Random Effects model.

The results obtained by Evolver software are as shown in table 2:

Table 2. Evolver Results

	Mixed Effects Model			Fixed Effects Model		
Variable	**Coefficient**	**t-Statistic**	**P**	**Coefficient**	**t-Statistic**	**Prob**
C	25,5925	6,81	**0,0000**	26,1716	6,96	**0,0000**
ROE	-26,7673	-1,99	**0,04582**	-26,7891	-1,99	**0,0482**
ROA	130,0012	2,37	**0,0173**	130,1319	2,38	**0,0191**
EPS	2,0161	2,59	**0,0094**	2,015	2,5954	**0,0108**
FL	-0,7191	-0,8	0,4235	-0,7195	-0,80	0,4251
CR	-0,1872	-0,08	0,9311	-0,1858	-0,08	0,9318
C_1	55,2388			54,6572		
C_2	-6,9079			-7,4855		
C_3	-13,9197			-14,5039		
C_4	-9,2661			-9,8443		
C_5	-9,2041			-9,7824		
C_6	-11,2174			-11,7987		
C_7	-7,8851			-8,4691		
C_8	7,9422			7,3618		
C_9	11,1754			10,596		
C_{10}	-10,1516			-10,731		
R^2	0.907972			0.907972		
SSR	7933,221	**SSR-RE**	441,065	7933,221		
		Chi-Sq. Statistic		**df**		**P**
Hausman Test		0,000112		5		**0,9999**

Source: by the researchers depending on Eviews outputs.

We see from the results shown by Table 2 that FE models estimated by Eviews and Evolver are the same, and the ME model shows as well ROE, ROA and EPS impact significance at $\alpha = 5\%$ with no significance of FL and CR.

We see also that there is no big difference between coefficients of FE and ME, which is confirmed by Hausman test that show a high significance (0,9999), thus, we accept the null hypothesis H_0 and take the ME model as a favorite model.

Comparing results of Tables 1 and 2, we see that characteristics of ME model are relatively better than RE model where:

- SSR of ME = 7933,221 < SSR of RE = 7961.3835: the value of global Summed Squared Residuals of Mixed Effects model is lower, which means that values are estimated with less residuals.

- SSR_{RE} of ME = 441,065 < SSR_{RE} of RE = 751,621: the value of Summed Squared Residuals related to random effects in Mixed Effects model estimation is lower, which means that values are estimated with less randomness
- R^2 of ME = 0,907972 > R^2 of ME = 0, 8993: The coefficient of determination of Mixed Effects model is better, which means a stronger correlation between the dependent variable and explanatory variables.
- These characteristics means that Mixed Effects Model provide more accurate estimation comparing to Random Effect model estimated by the traditional econometric method, this finding is consistent with studies related to econometric modeling using Genetic Algorithms such as Ong et al. (2005),Hong et al. (2013) and Deif et al. (2021).

Concerning Evolver (Genetic Algorithms) usage, we noted the following observations:

- The entrance of data and Outputs displaying are designed and adjusted according to user choices and preferences (tables, colors, font sizes…), which allows to the user more freedom, flexibility and facility to consult results that include: model coefficients, estimated values, residuals, statistical parameters and tests; all directly from one Excel sheet like a dashboard.
- Regarding the taken time, it takes few minutes to have a good solution, though, we let Evolver generating for 5 hours. After trying several times, we noticed that the time to achieve the final optimum solution is not constant, because it depends on random Genetic Algorithms operations; it is also related to computer's speed. We advise to let the running on as long as possible, to repeat several times and to shrink the search space and regenerate again after termination for more optimization.

The fittest model concluded by using Genetic Algorithms depending on Evolver software is as follows:

$$\widehat{SP}_{itME} = 25{,}59 - 26{,}76ROE_{it} + 130ROA_{it} + 2{,}01EPS_{it}$$
$$-0{,}71FL_{it} - 0{,}18CR_{it} + c_i$$

The model interpretation is as follows:

- The coefficient of determination R^2 = 0,90 means that the model variables determine statistically 90% of Stock Price value.
- There is a significant positive relationship between Stock prices and Return on Assets, where SP is raised by 130 of ROA, because a higher ROA indicates that the company is generating more profit per unit of asset investment, which is generally viewed positively by investors. This finding is consistent with the study performed by Sukmawati and Garsela (2016) and Mohamed et al. (2021)
- There is a significant positive relationship between Stock prices and Earning per Share, where SP is raised by 2,01 of EPS, because EPS is considered as one of the most commonly used metrics to evaluate companies in the stock market, a higher EPS indicates that the company is generating more profit for each share of common stock, which is also viewed positively by investors. This finding is consistent with the study of Mohamed et al. (2021).
- There is a negative relationship between Stock prices and Return on Equity but with less significance (0,045) comparing to ROA and EPS, where SP is reduced by 26,76 of ROE, this is possibly because of the of impact Total Equities (the denominator of ROE). This finding is consistent with Sukmawati and Garsela (2016) study.
- There is no significant relationship between Stock prices and Financial Leverage with coefficient of -0,71 which is consistent with Barakat (2014), besides no significant relationship either with Current Ratio that represents Liquidity with coefficient of -0,18 which is consistent with Asmirantho, Somantri (2017), Christina and Robiyanto (2018).

CONCLUSION

After addressing literature review about Genetic Algorithms aspects including its econometrical applications, basic elements and operations; we succeeded to apply it in Panel Data modeling optimization, so we obtained the optimum Mixed Effect model of the impact of financial performance variables on the stock price of ten (10) of leading listed companies in Saudi Arabia stock market in the last twelve (12) years. We found that the stock price have a significant relationship with Return on Equity, Return on Assets and Earning per Share. After comparing this model with Random Effects model obtained by usual econometric methods, we concluded that the Mixed Effects model estimated by Genetic Algorithms is relatively better according to the statistical characteristics; concerning its usage, it allows more freedom and flexibility.

Therefore, we conclude that the Genetic Algorithms can be used efficiently in Panel Data modeling, especially for Mixed Effects estimation, which makes it very helpful for decision support.

References

Adeli H., & **Sarma K., (2006). "**Cost Optimization of Structures Fuzzy Logic, Genetic Algorithms and Parallel Computing", *John Wiley & Sons*, England, 2006.

Alander J. T., (2012). "Indexed bibliography of genetic algorithms in Economics". University of Vaasa, Department of Electrical *Engineering and Automation*, Report, 94-1.

Asmirantho E., & **Somantri O. K. (2017).,** "The effect of financial performance on stock price at pharmaceutical sub-sector company listed in Indonesia stock exchange". *JIAFE* (*Jurnal Ilmiah Akuntansi Fakultas Ekonomi*), 3(2), 94-107.

Barakat A., (2014). "The impact of financial structure, financial leverage and profitability on industrial companies shares value (applied study on a sample of Saudi industrial companies)". *Research Journal of Finance and Accounting*, 5(1), 55-66.

Blickle T. & **Thiele L. (1996).** "A comparison of selection schemes used in evolutionary algorithms". *Evolutionary Computation*, 4(4), 361-394.

Bodie, Z. Kane, A. Marcus, A. J. (2011). "Investments, 9th edition". McGraw-Hill Irwin, NY.

Bollerslev T., & **Wooldridge J. M., (1992).** "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances". *Econometric reviews*, 11(2), 143-172.

Bourbonnais R., (2011). "*Econométrie : Manuel et exercices corrigés*", Dunod, Paris.

Breslow N. E., & **Clayton D. G., (1993).** **"**Approximate inference in generalized linear mixed models". J*ournal of the American statistical Association*, 88(421), 9-25.

Christina O., & **Robiyanto R., (2018).** "*The Effect of financial performance and firm size on stock prices of manufacturing company in 2013-2016*".Proceeding SENDI_U.

Coley D. A., (1999). "*An introduction to genetic algorithms for scientists and engineers*". World Scientific Publishing Company.

De Jong K., (1980). "Adaptive system design: a genetic approach". *IEEE Transactions on Systems, Man and Cybernetics*, 10(9), 566-574.

Deif M. A., Solyman A. A., & **Hammam R. E., (2021).** "ARIMA model estimation based on genetic algorithm for COVID-19 mortality rates". *International Journal of Information Technology & Decision Making*, 20(06), 1775-1798.

Dharma F., Shabrina S., Noviana A., Tahir M., Hendrastuty N., & **Wahyono W., (2020).** "Prediction of Indonesian inflation rate using regression model based on genetic algorithms". *Journal Online Informatika*, 5(1), 45-52.

Goldberg D. E., (1981). "*Robust learning and decision algorithms for pipeline operations*". Unpublished dissertation proposal, University of Michigan, Ann Arbor.

Golberg D. E., (1989). "*Genetic algorithms in search, optimization, and machine learning*". Addison-Wesley, USA.

Goldberg D. E., (1990). "A note on Boltzmann tournament selection for genetic algorithms and population-oriented simulated annealing". *Complex Systems*, 4, 445-460.

Haupt R., & **Haupt S., (2006).** "*Practical Genetic Algorithms*", 2nd edition, John Wiley & Sons, USA.

Hausman J. A., (1978). "Specification tests in econometrics". Econometrica: *Journal of the econometric society*, 1251-1271.

Holland John H., (1975). "*Adaptation in natural and artificial systems*". Ann Arbor: University of Michigan Press.

Hong W. C., Dong Y., Zhang W. Y., Chen L. Y., & **Panigrahi B. K., (2013).** "Cyclic electric load forecasting by seasonal SVR with chaotic genetic algorithm". I*nternational Journal of Electrical Power & Energy Systems*, 44(1), 604-614.

Hung J. C., (2009). "A fuzzy GARCH model applied to stock market scenario using a genetic algorithm". *Expert Systems with Applications*, 36(9), 11710-11717.

Jebari K., & **Madiafi M., (2013).** "Selection methods for genetic algorithms*". International Journal of Emerging Sciences*, 3(4), 333-344.

Karathanasopoulos A., Theofilatos K. A., Sermpinis G., Dunis C., Mitra, S., & **Stasinakis C., (2016).** "Stock market prediction using evolutionary support vector machines: an application to the ASE20 index". *The European Journal of Finance*, 22(12), 1145-1163.

Katoch S., Chauhan S. S., & **Kumar V., (2021).** "A review on genetic algorithm: past, present, and future". *Multimedia Tools and Applications*, 80, 8091-8126.

Koza J. R., (1990, August). "A genetic approach to econometric modeling". In *Sixth World Congress of the Econometric Society*, Barcelona, Spain (Vol. 27).

Kramer O., (2017). "Genetic Algorithms. In: Genetic Algorithm Essentials. *Studies in Computational Intelligence*", vol. 679. Springer, Cham.

Mirjalili S., (2019). "Genetic Algorithm. In: Evolutionary Algorithms and Neural Networks". *Studies in Computational Intelligence*, vol. 780. Springer, Cham.

Mohamed E. A., Ahmed I. E., Mehdi R., & **Hussain H., (2021).** "Impact of corporate performance on stock price predictions in the UAE markets: Neuro-fuzzy model". *Intelligent Systems in Accounting, Finance and Managemen*t, 28(1), 52-71.

Ong C. S., Huang J. J., & **Tzeng G. H., (2005).** "Model identification of ARIMA family using genetic algorithms". *Applied Mathematics and Computation*, 164(3), 885-912.

Rothlauf F., (2006). "*Representations for Genetic and Evolutionary Algorithms*", 2nd edition, Springer, Netherlands.

Sastry K., Goldberg D.E., & **Kendall G., (2014).** "Genetic Algorithms. In: Burke, E., Kendall, G. (eds) *Search Methodologies*". Springer, Boston, MA.

Shi Z., & **Aoyama H., (1997).** "Estimation of the exponential autoregressive time series model by using the genetic algorithm". *Journal of Sound and Vibration*, 205(3), 309-321.

Shin K. S., & **Lee Y. J., (2002).** "A genetic algorithm application in bankruptcy prediction modeling". *Expert systems with applications*, 23(3), 321-328.

Sivanandam S., & **Deepa S., (2008).** "*Introduction to Genetic Algorithms*", Springer, USA.

Sukmawati F., & **Garsela I., (2016, August).** "The Effect of Return on Assets and Return on Equity to the Stock Price. In 2016 *Global Conference on Business*", Management and Entrepreneurship (pp. 53-57). Atlantis Press.

Wedderburn R. W., (1974). "Quasi-likelihood functions, generalized linear models, and the Gauss—Newton method". *Biometrika*, 61(3), 439-447.